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Advancing retrievals of surface reflectance and vegetation indices over forest ecosystems by combining imaging spectroscopy, digital object models, and 3D canopy modelling

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Abstract

Imaging spectroscopy based methods offer unique capabilities for retrieving narrow-band vegetation indices which can be empirically related to functional traits of plants. However, in areas with complex topography, illumination effects affect the retrieval of such indices from high spatial resolution airborne or satellite data. Irradiance components at the pixel level are determined by atmospheric composition, as well as instantaneous illumination-surface-sensor geometries. An accurate pixel-wise description of direct and diffuse irradiance components is necessary to perform atmospheric corrections, finally resulting in improved surface reflectances and hence products. We assess three atmospheric correction strategies, differing in their approaches to simulate instantaneous as well as pixel-wise abundances of diffuse and direct irradiance. We use physically-based approaches in combination with either digital elevation models (DEM), fine resolution digital object models (DOM), or 3D modelling output from the Discrete Anisotropic Radiative Transfer (DART) model. The such obtained top-of-canopy reflectances at the Laegern test-site in Switzerland, are used to assess

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retrieval improvement for a set of indices (Normalized Difference Vegetation Index (NDVI), Photochemical Reflectance Index (PRI), as well as chlorophyll and carotenoid indices). We demonstrate that both, the DOM and the DART based approach, improve the retrievals for flat cast-shadows by $\leq 71\%$ compared to using a DEM. In dense forest areas, improvements are less significant. Remaining key issues are related to overestimating surface reflectance under extreme illumination conditions.

Keywords: Imaging spectroscopy, remote sensing, atmospheric correction, shadow, APEX, diffuse and direct irradiance, DOM, DART, NDVI, PRI, chlorophyll, carotenoids

1. Introduction

Imaging spectroscopy is often employed to infer physiological, biochemical, and structural vegetation traits that eventually allow assessing and monitoring spatio-temporal variations in vegetation functioning, health and status. A wide range of different analytical methods (e.g. vegetation indices, model inversion techniques) are available to retrieve such quantitative information from measured radiometric signals (Kokaly et al., 2009; Schaepman et al., 2009; Ustin et al., 2009). Increasing spectral resolution of optical sensors offers new opportunities in vegetation monitoring, which were not possible before. Besides biochemical vegetation information (e.g. leaf chlorophyll content and leaf water content), functional information such as the de-epoxidation state of xanthophylls (Gamon et al., 1990) and sun-induced chlorophyll fluorescence (Damm et al., 2015a; Rascher et al., 2015) can be retrieved nowadays. The retrieval of such vegetation information is achieved by either measuring subtle changes of leaf reflectance using reflectance based approaches or exploiting narrow atmospheric absorption features using radiance based approaches. Advancements in sensor technology allow combining high spectral with high spatial resolution (Wulder et al., 2004). This information is complex in its nature, in particular due to the increasing shadow fraction for each pixel, in particular in highly ver-

20 tically structured vegetation. In particular measurements of individual species,
 21 such as trees, are always composed of a mixture of sunlit and shaded parts,
 22 complicating retrievals of surface reflectance values as well as functional traits
 23 (Gastellu-Etchegorry et al., 1999). Further, highly accurate estimates of sur-
 24 face irradiance are of increasing interest for specialised applications (e.g. Damm
 25 et al., 2014). Irradiance varies in intensity and spectral composition, depending
 26 on atmospheric composition (Seidel et al., 2012). Direct irradiance at surface
 27 level represents radiation which remains un-scattered while diffuse irradiance
 28 contains radiation which was previously scattered by gases or aerosols in the
 29 atmosphere and by the surroundings of the target surface. Multiple scatte-
 30 ring within the atmosphere leads to a wavelength dependent increase of the
 31 atmospheric pathway and thus an increase of atmospheric molecular absorption
 32 compared to the direct path. It has been demonstrated that these wavelength
 33 dependent differences between direct and diffuse irradiance lead to considerable
 34 errors in retrieved surface reflectance and subsequently derived vegetation in-
 35 formation if pixel-wise estimates of direct and diffuse irradiance are uncertain
 36 (Damm et al., 2015b). Accurate and instantaneous atmospheric corrections of
 37 high spectral and spatial resolution data are challenging (Matthew et al., 2002;
 38 Seidel et al., 2010). The state of the atmosphere at acquisition time plays a
 39 vital role because local and temporal variations in water vapour and aerosol lo-
 40 adings impact spectral irradiance estimates (Cho et al., 2003). To overcome this
 41 limitation, a precise parameterization of the atmosphere for radiative transfer
 42 codes is required (Key & Schweiger, 1998). In order to properly describe these
 43 complex irradiance fields one can no longer assume uniformly flat Earth surfaces
 44 or use coarse digital elevation models (DEM) which do not resolve small scale
 45 height differences for correction (Richter, 1990, 1998). Several approaches have
 46 been discussed to minimize those uncertainties. Minimizing varying illumina-
 47 tion effects can be achieved by only considering sunlit pixels (Asner et al., 2015;
 48 Malenovsky et al., 2013). Other methods include the use of matched filtering
 49 of reflectance data to detect and correct shadows (Adler-Golden et al., 2002).
 50 More sophisticated approaches make intensive use of auxiliary data. Digital ob-

51 ject models (DOM) derived from LiDAR data are used to better represent the
 52 surface (Friman et al., 2011). Other approaches involving ray tracing through
 53 LiDAR based voxel grids have been proposed (Schläpfer et al., 2003; Kükenbrink
 54 et al., 2016). In this study we hypothesize that (1) more accurate irradiance
 55 fields can be modelled by using auxiliary, scene specific data and that (2) these
 56 irradiance fields can be integrated in the atmospheric correction process to mi-
 57 nimize product sensitivity to illumination effects. This will finally lead to (3)
 58 retrievals of vegetation indices showing a substantially reduced sensitivity to
 59 surface illumination. We evaluate three approaches for atmospheric correction
 60 that are all using four-stream theory (Verhoef & Bach, 2003) and account for
 61 direct and diffuse irradiance variations by employing different auxiliary data.
 62 All approaches are applied to data acquired with the Airborne Prism Expe-
 63 riment (APEX) imaging spectrometer (Schaepman et al., 2015), allowing an
 64 evaluation based on commonly encountered illumination situations. We derive
 65 vegetation indices (Normalized Difference Vegetation Index (NDVI), Photoche-
 66 mical Reflectance Index (PRI) and two pigment indices for chlorophyll (CHL)
 67 and carotenoids (CAR)) to demonstrate the impact of the correction methods
 68 on remote sensing products.

69 **2. Study site and data**

70 *2.1. Study site*

71 The Laegern study site is a limestone hill northwest of Zurich, Switzerland
 72 ($47^{\circ}28'54.75''\text{N}$ $8^{\circ}23'37.82''\text{E}$, 866m a.s.l.), stretching West to East. The site
 73 is mainly covered by a temperate mixed forest with a high diversity of tree
 74 species (dominated by beech, ash, sycamore and spruce) of different ages and
 75 sizes (Eugster et al., 2007). The Laegern is a well-studied site and contains a
 76 flux tower which is part of the AERONET (Holben et al., 1998) and FLUXNET
 77 (Baldocchi et al., 2001) measurement networks. The extent of the study site
 78 used here contains the Laegern forest as well as surrounding agricultural areas.

Figure 1: APEX flight line (at-sensor radiance, RGB colour composite) of the Laegern study site (June 26, 2010, 15:30 UTC). The background is a hillshaded DEM illustrating scene topography (DHM25 from Swisstopo, Switzerland).

79 2.2. Imaging spectrometer data

80 The main datasets used are two flight lines covering the study site (fig. 1).
81 They were acquired by APEX on the 26th of June 2010 at 15:30 UTC and on
82 the 29th of June 2010 at 10:00 UTC. The solar zenith and azimuth angles at
83 acquisition time are listed in tab. (1). APEX is an airborne pushbroom imaging
84 spectrometer covering the 372 nm to 2500 nm region in 312 contiguous spectral
85 bands. In this study, a spectral subset of the available bands is used, ranging
86 from 399 nm to 914 nm , as these bands contain the necessary information to
87 derive the desired vegetation indices and processing time is reduced. In this
88 wavelength range, APEX shows a spectral sampling interval of 0.45-7.5 nm and
89 a spectral resolution of 0.86-15 nm (Schaepman et al., 2015). The data was
90 pre-processed and provided as radiometrically, spectrally and geometrically ca-
91 librated radiances (level 1) (Hueni et al., 2009). The two datasets were then

georectified using the PARGE software (Schläpfer & Richter, 2002). The resulting pixel size was 2.0 m and based on 18 ground control points, a root mean square error (RMSE) of $2.05\text{ m} \pm 1.1\text{ m}$ was calculated. Most of the analysis is constrained to a spatial subset covering around 3.5 km^2 with a maximum width of 3.6 km and maximum length of 2.4 km due to the smaller spatial extent of the auxiliary data used. The dataset acquired on the 26th acts as primary dataset since it shows more extreme illumination conditions at acquisition time. The dataset of the 29th is used for cross-validation purposes.

Table 1: Solar zenith and azimuth angles at acquisition time for the two acquisitions.

Day	Time	Solar zenith	Solar azimuth
June 26	15:30 UTC	48.1	259.0
June 29	10:00 UTC	29.3	138.5

2.3. Elevation models and derived datasets

Two data sources were used to calculate elevation data for further analysis, 1) the swissALTI3D data product (Swisstopo, Switzerland), resolving terrain elevation in 2 m spatial resolution, and 2) an airborne laser scanning (ALS) based surface height measurements with a 1 m foot print size (cf. Schneider et al., 2014). The ALS dataset was integrated in the swissALTI3D elevation model to increase precision of available height and crown topography information. The spatial resolution of this combined data set was resampled to 2 m to fit the APEX resolution. Two elevation models are derived from this elevation data set and act for further analysis, a DOM and a DEM. The DOM features the surface height information of 2 m spatial resolution. For the DEM, elevation information was smoothed using a large window low-pass filter. This preserves overall canopy height over forested areas but single trees are not resolved due to the smoothing. From both elevation models, datasets of slope, aspect and illumination were derived using the PARGE software, neglecting reflected terrain irradiance from adjacent pixels. The illumination value is represented by the cosine of the local illumination angle ($\cos\theta_{il}$). For the DOM, a binary cast-shadow mask

117 was calculated using PARGE. The cast shadow calculation is based on a ray
 118 tracing algorithm which requires the solar azimuth and elevation angles as well
 119 as the DOM as input. Obscured pixels are flagged as cast shadows. These are
 120 pixels which cannot be reached by rays originating from the sun direction, due
 121 to topographic occlusion. The mask is applied to the illumination data so that
 122 the illumination equals zero in cast shadows.

123 **3. Methods**

124 *3.1. Atmospheric correction approaches*

125 According to (Verhoef & Bach, 2003), the radiative transfer in the atmosphere-
 126 surface system can be sufficiently approximated with the so-called four-stream
 127 theory comprising four spectral flux types. The fluxes considered are the do-
 128 wnward solar flux, the diffuse downward flux, the diffuse upward flux and the
 129 upward spectral radiance in the direction of the observer. This study focuses
 130 exclusively on radiative transfer modelling approaches based on this theory to
 131 determine TOC hemispherical-directional reflectance factors (HDRF). To elab-
 132 orate, irradiance is considered hemispherically while reflected radiances are
 133 measured by a sensor with a very small but non-zero IFOV (i.e., APEX IFOV
 134 is 0.025°). In theory this results in hemispherical-conical reflectance factors
 135 (HCRF). In practice, however, reflectances from such small IFOV measurements
 136 are generally referred to as HDRF to differentiate them from wide IFOV instru-
 137 ment results (cf. Schaepman-Strub et al., 2006, for details on terminology). Cali-
 138 brated radiance data is processed to HDRF data using a simplified atmospheric
 139 correction approach compared to the state of the art atmospheric correction
 140 software ATCOR-4 (Richter & Schlpfer, 2002, 2016). The simplified approach
 141 includes the complete four-stream radiative transfer calculations but excludes
 142 atmospheric parameter retrieval, spectral polishing, and radiometric fine tuning
 143 steps as implemented in ATCOR-4. We decided on a simplified atmospheric cor-
 144 rection approach to ease evaluations and adjustments of atmospheric correction
 145 strategies. We also applied ATCOR-4 and used obtained HDRF as a reference

146 to evaluate reliability of results stemming from the simplified atmospheric cor-
 147 rection approach. In general, the atmospheric correction process can be divided
 148 into the following four steps: i) the simulation and storage of atmospheric trans-
 149 fer functions in look-up tables (LUT), ii) the estimation of spectral shifts and
 150 band broadening, iii) the convolution of the atmospheric functions considering
 151 the actual spectral sensor configuration, and iv) the calculation of HDRF values
 152 by combining measured at sensor radiances and simulated LUT entries. The
 153 simulation of atmospheric functions is performed for five different ground heig-
 154 hts using MODTRAN5 (Berk et al., 2006) and the MODTRAN interrogation
 155 technique as introduced by Verhoef & Bach (2003). Atmospheric variables wa-
 156 ter vapour and aerosol optical thickness (AOT), required to parameterize MOD-
 157 TRAN5, were chosen based on sun-photometer measurements from a close by
 158 AERONET station (Holben et al., 1998) and ATCOR-4 image-based retrievals.
 159 The simulation of combined atmospheric functions (e.g., combined downward
 160 and upward transmittances) was performed in this step to avoid violation of the
 161 Beer-Lambert law in subsequent calculations with convolved functions (Verhoef
 162 et al., 2014). The estimation of potential spectral misregistrations, also known
 163 as spectral smile, common to pushbroom spectrometers, and band broadening
 164 of APEX was performed with a method included in ATCOR-4 (Richter et al.,
 165 2011). Obtained spectral characteristics of APEX are used to generate spectral
 166 response functions to eventually convolve simulated atmospheric functions. The
 167 atmospheric correction approaches used in this study are listed in tab. (2). The
 168 method of simulating irradiance is varied in three steps of theoretically increa-
 169 sing accuracy. Each method requires a different set of auxiliary data as input.
 170 The first approach approximates irradiance variations using a coarse DEM and
 171 serves as a reference (DEMAC). The second approach follows the same pro-
 172 cedure but uses a DOM to determine irradiance (DOMAC). Finally, the third
 173 approach utilizes irradiance scaling factors derived from top-of-canopy (TOC) ir-
 174 radiances simulated by the 3D Discrete Anisotropic Radiative Transfer (DART)
 175 model (Gastellu-Etchegorry et al., 2015) (DARTAC). The three methods are
 176 elaborated in the following sections.

Table 2: Reference for the atmospheric correction approaches used, their acronyms and auxiliary data inputs from which irradiance is derived.

Acronym	Input	Description
ATCOR	DEM	Atmospheric correction performed with the ATCOR-4 software
DEMAC	DEM	Simplified atmospheric correction procedure based on four-stream theory
DOMAC	DOM	Identical to DEMAC but using a DOM as input
DARTAC	parameterized voxel grid	Identical to DEMAC but utilizing DART derived irradiance fraction maps as scaling factors

3.1.1. DEMAC: Simple atmospheric correction using a smoothed digital elevation model

Verhoef et al. (2014) have used the four-stream theory to simulate top-of-atmosphere (TOA) radiances using combined models (e.g., SCOPE (Van der Tol et al., 2009), and MODTRAN4). According to them, the radiative transfer through the atmosphere yielding TOA radiance for a target (L_{TOA}) can be described as (eq . 1):

$$\begin{aligned}
L_{TOA} = & \rho_{so} \frac{E_s^o \cos \theta_s}{\pi} \\
& + \left[\frac{\tau_{ss} r_{so} E_s^o \cos \theta_s}{\pi} + \frac{(\tau_{sd} + \tau_{ss} \bar{r}_{sd} \rho_{dd}) E_s^o \cos \theta_s / \pi}{1 - \bar{r}_{dd} \rho_{dd}} r_{do} \right] \tau_{oo} \quad (1) \\
& + \left[\frac{(\tau_{sd} \bar{r}_{dd} + \tau_{ss} \bar{r}_{sd}) E_s^o \cos \theta_s / \pi}{1 - \bar{r}_{dd} \rho_{dd}} \right] \tau_{do}
\end{aligned}$$

Eq. (1) is formed by three additive terms including the atmospheric path radiance, the target's surface radiance, and the adjacency effect. The surface reflectance can be described by four terms: r_{so} is the bi-directional reflectance factor of the target (BRF), r_{do} the hemispheric-directional reflectance factor of the target (HDRF), $\bar{r}_{sd}$ is the smoothed directional-hemispherical reflectance factor

190 (DHRF) of the surroundings and $\bar{r}_{dd}$ is the smoothed bi-hemispherical reflec-
 191 tance factor (BHRF) of the surroundings. ρ_{so} is the atmospheric bi-directional
 192 reflectance and ρ_{dd} is the spherical albedo at the bottom of the atmosphere. τ_{ss}
 193 represents the direct atmospheric transmittance in sun-direction, τ_{oo} the direct
 194 atmospheric transmittance in view-direction, τ_{sd} the diffuse atmospheric trans-
 195 mittance for the solar incidence, and τ_{do} the directional atmospheric transmit-
 196 tance for diffuse incidence. E_s^o is the extra-terrestrial solar spectral irradiance on
 197 a plane perpendicular to the sun-rays. θ_s is the local solar zenith angle (Cogliati
 198 et al., 2015). Eq. (1) can be written following the T-18 system as introduced
 199 by Verhoef et al. (2014). When adding viewing factors for direct and diffuse
 200 irradiance (V_{sun} , V_{sky}) (Verhoef & Bach, 2012), L_{TOA} of a non-Lambertian,
 201 non-uniform and tilted surface can be expressed as (eq. 2):

$$L_{TOA} \approx T_1 T_2 + \frac{T_1 (T_8 r_{so} V_{sun} + T_9 r_{do} V_{sky} + T_{10} \bar{r}_{sd} + T_{11} \bar{r}_{dd})}{1 - \bar{r}_{dd} T_3} \quad (2)$$

202

203 While T_n represent atmospheric transfer functions (tab. 3), $\bar{r}$ indicate smoot-
 204 hed averaged reflectances and V_{sun} , V_{sky} can be expressed as (eq. 3, eq. 4):

$$V_{sun} = \cos \theta_t + \tan \theta_s \sin \theta_t \cos(\varphi_s - \varphi_t) \quad (3)$$

$$V_{sky} = \frac{1 + \cos \theta_t}{2} \quad (4)$$

205

206 V_{sun} and V_{sky} are scaling factors that express in a simple way how the direct
 207 irradiance of the sun and the diffuse irradiance of the sky are changed by the
 208 local topography. θ_t is the terrain slope inclination, φ_t the terrain slope azimuth,
 209 and φ_s the solar azimuth angle.

Table 3: Atmospheric functions and their abbreviations. Angled brackets represent convolved quantities.

Atmospheric function	Name
$\langle E_s^o \rangle \cos \theta_s / \pi$	T_1
$\langle \rho_{so} \rangle$	T_2
$\langle \rho_{dd} \rangle$	T_3
$\langle \tau_{ss} \rangle$	T_4
$\langle \tau_{sd} \rangle$	T_5
$\langle \tau_{oo} \rangle$	T_6
$\langle \tau_{do} \rangle$	T_7
$\langle \tau_{ss} \tau_{oo} \rangle$	T_8
$\langle \tau_{sd} \tau_{oo} \rangle$	T_9
$\langle \tau_{ss} \tau_{do} \rangle$	T_{10}
$\langle \tau_{sd} \tau_{do} \rangle$	T_{11}

210 Assuming a Lambertian Earth surface, reflectance quantities can be assumed
 211 similar (i.e., TOC reflectance (r) = r_{so} = r_{do} and TOC adjacent reflectance ($\bar{r}$)
 212 = $\bar{r}_{sd}$ = $\bar{r}_{dd}$) so that one can rewrite eq. (2) to yield r from the measured
 213 at-sensor radiance. However, since $\bar{r}$ is still unknown it must be estimated in
 214 two steps using a simplified version of eq. (2) where we assume a non-tilted,
 215 uniform Lambertian Earth surface and use filtered radiances ($\overline{L_{TOA}}$) (eq. 5).
 216 The employed kernel is sharply peaked towards the centre and was derived from
 217 the results of a Monte Carlo simulation of photon scattering, which allows a
 218 description of the adjacency effect by considering the contribution of photons
 219 from ring-shaped intervals of increasing distance to the target. Commonly,
 220 adjacency is estimated using only smoothed reflectance values (e.g. Richter,
 221 1998).

$$\bar{r} = \frac{\overline{L_{TOA}} - T_1 T_2}{T_1(T_8 + T_9 + T_{10} + T_{11}) + (\overline{L_{TOA}} - T_1 T_2)T_3} \quad (5)$$

222

223 This finally allows a retrieval of r as follows (eq. 6):

$$r = \frac{(L_{TOA} - T_1 T_2)(1 - \bar{r} T_3) - \bar{r} T_1 (T_{10} + T_{11})}{T_1 (T_8 V_{sun} + T_9 V_{sky})} \quad (6)$$

224

225 This reflectance retrieval method is applied in combination with the smoot-
226 hed DEM and further referred to as DEMAC.

227 3.1.2. DOMAC: Simple atmospheric correction using a digital object model

228 The smoothed DEM used in the DEMAC approach does not resolve single
229 canopies and therefore can't be employed to describe the strongly varying irra-
230 diance at canopy scale. In order to do this we use a LiDAR based DOM instead.
231 This effectively influences only the scaling factors V_{sun} and V_{sky} while the pro-
232 cessing steps remain identical to DEMAC, reflectance being retrieved with eq.
233 (6). The geometric surface description with a DOM has some limitations as it
234 will yield V_{sun} values of 0 for strongly inclined tree canopies with slopes facing
235 away from the sun as well as for cast-shadows. While a complete lack of direct
236 irradiance is unlikely in these situations, the assumption was deemed adequate
237 for this experiment and resulting overestimates of HDRF taken into account.
238 This reflectance retrieval approach is referred to further as DOMAC.

239 3.1.3. DARTAC: DART radiance output approach

240 The DART model (Gastellu-Etchegorry et al., 2015) is increasingly applied
241 in vegetation analysis, for example as a tool to simulate at-sensor radiance data
242 by parameterizing the model using LiDAR data (Schneider et al., 2014). The
243 potential of such 3D radiative transfer modelling frameworks to derive accurate
244 irradiance estimates has been suggested in previous work (Schläpfer et al., 2003).
245 For our study site, LiDAR point cloud measurements were acquired by an ALS
246 system close to the acquisition of APEX data. The point cloud was converted
247 into a voxel grid and associated with different properties. A tree canopy voxel,
248 for example, was assumed as turbid medium with certain leaf optical properties,

249 plant area index (PAI) and a specific angular distribution of leaves (Gastellu-
 250 Etchegorry et al., 2015). For a detailed description of the parameterization
 251 of the 3D voxel grid, we refer to Schneider et al. (2014) and Schneider et al.
 252 (2015), while details on the DART simulation process can be found in Gastellu-
 253 Etchegorry et al. (2015). Due to computational constraints, only 24 scattering
 254 directions were used and a maximum of 3 iterations were performed. Direct
 255 and diffuse irradiances at TOC were derived from DART simulation outputs as
 256 2D grids of irradiance in W/m^2 for four wavelengths representing blue, green,
 257 red and NIR. The irradiance fractions per pixel (henceforth K_{dir} and K_{dif})
 258 were derived relative to the maximum direct or diffuse irradiance, excluding
 259 outliers resulting from processing artefacts, and linearly interpolated for the
 260 wavelengths not simulated. For direct irradiance the scaling factors remain
 261 constant over all wavelengths, while for diffuse irradiance there are wavelength
 262 dependent differences. As the wavelengths used for further analysis lie close
 263 to the simulated wavelengths, this approximation is deemed sufficient. The
 264 fractions can be applied directly as scaling factors for the direct and diffuse
 265 fluxes to retrieve r (eq. 7):

$$r = \frac{(L_{TOA} - T_1 T_2)(1 - \bar{r} T_3) - \bar{r} T_1 (T_{10} + T_{11})}{T_1 (T_8 K_{dir} + T_9 K_{dif})} \quad (7)$$

266

267 This approach is further referred to as DARTAC.

268 3.2. Field spectrometer measurements

269 Two ASD field spectroradiometer (ASD FieldSpec, Analytical Spectral De-
 270 vices, USA) measurements acquired during the 2010 APEX validation campaign
 271 in Wettingen, Switzerland were used as ground-truth data for this study. The
 272 measured spectra allow an evaluation of the atmospheric correction method's
 273 performance. The reference surfaces were selected based on uniformity of the
 274 target, lack of inclination and are pseudo-invariant features. The surfaces are
 275 yellow tartan of the Wettingen sports-ground (47°28'02.30"N 8°18'33.90"E) and

276 a black roof of the swimming baths (47°27'58.84"N 8°18'38.86"E) which sho-
 277 wed near uniform reflectance over all wavelengths. The measurements were
 278 conducted close to acquisition time for both dates and perpendicular to the
 279 surfaces.

280 3.3. Deriving vegetation indices

281 A number of vegetation indices were derived from TOC reflectance data to
 282 evaluate the impact of irradiance effects and their compensation using the three
 283 approaches under evaluation. The use of vegetation indices is an empirical ap-
 284 proach to relate light measurements to vegetation information. Even if properly
 285 calibrated for a specific site, vegetation type and phenological period, wrong es-
 286 timates of surface irradiance pose an additional sensitivity to these indices and
 287 complicate their interpretation. We focus our choice on indices that incorpo-
 288 rate spectral information from the VIS/NIR wavelength regions since they are
 289 more strongly affected by illumination effects and estimated errors can serve as
 290 worst case scenarios. Calculated indices include the NDVI, commonly used as
 291 a proxy for canopy chlorophyll content and fAPAR (Tucker, 1979) (eq. 8) and
 292 the PRI, indicative for the de-epoxidation state of xanthophylls and often app-
 293 lied as proxy for LUE (Gamon et al., 1992, 1997) (eq. 9). Further, we applied
 294 two indices sensitive to the relative content of chlorophyll and carotenoids as
 295 proposed by (Gitelson et al., 2006) (eq. 10 and 11).

$$NDVI = \frac{r_{800} - r_{640}}{r_{800} + r_{640}} \quad (8)$$

$$PRI = \frac{r_{531} - r_{570}}{r_{531} + r_{570}} \quad (9)$$

$$CHL \propto [r_{540-560}^{-1} - r_{790}^{-1}] \times r_{790} \quad (10)$$

$$CAR \propto [r_{510-520}^{-1} - r_{560-570}^{-1}] \times r_{790} \quad (11)$$

Subscripts in eq. 10 and eq. 11 indicate wavelength ranges in nanometer used for the calculation of both indices. Gitelson et al. (2006) provide two models each for CHL and CAR, one incorporating green wavelengths and the other the red edge. We use the mean values over the proposed green wavelength ranges here as they should be more susceptible to differences in irradiance composition.

3.4. Assessment of irradiance effects on vegetation indices

The performance of the DEMAC, DOMAC and DARTAC approaches for the removal of illumination effects in vegetation products is evaluated by comparing obtained index values with reference values representing fully illuminated cases. We set up two tests, the first evaluating the performance of the three approaches in cast-shadows, the second focussing on a forest subset. For the cast-shadow test, a number of areas were chosen and divided into sparsely and densely vegetated surfaces. “Sparsely” vegetated surfaces are surfaces with very low vegetation fraction (e.g. below 10%), close to bare-soil. “Densely” vegetated surfaces have a vegetation cover of 100%. It must be noted that slight changes in the species composition are possible for sparsely vegetated surfaces. We assume, however, that these changes are negligible and do not impact our results. The reference value is extracted over horizontal, fully illuminated areas of the same surface type in the DEMAC result. For the forest test, reference values represent the mean of horizontal oriented and fully illuminated areas (tops of tree canopies) extracted from the DEMAC result. For both tests, mean values of pixel-wise absolute differences between the index and the reference mean value are calculated. The pixel-wise differences are used in order to reflect heterogeneity in the result. Pixel values outside of physically feasible ranges are omitted. Finally, the improvement of the DOMAC and DARTAC approaches over the DEMAC approach is expressed as percentage by which the difference of the index to the reference value for the DEMAC approach could be reduced with either the DOMAC or DARTAC approach. The significance of this difference is assessed using a paired t-test with 95% significance level ($p < 0.05$).

326 4. Results

327 4.1. DEMAC in comparison with ATCOR

328 An evaluation of DEMAC with ATCOR-4 was performed to confirm its suit-
329 ability for further analysis. We particularly compared derived HDRF obtained
330 from both approaches for two acquisition dates of pseudo-invariant features and
331 related them to surface HCRF measurements obtained with a field spectroradiometer (ASD FieldSpec, Analytical Spectral Devices, USA). The results for
332 one such surface are displayed in (fig. 2). For both the 26th and the 29th of
333 June 2010, the mean difference in percent over all bands between DEMAC and
334 ATCOR-4 is around 16% on average. Considering ASD measured HCRF, the
335 DEMAC approach differs by 8.7% for the 26th of June and 23.2% for the 29th
336 of June. ATCOR-4 HDRF values differ from ASD measurements by 9.2% for
337 the 26th and 5.0% for the 29th. Comparisons of HCRF with HDRF should be
338 made with caution as they represent different physical quantities. Furthermore,
339 the deviations between solar zenith angles during APEX and ASD acquisitions
340 are up to 20° . The mean difference in percent between ATCOR-4 based HDRF
341 for the two days is 14.5% while this difference is 13% for DEMAC. It is possi-
342 ble that this variation can be partly explained by the difference in solar zenith
343 angle in combination with reflectance anisotropy effects. Absolute deviations
344 of obtained HDRF values between DEMAC and ATCOR-4 are not detrimental
345 for subsequent analysis. However, some differences appear to be wavelength
346 dependent. ATCOR-4 results appear more robust over wavelengths, while the
347 DEMAC results fit better with each other and to the ASD spectrum in the
348 500-600 *nm* range but deviate more in the NIR. The precise reason, especi-
349 ally for the deviation in the NIR, could not be identified, but there are two
350 differences between the DEMAC approach and ATCOR-4 that likely explains
351 observed differences: i) ATCOR-4 uses the horizon algorithm providing a more
352 accurate value for V_{sky} than the slope based calculation used in DEMAC. ii) In
353 the chosen ATCOR-4 configuration, atmospheric conditions are specified with
354 a constant AOT across the scene but varying water vapour over the image, and
355

356 viewing angle dependent scattering functions for the correction of aerosol effects
 357 were used. In DEMAC, atmospheric parameters were obtained from AERO-
 358 NET and ATCOR-4 and only distributed considering ground and sensor height.
 359 The compensation of adjacency effects was evaluated by observing the averaged
 360 HDRF of a black rooftop (height 5 *m*) (fig. 3). ASD measurements suggest
 361 a spectrally featureless reflectance behaviour with average values of 5%. The
 362 rooftop is located in a valley situation and is surrounded by vegetation (trees
 363 and vegetated mountains). Scattering of adjacent vegetation surfaces would
 364 add a signal to the almost non-reflective roof-top contribution if not adequately
 365 corrected. There are no remnants of any vegetation signals visible in obtained
 366 HDRF spectra and barring a very slight slope towards NIR wavelengths, the
 367 adjacency effect compensation appears to be sufficient. It must be noted that
 368 HDRF values resulting from DEMAC were not smoothed or interpolated as is
 369 done in ATCOR-4, resulting in the visible spikes in the spectrum; differences at-
 370 tributed to this were deemed negligible. The spikes originate from residual errors
 371 in estimated spectral shift and band broadening. If such spectral information is
 372 used to convolve atmospheric functions to match the in-flight spectral setting of
 373 the sensor, spikes typically occur across strong atmospheric or solar absorption
 374 lines. Despite certain deviations between HDRFs obtained from ATCOR-4 and
 375 our implementation, for the evaluated situations the DEMAC procedure was
 376 deemed to perform within sufficient accuracy which is comparable to a more
 377 complex correction scheme in common use.

Figure 2: Comparison of reflectance spectra of a yellow tartan sports-surface, resulting from ASD measurements (HCRF), the DEMAC approach (HDRF), and the ATCOR-4 processing (HDRF). a) 26.06.2010 dataset. b) 29.06.2010 dataset. c) ATCOR-4 result comparison between the two dates. d) DEMAC comparison between the two dates. It must be noted that results for the DEMAC and DOMAC approach are identical for flat surfaces such as the investigated tartan.

Figure 3: Comparison of HDRF spectra averaged over a dark, spectrally uniform reflecting roof for the DEMAC approach and the ATCOR-4 processing, both for the 26.06.2010 dataset.

4.2. Improvement of reflectance retrieval with digital object models

The evaluated DOMAC approach incorporating a DOM to improve irradiance estimates by considering crown geometry yields diverse results. Shaded canopy areas show overestimates of obtained HDRF values (above 100% reflectance) (fig. 4). This is mainly since V_{sun} approaches 0 and due to the large slope angle ($\cos \theta_t$) for such canopy areas, the diffuse component is also heavily reduced through V_{sky} . For sunlit canopy areas, HDRF differences are reduced. This observation could be confirmed also for a large forest canopy subset, where small slope angles yielded improved corrections and steep angles led to overcorrections.

Figure 4: Left: HDRF at 800 nm along a tree-crown to meadow cast-shadow transect (left to right) resulting from DEMAC, DOMAC and DARTAC. The red dashed line indicates the expected true HDRF along the transect for the tree and meadow surfaces. Right: Illustration of the transect for the DEMAC, DOMAC and DARTAC based results as true colour RGB images (top to bottom). The red line indicates the transect as shown in the left figure.

Figure 5: Left: Surface elevation along a tree-crown to meadow cast-shadow transect for the smoothed digital elevation model (DEM) and the digital object model (DOM). Right: Image representation of the smoothed DEM (top) and DOM (bottom). The red line indicates the transect as shown in the left figure.

388 While an offset remains, areas affected by cast-shadows experience an im-
 389 proved correction of illumination effects when compared to fully illuminated

390 regions, as also visible in the transect of fig. 4 and the region of interest (ROI)
 391 comparison of fig. 6. Exceptions are transition zones from fully illuminated
 392 to fully shaded areas, visible as spikes in the transect (fig. 4). The observed
 393 effect is caused by a complex interplay of different factors, including residual
 394 geometric co-registration errors between the DOM and the spectroscopy data,
 395 the simplified radiative transfer scheme applied that neglects vertical radiation
 396 entering the surface, as well as canopy transparency at the outer crown leading
 397 to a very uneven illumination pattern in the transition zone of cast shadow and
 398 full illumination i.e. mixture of sun flecks and shade. The percentage deviation
 399 of retrieved HDRF in cast-shadows from illuminated areas was calculated. The
 400 DEMAC-illuminated pixels with little to no slope are considered as reference
 401 under the assumption that these are closest to the sought surface reflectance
 402 under illuminated conditions, as the surface covered by these pixels receives
 403 full direct and diffuse illumination. DEMAC-shade and DOMAC-shade belong
 404 to pixels of shaded vegetated surfaces. Since the DEM approach does not re-
 405 solve canopy topography (see fig. (5)), the approach assumes full illumination
 406 for these cast-shadow pixels although they predominantly receive diffuse irradi-
 407 ance. This yields an underestimation of retrieved reflectance because irradiance
 408 is overestimated (L/E). Conversely, the use of a DOM provides an improved
 409 estimate of E , thus retrieved reflectance is closer to the reflectance of the fully
 410 illuminated surface. The deviation of HDRF between illuminated and shaded
 411 ROIs decreased on average over all bands from 86.4% for DEMAC to 37.5%
 412 for the DOMAC approach. There are still deviations between calculated means
 413 of up to 56.55%, mainly around 700 nm. Finally, the spatial difference bet-
 414 ween illuminated reference and shaded ROIs guarantee variance but this was
 415 considered during selection and kept as small as possible.

Figure 6: Top: HDRF of shaded surfaces before and after correction. Left: HDRF from the DEMAC approach averaged over fully illuminated regions of interest (ROIs) on highly vegetated surfaces (illuminated), HDRF obtained from the DEMAC approach over cast-shadow ROIs on highly vegetated surfaces (shaded), corrected HDRF from the DOMAC approach averaged over the same cast-shadow ROIs (shaded corr), and the ribbons representing mean $\pm$ one standard deviation for each spectrum. Right: the same as left but with the correction from the DARTAC approach. Bottom: Deviation in percent of the cast-shadow reflectances in respect to the fully illuminated case. Left: Deviation of the DEMAC HDRF and the DOMAC HDRF. Right: the same as left but for DARTAC.

4.3. Improvement of reflectance retrieval with simulated irradiance fractions

Using scaling factors derived from DART simulations to adjust estimates of diffuse and direct irradiance components in atmospheric correction approaches should in theory provide benefits over the DOMAC approach: They are ray-tracing based which allows accounting for multiple scattering within the canopy. Indeed, we observe fewer overestimates of HDRF values over tree canopies in DARTAC results, but reflectance gradients seem to have been conserved for the

423 most part (fig. 4). Evaluating corrected HDRF values at 800 *nm* over a forest
 424 subset, there appear to be generally lower reflectances compared to the DEMAC
 425 with a number of single pixels showing seemingly arbitrary high reflectance.
 426 These over estimated HDRF values are associated with the aforementioned gaps
 427 between trees where both direct and diffuse irradiance drop to near zero. We
 428 did not find a significant correction of shadowing effects across the tree canopies.
 429 Overestimated HDRF values are mainly visible in transition zones from shade to
 430 full illumination, where we observe a spatial mismatch between simulated and
 431 actual cast-shadows in the order of up to two pixels (4 *m*) in the most extreme
 432 cases, as well as for small gaps between trees in the forest. The cast-shadow
 433 transect (fig. 4) reveals a spike where the simulated shadow extends further than
 434 the actual shadow but the difference between shaded and illuminated pixels is
 435 clearly reduced. In the ROI comparison, we found a far larger heterogeneity with
 436 small scale over and under corrections of HDRF values. When averaged, their
 437 reflectance is comparable to fully illuminated counterparts (fig. 6). Averaged
 438 over all bands, the deviation in percentage from illuminated areas to corrected
 439 shaded counterparts has decreased to 9.6% when using DARTAC. The highest
 440 deviation between the averages is 35.5% and is observable at the red-edge.

441 4.4. *Vegetation indices*

442 Results for the evaluation of correction approaches for all vegetation products
 443 are presented in tab. (4) and tab. (5) for the cast-shadow test and for the forest
 444 test in tab. (6). Differences between index and reference values larger than for
 445 the DEMAC case result in negative percentages for "Diff reduced" while an equal
 446 difference corresponds to 0% and a full reduction of differences and therefore
 447 a perfect match of index with reference values corresponds to 100%. A paired
 448 t-test with 95% significance level indicates that mean values of all DOMAC and
 449 DARTAC results are significantly different from the DEMAC result. Fig. (7)
 450 illustrates results for a subset of the scene containing a heterogeneous vegetation
 451 cover and illumination conditions, while Fig. (8) depicts the spatial differences
 452 from the DEMAC results as well as images of the direct illumination and DOM

453 for reference.

454 *NDVI*

455 The difference in NDVI between shaded and fully illuminated areas is very
456 small for both dense and sparse vegetation cover. Applying both, the DOMAC
457 and the DARTAC approach yields overestimated NDVI values in cast-shadow.
458 For densely vegetated surfaces this is a slight overestimation, leading to a re-
459 duction of the difference by 8.6% for DARTAC and next to no change for
460 DOMAC. For sparse vegetation the overestimation is more extreme, leading
461 to values deviating more from the illuminated reference (47.9% and 39.6% in-
462 crease). For the forest subset, both approaches do not yield any improvement
463 and DOMAC results show a 14.9% increased difference.

464 *PRI*

465 For the PRI, differences between shaded and fully illuminated areas are
466 large for dense and sparse vegetation cover. Applying both, the DOMAC and
467 the DARTAC approach yields slightly overestimated PRI values in cast-shadow.
468 The reduction of illumination effects is considerable: for sparse vegetation the
469 improvement is between 43.8% for the DOMAC approach and 65.7% for the
470 DARTAC approach. A similar picture can be observed for dense vegetation.
471 For the forest subset, the DOMAC approach slightly reduces uncertainties while
472 the DARTAC approach yields results close to the DEM result.

473 *Chlorophyll index*

474 Both, the DOMAC and the DARTAC approach yield consistent impro-
475 vements of CHL estimates compared to the DEMAC approach of 38.9 to 71.0%
476 for cast-shadows in sparse and dense vegetation. Of note is however that
477 the DARTAC approach increases the standard deviation considerably. The
478 DOMAC approach shows higher consistency across surface types. The impro-
479 vements for cast-shadows are clearly visible in Fig. (9), however, trees display an
480 overestimation of retrieved chlorophyll content in the DOMAC result (difference
481 to reference is increased by 84.5%). For the DARTAC approach, chlorophyll is

482 slightly underestimated.

483 *Carotenoid index*

484 Retrieved carotenoid contents in cast-shadow show significant improvements
 485 for both approaches. Improvements are consistently above 40% with DARTAC
 486 performing the best for sparsely vegetated areas with 52.2%. Here mean values
 487 are much closer to the reference but the standard deviation is clearly increased,
 488 accounting for the medium reduction overall. For the forest subset there is no
 489 notable change regarding the pixel-wise differences from the reference value.

Table 4: Impact of illumination effects on NDVI, PRI, chlorophyll and carotenoid index retrievals for densely vegetated surfaces. Index values in cast-shadow and fully illuminated areas were compared. The compensation of illumination effects using three atmospheric correction strategies (DEMAC, DOMAC and DARTAC approaches) was evaluated. Calculated statistics include mean, standard deviation, mean pixel-wise absolute difference to the illuminated reference value and percent reduction of this difference in respect to the DEMAC case.

		Mean	StDev	Abs Diff	% Diff reduced
NDVI	Reference	0.863	0.039	-	-
	DEMAC	0.860	0.057	0.046	-
	DOMAC	0.900	0.042	0.046	-0.2
	DARTAC	0.890	0.044	0.042	8.6
PRI	Reference	-0.012	0.014	-	-
	DEMAC	0.109	0.024	0.121	-
	DOMAC	0.061	0.024	0.074	39.4
	DARTAC	0.053	0.030	0.067	44.9
CHL	Reference	6.536	1.219	-	-
	DEMAC	3.678	1.202	2.912	-
	DOMAC	7.300	2.208	1.778	38.9
	DARTAC	6.448	1.837	1.504	48.3
CAR	Reference	7.435	2.137	-	-
	DEMAC	1.541	0.575	5.893	-
	DOMAC	4.222	1.357	3.249	44.9
	DARTAC	4.045	1.445	3.393	42.4

Table 5: Impact of illumination effects on NDVI, PRI, chlorophyll and carotenoid index retrievals for sparsely vegetated surfaces. Index values in cast-shadow and fully illuminated areas were compared. Statistics are described in tab. 4

		Mean	StDev	Abs Diff	% Diff reduced
NDVI	Reference	0.489	0.032	-	-
	DEMAC	0.450	0.069	0.063	-
	DOMAC	0.579	0.058	0.093	-47.9
	DARTAC	0.572	0.070	0.088	-39.6
PRI	Reference	-0.063	0.009	-	-
	DEMAC	0.039	0.024	0.103	-
	DOMAC	-0.006	0.022	0.058	43.8
	DARTAC	-0.030	0.023	0.035	65.7
CHL	Reference	2.226	0.232	-	-
	DEMAC	0.815	0.294	1.411	-
	DOMAC	2.127	0.498	0.409	71.0
	DARTAC	2.279	0.777	0.563	60.1
CAR	Reference	1.071	0.207	-	-
	DEMAC	0.101	0.104	0.970	-
	DOMAC	0.592	0.194	0.491	49.3
	DARTAC	0.979	0.561	0.464	52.2

Table 6: Impact of illumination effects on NDVI, PRI, chlorophyll and carotenoid index retrievals for a forest canopy. Index values in inclined and flat, fully illuminated areas were compared. Statistics are described in tab. 4.

		Mean	StDev	Abs Diff	% Diff reduced
NDVI	Reference	0.904	0.020	0.000	0.0
	DEMAC	0.902	0.026	0.015	0.0
	DOMAC	0.910	0.024	0.018	-14.9
	DARTAC	0.900	0.026	0.016	-1.8
PRI	Reference	-0.013	0.016	0.000	0.0
	DEMAC	-0.002	0.031	0.021	0.0
	DOMAC	-0.014	0.026	0.019	13.0
	DARTAC	0.000	0.028	0.021	3.5
CHL	Reference	9.146	1.654	-	-
	DEMAC	8.981	1.657	1.297	-
	DOMAC	10.645	3.058	2.393	-84.5
	DARTAC	8.738	1.801	1.401	-8.0
CAR	Reference	9.253	1.674	-	-
	DEMAC	8.107	2.593	2.109	-
	DOMAC	9.805	2.958	2.171	-3.0
	DARTAC	7.696	2.377	2.148	-1.9

Figure 7: Impact of illumination effects on HDRF data and subsequently calculated vegetation indices. Results indicate the impact and compensation considering three different atmospheric correction approaches. Displayed are the true colour RGB representations and vegetation products (NDVI, PRI, chlorophyll and carotenoid indices) for a subset of the scene including fields, trees and cast-shadows. Shadows are visible as dark patches in the DEMAC RGB depiction.

Figure 8: Top: Illumination map (relative direct illumination, with cast-shadow pixels in black) and digital object model (DOM) of the test scene. Bottom: Difference maps of vegetation indices derived from the DOMAC and DEMAC (left) and DARTAC and DEMAC approach (right).

490 5. Discussion

491 5.1. Capability to advance estimates of direct and diffuse irradiance

492 Simple atmospheric correction approaches typically assume flat Earth surfa-
493 ces or coarsely approximate topography with smoothed DEMs and need minimal
494 inputs to calculate reflectance (e.g. Ouaidrari & Vermote, 1999; Richter, 1990).
495 These approaches are not suitable for high resolution imagery and complex ter-
496 rain. In early approaches seeking to compensate terrain influences, the cosine
497 correction based on $\cos\theta_{il}$ is applied (often directly to TOA radiances), using
498 a DEM (Teillet et al., 1982). However, it was observed to be unsuitable for
499 terrain containing steep inclines where the solar incident angle approaches 90°
500 or above (Itten & Meyer, 1993; Teillet et al., 1982). Results of our DEMAC
501 approach show no extreme underestimation of surface irradiance due to the use
502 of a smoothed DEM. This strategy eliminates abrupt changes in geometry and
503 diffuse irradiance estimates in relation to $\cos\theta_t$. However, since the DEM does
504 not include single canopy geometries, correct irradiance values for tree crowns
505 and cast-shadows cannot be estimated. Small-scale illumination based HDRF
506 variations persist. The use of DOM's theoretically provides more accurate ir-
507 radiance estimates since complex canopy geometry can be considered. In our
508 experimental analysis, we however faced several difficulties and less consistent
509 results than expected. HDRF in shaded parts of tree canopies was strongly
510 overestimated due to an underestimation of irradiance, rendering an inherent
511 problem in the DOM's 2.5-dimensional smooth description of canopy surfaces
512 (Schläpfer et al., 2003). In regions with steep slopes, direct irradiance tends
513 toward zero while diffuse irradiance is also reduced due to the slope. Overes-
514 timates of HDRF due to geometric effects have been observed in other studies
515 and put down to inadequate spatial resolution of the DEM used (Sandmeier &
516 Itten, 1997). It is possible that the effect could be partly counteracted in our
517 case by a DOM resolution which is slightly higher (1 m) compared to the pixel
518 size of the image data (2 m). We expect that remaining effects are mainly cau-
519 sed by the fact that the canopies' 3-dimensional structure (e.g., leaf orientation)

520 is insufficiently represented. The binary nature of the applied cast-shadow mask
 521 causes an under estimation of the direct irradiance. Despite this we still observe
 522 an underestimation of reflectance in the result for most cast-shadows. This can
 523 be explained by the fact that flat surfaces receive an overestimated amount of
 524 diffuse irradiance due to the slope-based calculation. The whole hemisphere
 525 is considered when in fact a large part of it is obscured by the trees casting
 526 the shadow. Simply omitting all diffuse irradiances from these directions would
 527 however in turn ignore multiple scattering effects from neighbouring canopies.
 528 It is likely that the combination of these effects cause the observed deviations
 529 between the corrected and illuminated reference regions. Moreover, direct and
 530 diffuse irradiance gradients in tree-canopy cast-shadows are not well understood
 531 and warrant further study. Irradiance estimates using 3D radiative transfer mo-
 532 dels such as DART was judged to be the most adequate strategy to account for
 533 the complex 3D architecture of forest canopies. Surprisingly, illumination pat-
 534 terns in DARTAC HDRF data persisted and strong over and underestimates of
 535 irradiance partially occurred. The insufficient correction of irradiance effects can
 536 be mainly attributed to the voxel size being too large to accurately approximate
 537 the canopy shape, especially as there is no slope information to scale irradiance
 538 in this approach. The voxel size of $2 \times 2 \times 2$ m corresponds to the image pixel size
 539 of 2×2 m but ideally the resolution used for the radiative transfer simulation
 540 would be higher and up-scaled to sensor resolution (Malenovský et al., 2007).
 541 Concerning the large uncertainties when finally deriving HDRF products, pri-
 542 marily the irradiance scaling factors as obtained from DART are the underlying
 543 cause: DART simulations were limited in their complexity due to computation
 544 time constraints. The spatial distribution of resulting diffuse scaling factors dis-
 545 play a considerable deviation from the expected spatial distribution as obtained
 546 for direct irradiance. This kind of spatial mismatch is caused by an insufficient
 547 number of possible scattering directions during the simulation. A full conver-
 548 gence of diffuse and direct cast-shadows requires several hundreds to thousands
 549 of scattering directions in 4π space (as opposed to the 24 used in this study),
 550 requiring considerable processing power and time. Studies using DART to si-

551 mulate RS data of smaller scenes use 100+ angles (Gastellu-Etchegorry et al.,
 552 1996; Schneider et al., 2014). An efficient method to improve the simulation
 553 of canopy multiple scattering is an oversampling of certain angular regions, for
 554 example of the hot-spot configuration (Yin et al., 2013).

555 *5.2. Reducing irradiance-based variation in vegetation indices using advanced* 556 *atmospheric correction*

557 Spectral vegetation indices derived over complex structured forest ecosys-
 558 tems can be subject to substantial illumination effects. The evaluated DOMAC
 559 and DARTAC approaches yield in general more reliable HDRF and index in-
 560 formation but results are diverse. This diversity is mainly associated with the
 561 difficulty to accurately estimate shadow fractions and the wavelength depen-
 562 dency of illumination effects. For cast shadow where the actual fraction of
 563 direct irradiance can be reliably constrained, the DOMAC approach leads to
 564 most vegetation index products being significantly less sensitive to the illumi-
 565 nation differences in cast-shadow, by roughly 50%. An exception is the NDVI,
 566 which involves signals in the NIR that were affected by uncertainties in the esti-
 567 mation of direct irradiance. The main conceptual difference in forest canopies is
 568 that surfaces receiving purely diffuse irradiance are rare and, at the 2 m spatial
 569 scale investigated, varying amounts of direct and diffuse irradiance are actu-
 570 ally present. Consequently, the overall differences between the reference case
 571 and DEMAC values at varying illuminations are much smaller. The correction
 572 results appear to be more diverse, which can be explained by the increasing
 573 uncertainty in actual irradiance estimates in combination with a wavelength
 574 dependency of this uncertainty. While no correction effect was found for the
 575 CAR index, the evaluated DOMAC approach shows spatially more consistent
 576 vegetation index values across canopies for PRI but slightly worse results for
 577 NDVI and substantially worse for CHL. The calculation of PRI incorporates wa-
 578 velength regions in the visible strongly affected by fractional changes of direct
 579 and diffuse irradiance. The applied corrections seem overall to slightly improve
 580 HDRF retrievals at these wavelengths, possibly stemming from the DOMAC

581 inclined surfaces leading to a better representation of the actual diffuse irradi-
 582 ance field. The calculation of NDVI and CHL incorporates reflectance values
 583 in the NIR that are exaggerated if modelled direct irradiance is too small. Wa-
 584 velength dependent improvements of the applied DOMAC approach appear to
 585 mainly affect the visible and less the NIR for inclined surfaces. This might
 586 explain the increasing sensitivity of both indices for illumination effects when
 587 using DOMAC. Across dense forest, there seems to be no advantage in using
 588 irradiance estimates obtained from DART simulations; results are overall very
 589 similar to the DEMAC case or slightly worse. The lacking variability in model-
 590 led direct irradiance is the primary cause for this. It is likely that the smoothed
 591 DEM still provides a better approximation of canopy surfaces than the surface
 592 described by the voxel grid. A final issue of note is that we evaluated the im-
 593 provement of vegetation index retrievals by comparing values of partly shaded
 594 canopy areas to those of illuminated canopy areas. This strategy assumes that
 595 reflectances and thus indices are identical across illumination conditions if fully
 596 corrected. This is an imprecise assumption as the difference is not entirely due
 597 to wrong irradiance estimates but also surface properties and plant physiologi-
 598 cal responses. The PRI, for example, has been shown to vary throughout the
 599 day in response to a physiological reaction (de-epoxidation state of xanthop-
 600 hylls) to changing illumination conditions, being enhanced in low-light condi-
 601 tions (Gamon & Bond, 2013; Hall et al., 2008), while the discussed uncertainty
 602 on directional PRI caused by illumination effects is deemed to be of the same
 603 magnitude as the physiological response (Möttus et al., 2015). Separating the
 604 three influences on derived vegetation indices represents a challenge and would
 605 require extensive field physiological sampling.

606 *5.3. Towards a reliable retrieval of vegetation information in heterogeneous ca-* 607 *noopies*

608 The methods presented here are able to describe the geometrical optical scat-
 609 tering, which dominates at high resolutions, to a certain degree and can partially
 610 compensate it, as was demonstrated. However, they cannot sufficiently describe

611 volumetric scattering, as occurs within tree canopies. In order to incorporate
 612 these kinds of effects, so-called image-based methods are regarded as promising,
 613 which are methods that have an increased focus on retrieving unknown para-
 614 meters in the model based on information contained in the image. There are
 615 multiple different implementations of image based methods. Novel approaches
 616 seek to describe the radiative transfer in the coupled atmospheric canopy sy-
 617 stem and move the retrieval problem to the at-sensor radiance level (Laurent
 618 et al., 2013). The strength of these TOA approaches is that they avoid error
 619 propagation common in other methods due to i) the sequential processing (e.g.,
 620 posterior anisotropy correction), ii) the retrieval of plant traits via indices and
 621 empirical models, and iii) the comparison of different physical quantities (i.e.,
 622 BRF from canopy radiative transfer models versus HDRF derived from mea-
 623 surements (Laurent et al., 2011). Further methods which are currently being
 624 developed are based on empirical cast-shadow detection (Schläpfer et al., 2013)
 625 and use a comparison between cast-shadows and illuminated surfaces to derive
 626 accurate values for atmospheric visibility. Based on this, the irradiance descrip-
 627 tion for the entire scene can be improved, in turn leading to advanced vegetation
 628 information retrieval.

629 **6. Conclusions**

630 We provide further experimental evidence that scene reflectance and derived
 631 vegetation information is considerably uncertain if the relative contribution of
 632 direct and diffuse irradiance to total irradiance is not estimated accurately. We
 633 conclude that improvements in the retrieval of surface reflectance and spectral
 634 indices by ingesting further auxiliary data to account for varying irradiance
 635 fractions in atmospheric correction approaches are limited. Using a DOM or
 636 DART simulated irradiance fractions to estimate irradiance leads to some im-
 637 provements over a simplified approach using spatially coarse resolution DEMs.
 638 However, a number of issues and requirements were identified limiting the ap-
 639 plicability of the two proposed approaches. This includes the resolution of the

DOM and the DART voxel grid that should ideally be an order of magnitude larger than the image data. Further, applied approaches are limited in their physical representation of the complex radiative transfer in heterogeneous canopies. DOM based approaches being 2.5 dimensional represents an oversimplification while DART based approaches would require a very large number of scattering angles and iterations to accurately simulate irradiance. As currently the computational requirements for this are still prohibitive, we propose further investigating other options which are promising as operational solutions. Going forward, we emphasize the potential of image-based approaches to derive accurate irradiance fields and vegetation variables. Such approaches include the use of combined atmosphere-surface models with inversion schemes applied on at-sensor radiance data or more sophisticated empirical strategies to quantitatively describe the shadow fraction.

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List of Figures

1	APEX flight line (at-sensor radiance, RGB colour composite) of the Laegern study site (June 26, 2010, 15:30 UTC). The background is a hillshaded DEM illustrating scene topography (DHM25 from Swisstopo, Switzerland).	5
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