3D radiative transfer modelling of fire impacts on a two-layer savanna system

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\textbf{Abstract}

We present a new, detailed three dimensional (3D) approach to modelling the pre- and post-fire reflectance of a two-layer savanna system modelled as heterogeneous overstory (tree) and understory (grass) layers. The models were developed from detailed field measurements of structural and radiometric properties made at experimental burn plots with varying canopy cover in the Kruger National Park, South Africa. The models were used to simulate 400–2500 nm spectral reflectance at 10–500 m spatial scale for various viewing and solar geometry configurations. The model simulations closely matched pre-fire and post-fire ground-based, helicopter and satellite remote sensing observations (all r² values > 0.95 except one post-fire case). The largest discrepancies between modelled and observed reflectances occurred typically at wavelengths greater than 1200 nm for the post-fire simulations. The modelling results indicate that representation of overstory and understory structure and scattering properties are required to represent the burn signal in a typical savanna system. The described 3D modelling approach enables separation of the scattering contributions of the different scene components and is suited to testing and validating fire impact assessment algorithms at locations where the difficulty of obtaining both pre- and post-fire observations is a severe constraint.

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1. Introduction

Savanna ecosystems, land with grass and either scattered trees or an open canopy of trees, are important because of their widespread coverage, dynamics (particularly response to rainfall) and the ecosystem services they provide (Asner et al., 2004; Hill & Hanan, 2010; Sankaran et al., 2005; Skarpe, 1992). Fire is of particular interest in savanna ecosystems as it is thought to play a major role in creating and maintaining these ecosystems (Bond et al., 2005; Bond & Keeley, 2005; Higgins et al., 2000; Sankaran et al., 2007); it has a rapid and dynamic response to both short- and longer-term climate variability in terms of phenology and biomass accumulation (Sankaran et al., 2005; Skarpe, 1992). Fire tends to remove material from the overstory and/or understory, transform live leaf and woody material into char and ash, and may also expose the underlying soil (Perreira et al., 2004; Roy & Landmann, 2005; Trigg et al., 2005; Trigg & Flasse, 2001). Vegetation fires typically produce predominantly dark black char, the primary by-product following pyrolysis of volatiles, rather than white mineral ash that is only produced under complete or near complete combustion (Roy et al., 2010; Smith et al., 2005; Smith & Hudak, 2005; Trigg & Flasse, 2000).

Satellite data have been used to monitor fire at regional to global scale for more than two decades using algorithms that detect the location of active fires at the time of satellite overpass (Giglio et al., 2003, 2009; Roberts et al., 2009), and in the last decade using burned area mapping algorithms that map the spatial extent of the areas affected by fires (Roy et al., 2008; Roy & Justice, 2007). More recently, researchers have attempted to use satellite data to characterize fire properties (Archibald et al., 2010a; Lentile et al., 2006), and to understand the interaction between fire, climate and anthropogenic activities (Archibald et al., 2010b).
Satellite fire impact detection algorithms typically exploit the persistent (days to weeks) impact of the fire on the surface, usually by detecting changes in the observed surface reflectance over time, particularly in the visible and NIR (Roy et al., 2002, 2005; Smith et al., 2005; Trigg & Flasse, 2001). Many detection methods use empirical spectral indices that respond to the relative changes in reflectance in various parts of the spectrum (in the visible and NIR in particular) (e.g. Giglio et al., 2003; Tansey et al., 2008). However, thresholding spectral indices into burned and unburned classes requires local calibration and may be difficult to generalise spatially (Roy et al., 2006). For time-varying measures there is also the additional issue of variability introduced by varying view and illumination angle. For example, in southern Africa savanna ecosystems variations in reflectance due to angular sampling may in some cases be greater than the reflectance change induced by fire (Roy et al., 2002; Stroppiana et al., 2003). Methods have been developed to exploit expectations of the surface angular variation for detecting fire impacts, such as the MODIS burned-area algorithm (Rebelo, 2005; Roy et al., 2002, 2005, 2008). However, to enable systematic global application, simplified model approaches must be used. The MODIS algorithm for example, uses linear kernel-driven BRDF models developed for the MODIS BRDF/albedo product (Schaaf et al., 2002; Wanner et al., 1995).

The prevailing characteristics of fire impacts are of great interest to scientists and ecosystem managers as they can have an important impact on carbon emissions and post-fire vegetation regeneration. Various field-based measures of fire impact have been developed, from estimates of amount of material consumed, species mortality and the likely differential impact on ecosystem response post-fire (Key & Benson, 2006; Lentile et al., 2006). Although these measures may not always be amenable directly to optical remote sensing (Roy et al., 2006), various efforts have been made to parameterise and assess fire impacts using optical wavelength satellite data, particularly through the use of the normalized burn ratio (NBR), the difference between near-infrared (NIR) and middle-infrared (MIR) reflectance divided by their sum (Brewer et al., 2005; Cocke et al., 2005; De Santis & Chuvieco, 2009; Epting et al., 2005; Karau & Keane, 2010; Van Wagendonk et al., 2004).

Here, we develop a detailed 3D modelling approach to use as a virtual laboratory (Prusinkiewicz, 1998; Widlowski et al., 2007). This approach explicitly defines the 3D location of each scattering element in the canopy down to the leaf and twig level. Although such a model is time-consuming to develop, it has three key benefits. First, it requires minimal assumptions about canopy structure and is therefore ideally suited to understanding how canopy structural and spectral properties impact the resulting signal. Second, the model can be directly used to explore the effectiveness of a proposed model of fire impact. Here we use a relatively simple approach within the virtual laboratory, replacing grass plants explicitly with charred material under a 3D overstory, to directly match field observations. If some more complex impact were observed e.g. that leaves below a particular height were removed, or that branches below a certain size/ order were charred or consumed, this could be easily implemented. Third, a practical difficulty in assessing any approach to estimating fire impacts from remotely sensed data is the problem of obtaining both pre- and post-fire measurements. Once a detailed model of the sort proposed here has been developed, it can be used to simulate pre- and post-fire observations at arbitrary spatial scales and angular configurations.

While there are various ways of modelling fire impacts using radiative transfer (RT) models, difficulties can arise in translating observed changes in canopy structure into RT model parameterisations. The impacts of fire on vegetation are a combination of (coupled) structural and radiometric (spectral) effects, with the relative importance of these effects being determined both by the nature of the canopy and the type of fire. Simplified RT approaches are attractive for modelling fire impacts due to their ease of use and small requirement for parameterising information. The major advantage of simplified approaches is that they can then often be applied widely and rapidly. However, the simpler the model, the more difficult it becomes to represent observed heterogeneity and/or to understand the complex interplay of structure on the signal (Pinty et al., 2004). For example, to represent the savanna fires of the kind we consider here where a spatially heterogeneous understory is almost or totally removed and the (strongly shadowing), highly-clumped overstory is not affected at all, the parameters of an heterogeneous RT representation, even of multiple layers, would represent some approximate ‘effective’ property which may be difficult to measure in practice (Disney et al., 2004; Pinty et al., 2006).

Various recent efforts have been made to develop RT models of fire impacts. Pereira et al. (2004) used a simplified geometric-optics RT approach to simulate miombo woodlands and explore the detection of understory burns. This model considered only the 3D structure of the overstory canopy, using simple geometric crown shapes (ellipsoids), while the understory signal was represented as a uniform background spectral response. They concluded that the detectability of understory burns was largely insensitive to stand structure and viewing and illumination geometry and depended mainly on the age of the burned area. In this case, even the overstory model structural parameters were essentially ‘equivalent’ parameters, representing the combined impact of the real overstory and understory 3D structure on the modelled signal. Chuvieco et al. (2006) used a more realistic two-layer RT model to relate fire impacts to the composite burn index (CBI), by considering each layer as homogeneous, with different LAI, above a soil sub-surface. They modelled the impact of changes in soil reflectance (mixture of char and pre-fire soil signal), foliage reflectance (a linear mixture of green and brown leaf spectra) and changes in overstory and understory leaf cover. They concluded that in the SWIR and visible regions, the correlation between CBI and reflectance was positive, as the main effect of fire was removal of green vegetation and water. In the NIR, the correlation was negative, as the main effect of fire was reduction of LAI. De Santis and Chuvieco (2007) compared these RT simulations with field measurements, and noted model limitations due to the effects of dead leaf litter and vertical layering prevalent in the Mediterranean systems they considered. De Santis et al. (2009) coupled separate leaf and canopy RT models in a modified CBI (GeoCBI) to include some account of canopy structure by considering the fractional cover of each canopy layer. This approach provided an improvement over CBI in relating reflectance to fire impact. There has also been work on examining the impact of leaf and canopy properties on areas susceptible to burning (Bowyer & Danson, 2004; De Santis & Chuvieco, 2007, 2009), and how such methods can be used for mapping fire impacts (De Santis et al., 2010). In all these cases, the RT models are still relatively simple, for practical reasons (speed of application). In particular they tend to consider homogeneous vegetation, which, even if layered, will not account for an overstory that is typically unaffected by fire, or 3D spatial heterogeneity.

Recent work has shown that highly-detailed realistic RT models are particularly useful for benchmarking and testing simpler models (Widlowski et al., 2007, 2008) and for understanding the implications of model assumptions and observational limitations (temporal, spatial and spectral sampling). Here, we develop a detailed 3D model for use as a virtual laboratory, representing a two-layer savanna system composed of a mixed tree canopy with a variable grass understory based on extensive field measurements of canopy properties. We implement a model of fire impact and demonstrate that the model can simulate pre- and post-fire canopy reflectance at a range of scales through comparison with field-measured and satellite observations. We discuss the utility of this approach for understanding the canopy signal in this environment and for testing and benchmarking models of fire impact.
2. Materials and methods

2.1. Study area

Structural and radiometric measurements were made in Kruger National Park (KNP), South Africa, over a 2-week period in the late dry season, October–November 2008. The KNP is a protected savanna ecosystem covering a range of elevation and precipitation/climatic gradients with tree/grass dynamics dominated by fire and herbivory. Mean annual rainfall varies from around 350 mm in the north to around 750 mm in the south, but with significant inter-annual precipitation variability (van Wilgen et al., 2004).

Measurements were made at Skukuza (25.1097 S, 31.4172E) and Pretoriuskop (25.1639 S, 31.234E), both sited at long-term fire ecology experimental plots in the KNP (van Wilgen et al., 2000, 2004). Coordination with the KNP fire ecology experiment staff meant that the prescribed fires could be lit under controlled conditions and measurements made efficiently pre- and post-fire (an unusual and advantageous situation in fire remote sensing research). Two plots of 300m², no more than 1 km apart, were measured at each site: Skukuza Napi and Nwattwishaka (SNA, SNW); Pretoriuskop Kambeni and Numbi (PKA, PNU). At the time of the prescribed burning the majority of the vegetation was senescent and approximately 5% and 30% of the vegetation was green/photosynthetically active in Skukuza and Pretoriuskop respectively.

The plots at Pretoriuskop are characterised by higher precipitation and lower grazing pressure than those at Skukuza and hence have much more dense vegetation. Two plots were measured at each site, Skukuza Napi and Nwattwishaka (SNA, SNW); Pretoriuskop Kambeni and Numbi (PKA, PNU). The Skukuza plots are dominated by shallow-rooted deciduous Combretum species, in particular Combretum apiculatum (Red Bushwillow), Combretumhereroensis (Russet Bushwillow) and Combretumzyheri (Mixed Bushwillow). These trees make up a significant part of the total biomass, even though many of them lie horizontally after being felled by young elephants (pers. comm. N. Govender, SANParks). The Combretum species continue to grow even after being felled, often sprouting vertically. The remaining vegetation is made up of dry grasses of the order of 0.5–1 m in height, and a small number of large, dense green Marula (Sclerocaryaibarrae) trees. The Sclerocarya are deep rooted and hence act as a hydraulic and nutrient pump and remain green year-round, unlike the Combretum. Grazing lawns within the plots i.e. flattened grass caused by animal encroachment, act to prevent fire spread as the flattened grass only burns partially or not at all. The Pretoriuskop plots are dominated by Terminaliasericea (Silver cluster-leaf), a moderately large shrub-like tree (up to 4–5 m high), mixed with Combretum. The level of herbivory is much lower and the Terminalia do not regrow after being felled. This, combined with higher precipitation results in generally higher grass and litter fuel loads. The Skukuza woody, grass and litter fuel loads were measured as 0.085, 0.25 and 0.13 kg m⁻² respectively. The Pretoriuskop woody, grass and litter fuel loads were measured as 0.013, 0.55 and 0.14 kg m⁻² respectively. Skukuza plots had moderate amounts of exposed soil (10–30% by surfacearea), much more so than the Pretoriuskop plots (~5%), with the soil being highly reflective sandy material in all cases.

2.2. Prescribed fires

The prescribed fires in the Skukuza plots were set on 31/10/2008 at 09:45 GMT (SNA) and 13:00 (SNW). The Pretoriuskop fires were set on 03/11/2008 at 09:00 (PKU) and 12:00 (PNU). Backfires were lit on the downwind side of the plots first, before headfires were lit on the upwind side some 10–15 minutes later. Areas remaining unburned were relit within 30 minutes. Pre- and post-fire fuel load measurements showed that around 90-95% of the standing grass and 96% of the litter was burned in the Skukuza plots, and 100% of the grass and litter were burned in the Pretoriuskop plots. In both cases the overstory was not affected, a situation common to a range of arid African savanna fires (Archibald & Bond, 2003; Bond & Archibald, 2003).

Fig. 1 shows an aerial image of one plot from each site. The fire breaks between plots are clearly-visible due to the bright exposed soil. The patches of dense and sparse vegetation, and the paths created by animal encroachment are maintained both before and after burning. The predominant impact of fire is the darkening of the background due to the burning of the dense grass understory, plus some exposure of bright background soil in the sparser Skukuza plots. Fig. 2 illustrates the contrast in density of over- and understory between the Skukuza and Pretoriuskop sites.

2.3. Field measurements

At each plot a range of pre- and post-fire structural and radiometric measurements of the tree-dominated overstory and grass understory were made to enable the development and testing of the 3D models. Every effort was made to collect the radiometric measurements under stable atmospheric conditions, either clear skies, or completely overcast skies. These measurements are described below.

2.4. Structural measurements

In each plot, multiple 100 m transects were marked along the longer dimension of the plot, separated by 50 m laterally. Measurements were made of tree height, diameter-at-breast height (DBH), crown size of every tree within 1 m horizontally either side of the transects, representing an area of 600m² in each plot. The number of fallen trees was also recorded in each transect. Measurements are summarised in Table 1. The leaf area index (LAI) was measured at 10 m intervals along each transect using two LAI2000 (LI-COR Bioscience, Lincoln, NE, USA) instruments in master-slave mode, one situated outside the plot in a clearing. The LAI was recorded above and below the understory at each point to allow separation of overstory and understory LAI. Where illumination conditions were not overcast, a 90° solar occlusion lens cap was used on both instruments. All measurements within the canopy were made with the sun behind the user. Fig. 3 shows histograms of the LAI measurements in each plot. The mean LAI values were 1.02 (10±0.51) and 2.81 (10±1.16) at Skukuza and Pretoriuskop respectively.

At each LAI measurement location, upward-looking hemisphotos were taken using a Canon EOS5D camera with Sigma 8 mm F3.5 EX DG Circular fisheye lens (180° field-of-view). Hemisphotos were taken above (at a height of 1.5 m) and below (0.2 m) the understory, to enable separation of overstory and understory LAI and gap fraction. Hemisphotos were processed using the CanEYE software (INRA, Avignon, http://147.100.66.194/can_eyes). Following Warren-Wilson (1959) and Ross (1981), the CanEYE algorithm assumes a random spatial distribution of infinitely small leaves. A Poisson model for relating the gap probability \( P_0(\theta_v, \phi_v) \) at view zenith angle \( \theta_v \) and azimuth angle \( \phi_v \) respectively, to the theoretical contact frequency \( N(\theta_v, \phi_v) \) (i.e. the number of contacts a ray of light would make with vegetation as function of penetration through the canopy), was used as:

\[
P_0(\theta_v, \phi_v) = e^{-N(\theta_v, \phi_v)} = e^{-G(\theta, \phi, f, h)}
\]

where \( G(\theta, \phi, f, h) \) is the leaf projection function i.e. the mean projection of a unit foliage area. Eq. (1) assumes that \( G(\theta_v, \phi_v) \) is independent of height \( h \) in the canopy. Following Nilson (1971), the gap probability can be shown to be exponentially related to LAI, even in cases where the turbid medium assumption underlying the Poisson model is not met, through the inclusion of a canopy clumping parameter \( \lambda_0 \) (<1) describing the non-random nature of the canopy structure i.e.

\[
P_0(\theta_v, \phi_v) = e^{-\lambda_0 G(\theta, \phi, f, h)}
\]
In this case the effective LAI$_{eff}$ estimated from indirect (hemiphoto) methods, is then $\lambda_0 L_{\text{true}}$, where "true" LAI is that measurable directly e.g. via destructive sampling. The hemiphoto measurements are summarised in Table 2. Estimates were made of the density of grass plants in each plot (plants per unit area), ranging from 21–43 m$^{-2}$ across all plots.

2.4.1. Radiometric measurements

2.4.1.1. Scene components. Measurements of the spectral reflectance of the various canopy components (leaf, bark, soil, dry grass, burned leaf, burned bark, char, ash) were made using an ASD FieldSpec Pro Spectroradiometer (ASD Inc., Boulder, CO, USA). For component reflectance measurements the ASD was used with a contact probe (soil and bark), or with a leaf clip attachment. The probe was placed against the target (or in the leaf clip) and the reflectance recorded relative to that of a calibrated white spectrason reflectance panel (calibrated by the NERC Field Spectroscopy Facility, University of Edinburgh, www.fsf.nerc.ac.uk).

2.4.1.2. Understory bidirectional reflectance. Two intensive sets of directional reflectance measurements were made in each of the Skukuza and Pretoriuskop plots. A 3x3m area of unburned grass was measured in each plot under clear sky conditions, using the ASD FSPPro Spectroradiometer on a 1.5 boom mounted 1.5 m above the top of the grass canopy, with an 8° field-of-view (FOV) foreoptic. Multiple measurements were made at view zenith angles of 0°, 30° and 60° into and across the solar principal plane.

2.4.1.3. Top-of-canopy (TOC) reflectance. TOC reflectance measurements were made using two ASD instruments in dual radiance/irradiance mode, one on the ground and one mounted on a helicopter flying at an altitude of 100-150 m. The ground-based instrument was mounted on a tripod within 500 m of both plots at each site, with an...
Table 1
Tree structural measurements from all four plots.

<table>
<thead>
<tr>
<th>Site, Transect</th>
<th>No. in transect, no. fallen</th>
<th>Height (mean, σ), m</th>
<th>Crown diameter (mean, σ), m</th>
<th>Tree density (ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNA</td>
<td>29, 10</td>
<td>4.25, 0.875</td>
<td>2.76, 1.14</td>
<td>600-850</td>
</tr>
<tr>
<td>SNW</td>
<td>29, 15</td>
<td>3.92, 1.13</td>
<td>3.27, 1.53</td>
<td>700-750</td>
</tr>
<tr>
<td>PKA</td>
<td>46, 1</td>
<td>5.21, 1.76</td>
<td>2.79, 0.96</td>
<td>1100-1200</td>
</tr>
<tr>
<td>PNU</td>
<td>65, 2</td>
<td>5.91, 2.55</td>
<td>2.78, 1.24</td>
<td>1600-1700</td>
</tr>
</tbody>
</table>

Table 2
Summary of gap fraction, LAItrue and LAIeff derived from analysis of hemiphotos.

<table>
<thead>
<tr>
<th>Site</th>
<th>Gap fraction (mean, σ)</th>
<th>LAItrue</th>
<th>LAIeff</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNW upward (BELOW)</td>
<td>0.78, 0.05</td>
<td>0.98</td>
<td>0.42</td>
</tr>
<tr>
<td>SNW upward (ABOVE)</td>
<td>0.94, 0.05</td>
<td>0.22</td>
<td>0.18</td>
</tr>
<tr>
<td>SNW postfire, upward (ABOVE)</td>
<td>0.96, 0.03</td>
<td>0.14</td>
<td>0.08</td>
</tr>
<tr>
<td>PKA prefire, upward (BELOW)</td>
<td>0.81, 0.06</td>
<td>0.77</td>
<td>0.31</td>
</tr>
<tr>
<td>SNW prefire, upward (ABOVE)</td>
<td>0.93, 0.06</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>SNA prefire, upward (ABOVE)</td>
<td>0.94, 0.03</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>PKA prefire, upward (BELOW)</td>
<td>0.60, 0.04</td>
<td>1.70</td>
<td>0.42</td>
</tr>
<tr>
<td>PKA prefire, upward (ABOVE)</td>
<td>0.93, 0.02</td>
<td>0.22</td>
<td>0.14</td>
</tr>
<tr>
<td>SNA prefire, upward (ABOVE)</td>
<td>0.93, 0.05</td>
<td>0.16</td>
<td>0.12</td>
</tr>
<tr>
<td>PNU prefire, upward (BELOW)</td>
<td>0.73, 0.05</td>
<td>1.01</td>
<td>0.44</td>
</tr>
<tr>
<td>PNU prefire, upward (ABOVE)</td>
<td>0.90, 0.04</td>
<td>0.28</td>
<td>0.22</td>
</tr>
<tr>
<td>PNU postfire, upward (ABOVE)</td>
<td>0.92, 0.03</td>
<td>0.20</td>
<td>0.06</td>
</tr>
</tbody>
</table>

where 1 km MODIS active fires were detected were considered. In this way 224 pre- and post-fire MODIS 500 m NBAR pixels for two separate fire-affected areas were selected, identified as having burned by the MODIS active fire product on 6/9/2008 (97 pixels centred on 31.35, -25.21) and 14/9/2008 (127 pixels, centred on 31.30, -25.23). The areas covered by the MODIS pixels generally had very similar tree and understory cover to the burn sites.

To compare the angular variation of MODIS observations with 3D simulations, daily MODIS reflectance data were collected for the central pixels of the two fire-affected areas described above. MODIS gridded TERRA (MOD09GA) and AQUA (MYD09GA) data were collected for a 21-day period either side of the fire date and filtered to remove cloud and haze-contaminated pixels based on the QA values and on visual inspection of the image quicklooks. The resulting data contained 6 observations pre- and post-fire for the 6/9/2008 fire-affected area, and 8 pre- and 5 post-fire observations for the 14/9/2008 fire fire-affected area respectively. The angular configurations of these observations were not ideal for BRDF comparisons as the relative azimuth between the view and illumination vectors was between 50°-65° and so far from the solar principle plane (relative azimuth close to 0° or 180°) where angular variations due to shadowing are at a maximum.

2.5. Model generation

Using the information from the field measurements, 3D tree and grass models were generated to produce 3D savanna scene models of 100 × 100 m extent. 3D model canopies covering a range of vegetation density (tree and grass LAI) were produced to match the range of field measurements, over a soil understory using measured soil reflectance properties. In all cases where plant models re located within the scenes, a uniform random distribution is used.

2.5.1. Overstory canopy objects

For the Combretum, Sclerocarya and Terminaliastructure, OnyxTREE© software (www.onyx.com) was used. This software has been used to simulate the structure of deciduous broadleaf canopies for simulation of various remote sensing signals (Disney et al., 2009, 2010). Tree structure was generated by using examples of existing

Fig. 3. Histograms of the LAI values recorded along transects in each of the two sites.
tree models within OnyxTREE, parameterised according to the KNP measured tree data, in particular, the height and tree crown size information. Ten individual *Combretum* and *Sclerocarya* trees were generated, spanning the observed range of height and crown size. Modelled tree sizes are shown in Table 4. Individual trees were randomly located in order to generate synthetic plot-sized scenes spanning the range of tree stem densities shown in Table 1.

2.5.2. Understory canopy objects

The grass understory in this system dominates the change in surface reflectance due to the effects of fire. As can be seen from Fig. 1, the larger trees remain untouched below approximately 2 m due to the relatively low intensity and rapid spread of fire. However, it is also clear from Fig. 1 that the overstory tree crowns cast significant shadows. This is characteristic of a two layer savanna system and, combined with the changing understory signal, is a key reason for using a 3D model (particularly to test simpler models): a model that is unable to properly represent the shadowing and understory effects will be unable to model the pre- and post-fire signal correctly.

Because of the number of grass plants required, even for the relatively small 1 ha plot sizes considered here (10^6 potentially), a small, computationally efficient object is required which can be ‘cloned’ rapidly and efficiently during the simulation process. As a result, cylinders were used to represent the grass objects. Each plant was modelled as 10 stems of radius 0.005 m, with base length 1.2 m varying randomly by up to ±0.5 m in height. The stems were distributed in a Fibonacci spiral phyllotaxy (spatial arrangement) around the central point, with the angle from the vertical determined by the degree of rotation through the spiral. This ensured that no two stems were arranged at the same rotation angle and avoided unwanted geometric regularity (Disney et al., 2006). For the post-fire scenes, the grass plants were reduced in size to a mean height of 0.1 m, with random variation of ±0.05 m to represent the post-burn grass ‘stubble’. Examples of *Combretum*, *Sclerocarya* and grass model objects are shown in Fig. 5.

2.5.3. 3D scene models of pre- and post-fire scenarios

Full 3D scene models of 100×100 m were generated across the range of tree and grass stem densities (tree cover/LAI), seen in the field measurements. Below we focus on the upper and lower tree stem densities seen in Table 1 i.e. 600 and 1400 trees ha\(^{-1}\). Trees were located with a random spatial arrangement according to the measured number densities. Horizontal (fallen) *Sclerocarya* were added to all scenes, at a rate of 30% (of total *Sclerocarya*) in the lower tree density cases, and at a rate of 10% to the higher tree density cases. While the fallen trees themselves do not make much difference to reflectance, they can cause the grass cover to change significantly (Scholes & Archer, 1997).

Grass cover was low close to standing or fallen trees and post-fire this resulted in patches of exposed bright soil. A tree ‘buffer map’ was created by simulating the scene containing only the 3D tree models, from directly overhead (essentially a tree presence/absence map): where a tree exists, grass was excluded, otherwise the grass plants were located randomly number densities spanning the observed range (20–60 plants m\(^{-2}\)) using the buffer map (and not within 10 cm of each other). In the post-fire equivalent scenes, each grass plant was replaced at the same location with the small ‘stubble’ version. A second ‘soil map’ was then generated in the same way as for the tree buffer map. A radius of 10 cm around each grass plant was then specified, permitting the mapping of the post-fire background char spectral properties onto the surface (see Fig. 4). All areas of exposed soil were modelled as a flat Lambertian surface with the reflectance properties described in 2.3.2.1. The spectral properties of the post-burn grass plants were also changed to char. All tree bark within 1.5 m of the surface was also replaced post-fire with the burnt bark spectral properties (Fig. 4). Fig. 6 shows examples of a tree buffer and the corresponding post-soil fire map.

2.5.4. Simulating 3D model canopy reflectance

To simulate the reflectance signal the *librat* Monte Carlo ray tracing (MCRT) model was used. *Librat* is a development of the ararat/drat model of Lewis (1999). In brief, MCRT involves estimating the RT regime within a canopy stochastically by following the interactions of sample ‘rays’ propagating through a scene from source to sensor (forward) or vice versa (reverse) (Disney et al., 2000). Typically the *librat* model is applied in reverse mode i.e. primary rays are ‘fired’ (originate) from the sensor in the direction of the scene. Where a ray intersects an object in the scene (leaf, branch, soil etc.), a test is performed to determine whether the intersection point can directly receive radiation from an illumination source (the sun, or sky for example). At each ray intersection further ray paths are randomly generated to sample the possible routes by which diffuse (multiple scattered) illumination from the source(s) might arrive at that point, in addition to the direct illumination field (Lewis, 1999). Termination of a diffuse sampling ray path is achieved when either the ray escapes from the scene to an illumination source (sky, sun, lidar illumination etc.), or when a fixed number of interactions (scattering orders) is reached. Attenuation along a ray path is calculated by modulating the signal at each intersection point by the spectral reflectance and transmittance properties of the scene elements. In this study the illumination is the sun and sensor characteristics are matched to those against which comparisons are made (helicopter-mounted ASD FS Pro, CHRIS-PROBA, MODIS).

The *librat* code has been tested against a range of other models as part of the Radiative Transfer Model Intercomparison (RAMI) exercise (Pinty et al., 2004; Widlowski et al., 2007), as well as against observations (Disney et al., 2006, 2009). The *librat* code is available as an unsupported source code distribution from www.geog.ucl.ac.uk/~plewis/bpmns/src/lib.

Examples of the simulated pre- and post-fire reflectance of the 3D modelled savanna scenes are shown in Fig. 7. The overstory shadowing and the exposed areas of bright soil reinforce the importance of getting the relative proportions of over- and understory cover right.

### Table 4

<table>
<thead>
<tr>
<th>Tree type</th>
<th>Height (m) (mean, σ)</th>
<th>Crown dia. (m) (mean, σ)</th>
<th>DBH (m) (mean, σ)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Combretum</em></td>
<td>3.99, 0.98</td>
<td>2.88, 1.11</td>
<td>0.11, 0.04</td>
</tr>
<tr>
<td><em>Sclerocarya</em></td>
<td>7.57, 4.34</td>
<td>3.45, 1.85</td>
<td>0.54, 0.11</td>
</tr>
</tbody>
</table>

Fig. 4. Component reflectance spectra collected in the field pre- and post-fire and used in the 3D canopy model simulations.
3. Results

We first describe the validation of the structural components of the 3D models. We then show the results of simulating fire impacts on a two-layer savanna system at a variety of spatial and spectral scales, and compare these simulations with observed spectral reflectance data.

3.1. Validation of understory and overstory canopy cover

Comparisons were performed between measured and modelled understory (grass) and overstory (tree) cover, to establish the optimal cover to allow accurate simulation of the canopy reflectance using the 3D models.

3.1.1. Understory (grass) cover

Comparisons of 3D model simulations of understory grass canopy reflectance, ρ, with measured reflectance over a range of understory grass plant densities are shown in Fig. 8. Simulations were carried out using the same FOV, view and illumination configurations as in the measured data (2.3.2.2). The match between modelled and measured understory reflectance is generally very good ($r^2 > 0.85$), with results indicating that the most appropriate grass cover is 30 plants m$^{-2}$, corresponding to LAI of 1.57. This is an overestimate compared to the measured understory grass LAI values seen in Table 2, however this arises due to the shape of the cylindrical grass stems, rather than using a mix of flat leaves and stems.

3.1.2. Overstory (tree) cover

Measured and modelled overstory and total canopy LAI and gap fraction were compared over a range of overstory tree cover. For each 3D model scenario simulated ‘hemiphotos’ were generated in the same configuration as those taken in the field (and summarised in Table 2). Hemiphoto images were simulated from 0.2 m and 1.7 m above the ground with the same FOV as described in 2.3.1, at 10 m intervals along transects in the 3D model scenes and for overstory tree stem density varying across the range of observed values, from 400–2000 tree ha$^{-1}$ in steps of 200. The 3D model canopy gap fraction was calculated directly from these simulations i.e. the fraction of first order ‘rays’ originating from the focal point in each simulation escaping the scene without being intercepted. Values of LAI were calculated explicitly for each scene from the 3D object definitions. To enable direct comparison between the 3D model and field-measured estimates of gap fraction and LAI, the resulting hemiphoto simulations were processed using CanEYE in the same way as the real hemiphotos. This enabled any bias between the 3D model-estimated and field-measured values to be identified.

Examples of the 3D model-simulated hemiphotos are shown in Fig. 9. Table 5 shows the gap fraction and LAItrue values calculated directly from the 3D model simulations. For tree densities most closely corresponding to field measurements the modelled gap fraction is ~0.76, compared to values of around ~0.9 derived from real hemiphotos in the Skukuza plots (Table 2). For the higher density case, the modelled gap fraction is 0.55-0.65, compared to the measured values of around 0.8 in the Pretoriuskop plots. The 3D model-derived gap fraction estimates are lower than values derived from field-measured data.
from processing real hemiphotos for a number of reasons. In the case of processing real hemiphotos, image-based segmentation of canopy/non-canopy elements will never be perfect. In addition, the requirement for processing images over finite zenith and azimuth bins means smaller branches and foliage elements will tend to be under-represented in these estimates. The model simulations require none of the assumptions made in Eq. (2) and the simulations are carried over an infinitesimal FOV (single direction) for each ray. Similarly, LAI values were derived from the 3D structural models directly by calculating the area of every scene element. As a result these values will always be larger than those derived from hemiphot estimation.

Fig. 10 compares gap fraction and LAI values calculated directly from the 3D models with values derived indirectly via processing the simulated hemiphotos. The resulting relationships express the bias in estimating gap fraction (GF) and LAI due to assumptions and uncertainties in the CanEYE processing. These relationships were used to convert field-measured values to values directly comparable with the 3D model values i.e. 

\[
GF_{\text{corrected}} = (GF_{\text{hemi}} - 0.15) / 0.89
\]  

(3)
LAI_{corrected} = (LAI_{hemi} + 0.05) / 0.79  

Corrected field-estimated overstory LAI values for the Skukuza plots range from 0.14-0.42, corresponding to the model tree density of 400–800 ha$^{-1}$; for the Pretoriuskop plots, overstory LAI ranges from 0.33-0.63, corresponding to model tree density of 700–1400 trees ha$^{-1}$. Consequently, tree number densities of 600 and 1000 ha$^{-1}$ were used in the Skukuza and Pretoriuskop pre- and post-fire reflectance simulations respectively.

### Table 5
Variation of gap fraction and LAI_{true} as a function of tree density derived directly from the 3D models. Those marked in bold show the values of tree density measured in the Skukuza (low density) and Pretoriuskop (high density) plots.

<table>
<thead>
<tr>
<th>Tree density (ha$^{-1}$)</th>
<th>Gap fraction (mean, 1σ)</th>
<th>LAI_{true}</th>
</tr>
</thead>
<tbody>
<tr>
<td>400</td>
<td>0.85, 0.08</td>
<td>0.17</td>
</tr>
<tr>
<td>600</td>
<td>0.80, 0.07</td>
<td>0.27</td>
</tr>
<tr>
<td>800</td>
<td>0.72, 0.08</td>
<td>0.35</td>
</tr>
<tr>
<td>1000</td>
<td>0.67, 0.09</td>
<td>0.44</td>
</tr>
<tr>
<td>1200</td>
<td>0.68, 0.11</td>
<td>0.53</td>
</tr>
<tr>
<td>1400</td>
<td>0.57, 0.12</td>
<td>0.61</td>
</tr>
<tr>
<td>1600</td>
<td>0.53, 0.07</td>
<td>0.71</td>
</tr>
<tr>
<td>1800</td>
<td>0.49, 0.16</td>
<td>0.80</td>
</tr>
<tr>
<td>2000</td>
<td>0.42, 0.08</td>
<td>0.89</td>
</tr>
</tbody>
</table>

**3.1.3. Scene components**

In Fig. 11 examples of the angular variation of 3D model scene scattering components are shown, for the grass plant densities corresponding to the Skukuza and Pretoriuskop plots. Results are shown for the sunlit scene scattering components only which will tend to dominate the scattering. In the pre-fire case (left panel) the modelled Skukuza scene is dominated by the sunlit soil due to the low understory and overstory cover, particularly at view angles close to nadir. The fraction of sunlit soil falls with increasing view angle away from nadir, while the sunlit understory fraction rises correspondingly to the point where they are approximately equal. For the modelled Pretoriuskop scene, sunlit soil only exceeds sunlit understory at nadir. As view zenith angle increases away from nadir, the fraction of sunlit understory stays approximately constant, while the sunlit soil decreases to near zero. This indicates that pre-fire scene scattering is dominated by the soil and understory reflectance.

In the post-fire case (right panel of Fig. 11), both modelled scenes are dominated by the fraction of charred material, either soil with char mapped onto it or charred grass. The lack of understory vegetation cover also manifests itself as a generally reduced view angle dependence, although for the Pretoriuskop scene the sunlit char crown increases at the expense of the sunlit char, due to tree shadowing. The single scattered (first order) signal is simply the sum of the proportions of each sunlit scene component multiplied by their respective reflectance properties. This emphasises the need to get the fraction of grass cover correctly parameterised to represent the burn signal. This also suggests that the result of grass cover being removed...
during a fire may be to expose other, brighter surface materials (soil here) in some cases, particularly when seen at higher view angles (also seen in Fig. 1). This is a result of the differences between the (3D) structure of the canopy layers (overstory and understory), and will not be seen in simple models which do not treat the understory and overstory as separate 3D layers. For the Pretoriuskop case the char signal dominates, reaching close to 0.8 of the scene fraction at nadir, falling away to around 0.5, the same as for the Skukuza scene despite their very different initial grass cover.

3.2. Model comparisons with helicopter data

The helicopter-mounted ASD FSPro measurements were compared with simulations from the 3D models. Simulations were performed using the same field-of-view (5° foreoptic) as the ASD, every 10 m along 3 × 50 m transects in each plot, varying the plot grass cover from 20–40 plants per m² and for high and low tree cover. The simulated instrument height was varied randomly within 10 m around a mean height of 120 m for each footprint, corresponding to the height variation seen in the helicopter measurements. This resulted in footprint diameters of 9.5-11.5 m on the surface. Simulations were performed at the mean solar zenith and azimuth angles of the measured data for each site (described in 2.3.2.3), as well as ±10° either side of these angles. Simulations were carried out from 400-2500 nm in 10 nm intervals. In total 810 ‘helicopter’ simulations were carried out per site, pre- and post-fire i.e. 3240 simulations in total.

Fig. 12 shows the comparison between the pre- and post-fire reflectance measurements made over both sites with the equivalent 3D modelled values, both spectrally and as scatter plots. The error bars in the measurements represent 1σ across all footprints within each plot. For the model values error bars represent 1σ due to the multiple footprints simulated across each plot (spatial variability) and the variation in view and sun angle. The much greater variance in the measured data compared to the modelled data is mainly due to varying sky conditions during the measurements. Although every effort was made to collect spectra under stable measurement conditions (either clear sky, or completely overcast) this was not always possible. Variation in the modeled data arises purely from the spatial variation from footprint to footprint.

The pre-fire results in Fig. 12 (top row) indicate very good agreement between the modelled and measured reflectance (r² Skukuza = 0.98; RMSE = 0.016; r² Pretoriuskop = 0.97, RMSE = 0.014), particularly in the visible and SWIR up to around 1600 nm. The spectral behaviour of both sites is similar, generally dominated by brown leaf and soil material, but with a small amount of green vegetation in the

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1 Each scenario required 1–2 hr on a 3.0 GHz Intel Xeon CPU running RedHat Linux 2.6.18-53.1.14.el5xen with 4 GB RAM. Running on 50 CPUs simultaneously allowed this set of simulations to be performed in ~4 days.
Pre- and post-fire differences in the measured reflectance can be explained by considering the sunlit scene components. For example, the measured reflectance at 2000 nm for Skukuza (0.03) and Pretoriuskop (0.03) is noticeably different. In both cases, post-fire reflectance is lower, with a much greater reduction in Pretoriuskop, due to the much denser understory vegetation being turned to char (see Fig. 1). The slight presence of green vegetation is still apparent in Pretoriuskop as the trees did not burn. The post-fire modelled values also agree well with measurements ($r^{2}\text{Skukuza} = 0.95$, $\text{RMSE} = 0.015$; $r^{2}\text{Pretoriuskop} = 0.82$, $\text{RMSE} = 0.010$), but slightly worse than for the pre-fire case, particularly at wavelengths beyond 2000 nm, although they still lie within 1σ. The largest post-fire difference between modelled and measured values occurs at 2300 nm for Skukuza (0.03), and 2134 nm for Pretoriuskop (0.02) for Pretoriuskop plots. The post-fire modelled values are a slight underestimate at visible wavelengths for Skukuza, and a slight overestimate for Pretoriuskop. However, beyond around 1600 nm the post-fire simulations exceed the measured values in both cases, while remaining well within the measurement variation. The largest pre-fire difference between modelled and measured values occurs at 2000 nm for Skukuza (0.03) and at 1600 nm for Pretoriuskop (0.03).

For the post-fire cases (Fig. 12, bottom row), reflectance behaviour is noticeably different. In both cases, post-fire reflectance is lower, with a much greater reduction in Pretoriuskop, due to the much denser understory vegetation being turned to char (see Fig. 1). The slight presence of green vegetation is still apparent in Pretoriuskop as the trees did not burn. The post-fire modelled values also agree well with measurements ($r^{2}\text{Skukuza} = 0.95$, $\text{RMSE} = 0.015$; $r^{2}\text{Pretoriuskop} = 0.82$, $\text{RMSE} = 0.010$), but slightly worse than for the pre-fire case, particularly at wavelengths beyond 2000 nm, although they still lie within 1σ. The largest post-fire difference between modelled and measured values occurs at 2300 nm for Skukuza (0.03), and 2134 nm for Pretoriuskop (0.02) for Pretoriuskop, although this is clearly a larger relative overestimate.

The behaviour of the post-fire 3D modelled reflectance in Fig. 12 can largely be explained by considering the sunlit scene components that dominate the scattering behaviour (see Fig. 11) i.e. sunlit char and soil. The first order (single scattered) modelled reflectance is the sum of the viewed scene fractions, $f$, multiplied by their respective spectral scattering properties $\rho(\lambda)$ (Fig. 4) i.e. $\rho_{\text{3D,sscatt}} = \sum f_\lambda \rho(\lambda)$. In the pre-fire cases, although multiple scattered interactions (and hence shadowed scene components) are a significant part of the signal, particularly at zenith angles further from nadir, the majority $\rho_{\text{3D,sscatt}}$ sunlit soil and grass components explain 88% of the measured signal for Skukuza. For Pretoriuskop, the $\rho_{\text{3D,sscatt}}$ combination of sunlit soil, grass and overstory explains 94% of the measured signal. The post-fire signal is dominated by the proportion of sunlit charred material, making up to 50-60% of the sunlit fraction for the Skukuza plots, with the remainder of the signal being mostly sunlit soil. Here, $\rho_{\text{3D,sscatt}}$ explains 87% of the signal. For the Pretoriuskop plots, the proportion of sunlit charred material dominates the scene to a much greater extent (70-80%), with some fraction of the remainder being sunlit overstory. In this case $\rho_{\text{3D,sscatt}}$ explains only 81% of the signal, due to the overestimation beyond 2000 nm. This rises to 97% if only wavelengths < 2000 nm are considered. The dominance of sunlit char results in overestimation in the modelledPretoriuskop cases, as the spectral behaviour of the charred material remains flat beyond 2000 nm (see Fig. 4). The measured spectra suggest some unburned grass remains, which would cause a slightly lower reflectance beyond 2000 nm. This illustrates the utility of the 3D model approach in explaining the modelled signal in terms of the most important scene components.

3.3. Model comparisons with CHRIS-PROBA data

Simulations were carried out for all 62 CHRIS-PROBA mode 1 wavebands using a 36 m footprint over a range of grass cover from 20 to 40 plants m$^{-2}$ and for high and low tree covers. Twenty footprints were simulated within each 3D scene to represent spatial variability in the resulting simulated reflectance. Simulations were compared with pre-fire CHRIS-PROBA data collected over the pre-fire experimental plots on 11/08/2008.
Fig. 13 shows modelled and measured angular reflectance (BRDF) variation for the pre-fire case, over multiple experimental plots. Fig. 14 shows the spectral variation of model simulations and measured CHRIS-PROBA reflectance, as well as scatterplots for each of the three pre-fire CHRIS-PROBA scenes. The spectral agreement is generally very good ($r^2$ 0.98 in all cases; RMSE = 0.025, 0.037 and 0.022 for the three angles respectively). The modelled and measured angular reflectance fits the expectation of a largely shadow-dominated downward bowl-shaped BRDF i.e. decreasing reflectance with increasing zenith angle away from nadir (Li & Strahler, 1992), albeit weakly-varying. There is a slight over-estimation of the model values at shorter wavelengths (maximum ~0.02 at 505 nm), and slight under-estimation at longer wavelengths ($\sim 0.09$ at 954 nm).

3.4. Model comparisons with MODIS data

Spectral comparisons between 3D model-simulated and pre- and post-fire MODIS NBAR (Table 3) are shown in Fig. 15. Fig. 16 shows an angular comparison between the 3D model simulations and the daily MODIS reflectance observations. The model simulations were carried out at the same view and illumination configurations as those in the MODIS data using a pixel size of 500 m, with spatial variability represented by randomly jittering the simulated footprint across the 3D scenes, providing 20 instances of simulated MODIS reflectance per scene. For the MODIS daily reflectance data, observations were binned by zenith angle in 2° steps and simulations performed for all sun angles in each bin. The resulting 3D model values were a mean across the different instances and sun angles.

The spectral comparison of 3D simulations with the MODIS NBAR data illustrated in Fig. 15 shows that modelled and measured values generally agree well, particularly in the visible part of the spectrum, with $r^2$ values of 0.98 for the pre-fire case (RMSE = 0.022, zero bias and offset i.e. model underestimate of 0.1% and 0.05 for the post-fire case (RMSE = 0.021, bias of 0.1 and offset of ~0.013). For the pre-fire case, the model values are always a slight underestimate, with an absolute difference of 0.002-0.005 in the visible and beyond 1650 nm, and a difference of 0.04 in the NIR (840 nm). For the post-fire case, the model values slightly overestimate in the visible by 0.005, underestimate in the NIR by 0.03 at 1240 nm before becoming a slight overestimate again of 0.02 at the longest wavelength, 2220 nm. The generally close agreement across the spectrum as illustrated by the scatter plots.

Fig. 16 shows the angular comparison of 3D model-simulated values with MODIS daily reflectance observations as a function of view angle, pre- and post-fire, for the central pixels of the two separate fires described in 2.3.2.4. The angular signal, such as it is, is quite weak. This is likely to be a result of the relatively small number of samples and the lack of principle plane sampling. There is a slight increase of reflectance with view zenith angle in the NIR for the pre-fire case, which is not present post-fire, in addition to the general reduced brightness in the post-fire case. The 3D model simulations agree well with the MODIS observations in all cases, with only one of the two cases lying outside the 1σ range (pre-fire red, view zenith 58°; post-fire NIR, view zenith 40°). The observed behaviour is consistent with a scene dominated by volume scattering (increasing reflectance with view angle in the NIR due to increased path), unlike the pre-fire CHRIS-PROBA observations. These differences are likely to be due to spatial scale, as the impact of shadowing will tend to decrease with increasing scale much beyond the size (height, width) of shadowing objects on the surface, trees in this case.

4. Discussion

The results presented above demonstrate the ability of the developed 3D models to represent the pre- and post-fire signal of a two-layer savanna system, across a range of understory and overstory covers. The difficulty of assessing the amount and structural veracity of 3D model cover was overcome by carefully matching the 3D model-derived overstory and understory canopy properties to field measurements: canopy LAI and gap fraction in the case of the overstory; simulated BRDF in the case of the understory. These model comparisons required making a range of field structural and radiometric measurements across various canopy densities in experimental fire plots. For the overstory, we used 3D model simulations to quantify the bias arising from comparing model-estimated canopy structural parameters derived indirectly from real hemisphotos with those derived directly from the 3D models. This was done by simulating hemisphotos, which were then processed in the same way as real hemisphotos collected in the field. We have used CanEYE to process hemisphotos here, but the same method could be applied with any of the hemisphoto processing tools currently in use.

In order to test the radiometric performance of the 3D models, we compared the model simulated reflectance to range of spectral and angular measurements, including: helicopter-mounted hyperspectral data at ~10 m scale across the 400–2500 nm range; CHRIS-PROBA measurements at ~36 m scale, in 62 wavebands from 415–1007 nm; and MODIS measurements at ~500 m scale in seven bands from 490–2220 nm. These measurements encompass the range of remote sensing scales that are typically available. The angular and spectral pre- and post-fire behaviour is consistent between scales i.e. increasing reflectance across the visible and SWIR, with a peak between 1200-1600 nm, followed by reduction at longer wavelengths. The post-fire case follows a very similar pattern, with a lower overall reflectance and a less pronounced peak at slightly longer wavelengths. Although there are key regions of the spectrum where the burn signal is manifested most strongly, empirical spectral indices such as NBR/ANBR may be relatively insensitive to fires of the type seen here due to the similar spectral contrast pre- and post-fire in the NIR and MIR regions (Roy et al., 2006). However these properties are difficult to measure in practice for reasons outlined above, and we suggest that the modelling methods we present may help.

It is noticeable that the CHRIS-PROBA sensor with a maximum wavelength at 1007 nm misses the part of the spectrum where the largest differences between pre- and post-fire signal occurred, both measured and modelled ($\sim$1200 nm). This would also be true for other sensors, such as the ESA MERIS instrument that has a longest wavelength of 900 nm. However, the angular signal can help to distinguish pre- and post-fire cases, as has been shown by Roy et al. (2002). The results we show here indicate why this is of particular use in a two-layer savanna system, where the 3D canopy structure resulted in a strong angular signal. The 3D model results are (unsurprisingly)
strongly dependent on the understory cover, as the change from pre-fire grass cover to post-fire char material dominated the difference between the pre- and post-fire scenes.

By analysing the viewed and illuminated scene components in the 3D model simulations we showed that the pre- and post-fire changes in scene reflectance were not simply a spectral change but also a function of the 3D interaction between the overstory and understory canopy. The results indicated that the result of grass cover being removed during a fire may act to expose other, brighter surface materials (soil here) in some cases, particularly when seen at higher view angles. This is a result of the 3D structure of the canopy: a simpler model which does not consider a heterogeneous 3D understory and overstory that can interact with each other will not be able to describe this variation correctly. We note that the fires considered here are relatively simple, in that the effects are limited to the understory only. However there is evidence to suggest this is rather typical of arid African savanna fires (Archibald & Bond, 2003; Bond & Archibald, 2003), suggesting our results are likely to be more generally applicable across these areas. However, in areas where either the canopy structure differs and/or the fire impacts differ these

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**Fig. 14.** Comparison of 3D model simulated and CHRIS-PROBA measured ρ for three view angles. The top row shows the spectral variation across all 62 CHRIS-PROBA bands, with the error bars representing ± 1σ for the modelled values (due to spatial variation) and over 48 plots for the CHRIS-PROBA data. The bottom row shows the agreement between the modelled and measured values.

**Fig. 15.** Comparison of MODIS pre- and post-fire observations against 3D modelled values. Error bars represent ± 1σ due to spatial variation for both modelled and measured values. Lines are used to join points in the left-hand plot to aid in distinguishing points.
results will not hold true (Australian savannas for example), and new 3D structural models would be required.

A major advantage of the 3D modelling approach is the ability to provide a high level of (physically meaningful) detail for analysis. Although significant effort was required to set up the models initially, once done, the impact of assumptions that might be made in simpler approaches can be explored directly, such as removing fractions of grass cover, or burning branches of a particular size distribution. Collecting pre- and post-fire data at appropriate scales to test burn detection algorithms is very difficult in practice due to the difficulty of either knowing where fires will occur in advance, and/or identifying them unambiguously after the event. Simpler 1D RT methods are more computationally efficient, require far less parameterization, and may be able to simulate much of the spectral variation (in particular). However, they will not be able to separate the spectral and structural components of the signal. Consequently, perhaps the most important role of the detailed 3D model approach might be for generating surrogate pre- and post-fire ‘measurements’ for testing simpler model approaches and fire impact algorithms. The advantage over existing work using RT models in this way is that very few assumptions regarding 3D structural or radiometric properties are required. It is certainly possible to use these models for parameter retrieval in an inverse sense by building look-up-tables (LUTs) of model outputs across a range of structural and radiometric properties. However, the level of structural data required for parameterizing the models means that, depending on the application, simpler approaches are likely to be better suited for operational algorithms.

5. Conclusions

We present a new approach to modelling the pre- and post-fire reflectance of a two-layer savanna system using highly-detailed 3D structural models. A range of models was developed to represent pre- and post-fire canopy reflectance behaviour of a measured savanna system. The 3D models were developed from detailed field measurements of overstory (tree) and understory (grass) structural and radiometric properties made at experimental burn plots with a range of overstory and understory cover.

The 3D models were used to simulate reflectance values at spatial scales from 10–500 m across the spectral range 400–2500 nm and for various angular configurations. These values were compared with measured data across the same range of scales and configurations to test the performance of the models. Measured reflectance data showed consistent spectral trends across scales with the impact of fire being manifested largely as a reduction in overall magnitude rather than a clear change in spectral shape, particularly at increasing spatial scale and reduced spectral resolution. The 3D model simulations matched observed data from three different sources (ASD, CHRIS–PROBA, MODIS) very closely for both pre-fire and post-fire scenarios and across angular and spectral configurations. The largest differences between modelled and measured values typically occurred in the post-fire simulations at wavelengths beyond 1200 nm where the simulations tended to overestimate observed values at finer spatial scales, but underestimate slightly when compared to MODIS observations.

We show that a RT modelling approach that can separate the different structural properties of the over- and understory canopy is required to represent the burn signal in a two-layer system such as the one used here. Although the 3D model approach requires significant initial work to parameterise, it is in many ways ideally suited to applications requiring pre- and post-fire simulation, due to its ability to provide detailed information on the scattering contributions of the various scene components to the burn signal, and explain the interplay between the overstory and understory. In particular, it is simple to represent a particular model of fire impact within the model framework. The difficulty of obtaining pre- and post-fire data in practice means that validating simplified approaches to burn mapping and modelling can suffer from a lack of test data. In these cases, the 3D model approach may be of real benefit.

Acknowledgements

This work was supported by ESA under project 1428/08/NL/HE. We gratefully acknowledge the NERC Field Spectroscopy Facility (FSF) for provision of equipment and technical support. We would like to thank various colleagues for help in data collection, namely Patrick Freeborn, Robert Lawson, Ronan Paugatch, Gareth Roberts, Ewan Shilland and Maria Tattaris. We are extremely grateful for the support of the SANPARKS staff in providing logistical and technical help in the field, particularly Navashni Govender and the SANPARKS helicopter pilots.

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Fig. 16. Comparison of pre- and post-fire MODIS daily reflectance data with 3D model simulations. The MODIS data are from a single pixel on two different dates (day-of-year 249 and 257 2008). 3D model values were simulated at the same angular configurations. Error bars represent 1σ across all sun angles corresponding to each MODIS observation.


**Internet**


www2: [http://www.brockmann-consult.de/cms/web/beam/welcome](http://www.brockmann-consult.de/cms/web/beam/welcome)

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