Direct retrieval of canopy gap probability using airborne waveform lidar

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Significant progress on quantifying state and trends in vegetation structure in savanna and woodland ecosystems has been made by integrating in situ measurements with lidar datasets. However, large area ground-based monitoring campaigns required for calibration are both costly to maintain, and reduce the generality of results. Estimation of directional gap probability ($P_{gap}$) from waveform lidar which is both direct (i.e. physically-based) and minimises or removes requirements for field calibration would be a significant advance for large area sampling. We present a new model for estimating $P_{gap}$ from small footprint airborne waveform lidar data that accounts for differences in canopy ($P_c$) and ground ($P_g$) reflectivity and compare this new method with published discrete return lidar methods. We use lidar surveys acquired at multiple altitudes using RIEGL LMS-Q680i and RIEGL LMS-Q560 waveform systems over a savanna woodland in the Einasleigh Uplands bioregion of northern Queensland, Australia. The waveform model for $P_{gap}$ was found to fit observed waveform data in cases where the assumption of constant $P_c$ and $P_g$ was satisfied. $P_{gap}$ estimates from the waveform model were shown to be relatively insensitive to variation in sensor altitude. This was in contrast to other methods of estimating $P_{gap}$ where differences up to ~0.15 $P_{gap}$ have been observed. Comparison of lidar-derived $P_{gap}$ with ground measurements showed the new waveform model produced estimates corresponding to within 5% $P_{gap}$. We suggest the waveform model to retrieve $P_c/P_g$ and $P_{gap}$ is a significant advance in retrieval of canopy structure parameters from small footprint lidar, reducing the need for local calibration, and providing direct estimates of $P_{gap}$. If the assumptions of relatively stable $P_c/P_g$ are shown to hold across a greater range of sensor, survey, and canopy structure configurations we suggest this method may have wide practical application for retrieval of $P_{gap}$.

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1. Introduction

Savanna and woodland ecosystems with a discontinuous tree layer of 10–30% cover make up a significant part of the terrestrial land surface, up to 1.8 million km² in Australia alone for example (Danaher et al., 2010). As a result, even relatively minor changes in vegetation extent and structure can have significant implications for carbon stocks and maintenance of biodiversity. Satellite remote sensing is the only feasible tool for providing quantitative datasets on vegetation extent and structure systematically over large areas (>10⁶ km²) for input to mapping, monitoring and modelling applications (Wulder et al., 2008). Fractional vegetation cover, biomass, leaf area index (LAI) and canopy height are some of the most important vegetation structure parameters that are used to directly interpret the transfer of radiation, carbon, and related processes in physical systems (Ross, 1981; Verstraete et al., 1996). Significant progress on quantifying state and trends in vegetation structure in savanna and woodland ecosystems has been made by integrating in situ measurements with satellite imaging datasets (Danaher et al., 2010; Lucas et al., 2010). However, large and regularly repeated field-based inventory and monitoring programs are expensive to maintain and there are often insufficient resources to accurately capture the spatial and temporal variability in structure, especially for scaling up to satellite remote sensing.

Airborne lidar has shown potential as a sampling tool to capture this variability and greatly improve the link between in situ and satellite monitoring of these biophysical parameters (Asner, 2009; Wulder et al., 2012). Canopy height and directional gap probability ($P_{gap}(\theta)$) are the only two structural parameters that may be near-directly retrieved from airborne lidar measurements (Ni-Meister et al., 2001). $P_{gap}(\theta)$ is defined as the probability of a beam of infinitesimal width...
at zenith angle $\theta$ to the local normal, being directly transmitted through a canopy. Hence $P_{\text{gap}}(\theta)$ is equivalent to the probability that the ground surface is directly visible from airborne and spaceborne remote sensing platforms. Since $P_{\text{gap}}(\theta)$ represents the integrated effect of several scale-dependent canopy structural properties, other canopy structure parameters (e.g. LAI) and above-ground biomass may be modelled using different expressions, combinations or spatial variance of canopy height and $P_{\text{gap}}$ (Campbell and Norman, 1989; Ni-Meister et al., 2010). $P_{\text{gap}}$ is also a key determinant of canopy radiative properties (particularly absorption) and is widely used in models of canopy scattering, as well as to describe the impact of canopy structure on the transfer of radiation, water and carbon more generally (Ross, 1981). The vertical distribution of lidar derived $P_{\text{gap}}$ is indirectly related to the vertical distribution of plant area (Ni-Meister et al., 2001), forest ecological structure in the context of biodiversity assessment (e.g. Miura and Jones, 2010), and the structure of regenerating and old-growth forests (e.g. Lefsky et al., 1999b). Airborne lidar estimates of the vertical distribution of $P_{\text{gap}}$ are also sufficiently simple to derive, therefore large volumes of data across wide areas and over long time-periods can be processed rapidly.

Current airborne lidar systems use either discrete return or waveform sensors. Discrete return sensors use analogue detectors to record discrete, time-stamped trigger pulses from the received waveform in real time. Waveform sensors digitize the entire return signal at a particular temporal sampling interval (1–10 ns). Airborne waveform systems have historically been large footprint (>5 m) experimental sensors such as the Land, Vegetation, and Ice Sensor (formerly named the Land Vegetation Imaging Sensor (LVIS); Blair et al., 1999) and Scanning Lidar Imager of Canopies by Echo Recovery (SLICER; Blair et al., 1994). Small footprint lidar systems (<5 m) have typically been discrete return commercial systems originally designed for topographic mapping, hence the footprint size is often kept to 0.1 to 3 m by using a small beam divergence angle. Small footprint lidar systems are ubiquitous in forestry and remote sensing, and the current status of these systems was comprehensively reviewed by Mallet and Bretar (2009).

The last two decades have seen rapid advances in pulse rates, storage capacity and positional accuracy of airborne lidar systems (Shan and Toth, 2009). Key differences between discrete return systems over this time include sensor ‘dead time’ caused by time delays in the receiver electronics (≈1–5 ms; negligible in some current sensors), range resolution determined by the length of the transmitted pulse, and the maximum number of returns that can be recorded by the sensor (1–6). Signal processing algorithms used to detect returns are often proprietary and differ between discrete return sensors as well (Disney et al., 2010). The implication of these differences is that different discrete return lidar instruments are unlikely to provide repeatable estimates of canopy height and $P_{\text{gap}}$ across different lidar instruments, survey configurations, and environmental conditions. Hence many published empirical relationships between field and lidar estimates of canopy structure have limited wider application (e.g. Solberg, 2010; Armston et al., 2009; Rosette et al., 2009). Current best practice is to repeat ground-based calibration for new discrete return lidar acquisitions in order to ensure estimates of vegetation structure parameters, as opposed to the objective of deriving a denser point cloud for classification (e.g. Chasmer, 2009) used different ratios of summed intensity values from the canopy to the total summed intensity, however they did not account for differences in canopy and background reflectivity. Gill et al. (2009) and Solberg (2010) also used a summed intensity ratio, but normalised the ground return sum by an estimate of the canopy and ground reflectivity ratio derived from single return intensity values and plot-based calibration, respectively. The primary limitation of these discrete return intensity based approaches is a poor understanding of what the intensity value is a measure of (e.g. peak integral, peak amplitude, peak leading edge), if the recorded intensity is linearly related to received power, and what the impact of the aforementioned differences between discrete return sensors are on the summed values. Many of the details required are treated as proprietary knowledge by commercial lidar instrument manufacturers, hindering the development and application of methods for direct retrieval. Waveform lidar does, in part, avoid these issues by sampling, through range bin discretization, the complete return intensity signal. Therefore it provides a line of investigation to test physical models of pulse–canopy interactions and pursue a more quantitative approach to estimation of $P_{\text{gap}}$ and other structural parameters (Disney et al., 2010; Næsset, 2009).

Despite increasing volumes and accessibility of small footprint waveform lidar data, there are few examples in the literature evaluating these data against discrete return lidar for estimating vegetation structure parameters, as opposed to the objective of deriving a denser point cloud for classification (e.g. Chauve et al., 2009; Reitberger et al., 2009). There is evidence that small footprint waveform data may improve estimates of canopy height. Hancock et al. (2011) showed in a simulation experiment that a signal noise tracking method provides unbiased estimates of range compared to traditional discrete return trigger methods, however validation with measured waveform data is required. Magruder et al. (2010) found that local aggregation of waveforms could improve the detection of low signal-to-noise ratio (SNR) ground returns in dense vegetation, which is a known limitation of discrete return data in closed canopies (Mallet and Bretar, 2009). Some studies have attempted to estimate foliage profiles from small footprint waveform data. Lindberg et al. (2011) used the Beer–Lambert law to normalise waveforms for occlusion, and found that estimates of total vegetation volume were of higher accuracy than discrete return in reference to field measurements. Adams et al. (2012) proposed a exponential decay parameter based on the Beer–Lambert law that may be regressed against field estimates of foliage area density, however initial correlations with field data were poor. Both these examples made the turbid medium assumption, which may not be valid for the clumped coniferous canopies studied (Chen et al., 1997). Estimation of $P_{\text{gap}}$ using the ratio of canopy to

\[ P_{\text{gap}} = 1 - \text{fractional cover} \]
total received energy from waveform lidar was implicit in the method of Lindberg et al. (2011), however these estimates were not validated. To our knowledge there has been no published work on the estimation and validation of $P_{\text{gap}}$ from small footprint waveform lidar.

Theory and methods for direct retrieval of $P_{\text{gap}}$ have been developed and applied for large footprint waveform lidar (Means et al., 1999; Ni-Meister et al., 2001, 2010). Lovell et al. (2003) adapted these methods to small footprint discrete return lidar data, highlighting that they are equally applicable to small footprint waveform data. However, no studies have demonstrated an improvement in $P_{\text{gap}}$ estimates derived using airborne waveform data. Estimates of $P_{\text{gap}}$ are known to be sensitive to the canopy/ground reflectivity ratio and therefore the wavelength of the sensor (Ni-Meister et al., 2001; Tang et al., 2012). Therefore prior knowledge of this ratio is required to obtain unbiased estimates of $P_{\text{gap}}$ from waveform data and avoid field calibration. This is especially true in savannas where estimates of $P_{\text{gap}}$ will be most sensitive due to sparse canopies and variable backgrounds. Previous studies have suggested using a constant (e.g. $\nu\delta/\beta_g = 2$ for 1064 nm; Lefsky et al., 1999b), however canopy and ground properties often change between stands. Ni-Meister et al. (2010) suggested that estimates of the canopy/ground reflectivity ratio could be derived from canopy and ground waveform integrals for large footprint waveform lidar, however no results were published. Such an approach has not been developed and validated for small footprint lidar systems.

1.1. Aim and research objectives

The aim of this study was to investigate if waveform lidar data can improve the estimation of $P_{\text{gap}}$ from airborne platforms compared to discrete return lidar data. Airborne lidar is potentially a very direct way to estimate $P_{\text{gap}}$, however current methods generally use discrete return data and often rely on site, sensor and survey specific calibration. A physically-based method for direct retrieval of $P_{\text{gap}}$ from waveform lidar, if validated, would reduce local field calibration requirements and be a significant advance for the wider application of airborne lidar. We focussed our investigation on lidar surveys acquired using RIEGL LMS-Q680i and RIEGL LMS-Q560 waveform lidar systems over a savanna woodland in the Einasleigh Uplands bioregion of northern Queensland, Australia. These data were used to develop coincident waveform and discrete return datasets to enable a controlled comparison between the two types of lidar data. The site is well suited for testing the waveform method, and the results will have application in state and national mapping and monitoring programs currently underway across Australia, but also more widely in discontinuous cover systems.

The specific research objectives were:

1. Develop an approach to account for ground and canopy reflectivity differences in small footprint waveform lidar estimates of $P_{\text{gap}}$.
2. Assess the impact of variation in sensor and survey properties on waveform and discrete return estimates of $P_{\text{gap}}$.
3. Determine if waveform estimates of $P_{\text{gap}}$ are more accurate than discrete return estimates.

2. Study site and sampling design

2.1. Einasleigh Uplands savanna transect

The study site is located near Charters Towers in northern Queensland, Australia, and is within the Einasleigh Uplands bioregion at approximately 400 m elevation. This is a region of savanna and woodlands and its primary land use is livestock grazing. Three 100 m by 100 m structurally contrasting savanna open woodland field plots were sampled (CHAT0101, CHAT0102, CHAT0103; Fig. 1). These are part of a larger network of sites in Queensland for calibration and validation of Landsat-derived woody and herbaceous fractional cover products (e.g. Armston et al., 2009).

The woodlands at CHAT0101 (20.0047°S, 145.6224°E) were dominated by Eucalyptus drepanophylla with Corymbia dallaschens sub-dominant in the 12–20 m height canopy, Petalesitogia pubescens and Maytenus cunninghamii are also occasionally present in the understory (3–7 m height). Within CHAT0102 (19.9796°S, 145.6490°E), Eucalyptus melanophloia dominated the sparse canopy (8–19 m height) with Corymbia setosa also present. $P_{\text{pubescens}}$ dominates a higher density understory compared to the other two sites (2–6 m height). The canopy at the CHAT0103 (20.0023°S, 145.6029°E) site was very sparse with Eucalyptus brownii forming the overstorey (5–18 m height) and the occasional Acacia salicina and Acacia farnesiana in the understory (0.5–2 m height). CHAT0101 and CHAT0102 were located on sand plains with relatively uniform grass cover. CHAT0103 was located on basalt plains with occasional surface basalt boulders and grey to black cracking soils. The grass cover is clumped at CHAT0103 with large areas of bare soil exposed. The terrain at all three sites was flat.

2.2. Field and lidar surveys

The lidar surveys used in this study were acquired on two different dates as shown in Table 1. A RIEGL LMS-Q680i waveform lidar survey was acquired on the 18th June 2010 to quasi-simultaneously capture a range of survey properties (A2–A4). In consultation with the data provider, the A2–A4 survey properties were designed to capture a range of sensor and survey configurations within limits recommended by RIEGL for instrument operation over vegetation. Parallel flight tracks were designed to have 60% overlap at each altitude to ensure a multi-angular airborne dataset over the field sites. Multiplane flying heights were designed to capture the changing footprint size and SNR of received waveforms due to the inverse square loss of power per unit area with range. Only the centre flight track at each nominal altitude were used in the present study, as directly measured $P_{\text{gap}}(\theta)$ validation data were only available at a zenith angle of zero degrees. A RIEGL LMS-Q560 survey was also acquired on the 3rd November 2008 as part of ongoing monitoring at the study site (A1). This survey was acquired with the same centre flight track as the A2–A4 surveys.

Estimates of $P_{\text{gap}}(\theta)$ at a nominal zenith of zero were directly measured using three 100 m point intercept (1 m spacing) transects oriented 0°, 60° and 120° from magnetic north. At each 1 m interval along each transect, vertical intercepts were recorded from the overstorey (woody plants greater than or equal to 2 m height) using a GRS densitometer®. This instrument employed a mirror, two bubble-level lines and a centred cross-hair to project an exact vertical line-of-sight from the sample point in the canopy to the observer. Vertical intercepts were recorded from the midstorey (woody plants less than 2 m height) if plant material was touching the side of the densitometer pole closest to the observer. Vertical intercepts were recorded from the understory (herbaceous plants and graminoids less than 2 m height) using a laser pointer attached to the densitometer pole. Since $P_{\text{hi,m}}$ is conditional on $P_{\text{hi,o}}$ from the vertical view of airborne lidar, the total $P_{\text{gap}}$ was calculated as:

$$P_{\text{gap}} = 1 - \left[ P_{\text{hi,o}} + (1 - P_{\text{hi,o}}) P_{\text{hi,m}} \right]$$

where $P_{\text{hi,o}}$ was the fraction of overstorey observations that were leaf or wood intercepts and $P_{\text{hi,m}}$ was the fraction of midstorey observations that were leaf or wood intercepts. Eq. (1) assumes that the horizontal spatial distribution of midstorey canopy elements is random.
3. Methods

3.1. Waveform processing

Raw waveform data were made available for the RIEGL LMS-Q560 airborne surveys. The data provider was unable to deliver raw waveform data for the RIEGL LMS-Q860i airborne surveys. Common data that were provided for both airborne surveys were GPS time, cartesian coordinates (easting, northing, elevation), Gaussian parameters (range, amplitude and full-width half-maximum) and pulse parameters (scan zenith, time) that were produced for each detected return using the RIEGL RiAnalyze® software (RIEGL, 2008).

Since only the Gaussian parameters were available to this study for all airborne surveys, it was assumed that the Gaussian model was a valid representation of received waveforms (R) for the study site. Limited validation of Gaussian modelled canopy (Rc) and ground (Rg) return integrals was undertaken for the study site using measured waveform integrals derived from the Q560 airborne survey data (Table 1).

The method described by Wagner et al. (2006) was used to implement a Gaussian decomposition procedure for the Q560 waveform data. Initially a dark current offset of 2 was subtracted from the raw waveforms (RIEGL, 2008). Estimates of the Gaussian parameters were then derived using non-linear least-squares fitting with the Levenberg–Marquardt method (Marquardt, 1963) to Eq. (2):

\[ R(t) = \epsilon + \sum_{i=1}^{N} A_i e^{-\frac{(t-t_i)^2}{\sigma_i^2}} \]  

where for each return, \( \epsilon \) is the noise level, a nominal value greater than background solar irradiance and photon counting noise contributions. \( A_i \) is the amplitude of Gaussian \( i \), \( t_i \) is the time (or range) and \( \sigma_i \) is the standard deviation of Gaussian \( i \). Starting parameters for the fitting were determined from the zero-crossings of the waveform first derivative. Only peaks that had an uncalibrated intensity value greater than 9 were fitted, which was the default value provided by RIEGL (2008). False returns or ‘ringing’ that followed bright waveform peaks due to the impulse response of the receiver electronics amplifier were omitted from the fitting if their amplitude was less than \( \epsilon_d \). This was defined as \( \epsilon \) plus the value from a time decay function on the amplitude of preceding local maxima (Eq. (3)):

\[ \epsilon_d = \epsilon + A_i e^{-\frac{t-t_d}{\tau}} \]  

where \( \tau \) is the decay value in units of time, for which a default value of 10 was used. This value was determined through experimentation with high amplitude ground returns.

For direct comparison of the ground (Rg) and canopy (Rc) integrals of the raw and Gaussian model received waveforms, their separation was at the first occurrence of the minimum signal between the ground and canopy Gaussian model peaks. This often corresponded to dead time (i.e. a period when no signal is recorded by the sensor) in the raw waveform data when the ground and canopy return were well separated in time. The RIEGL LMS-Q560 and LMS-Q680i instruments record waveform samples in 60 ns sample blocks, with recording of blocks initialised by the signal exceeding a noise threshold (RIEGL, pers. comm.). Comparison between the measured and Gaussian model waveforms was made using the root mean square error (RMSE). The normalised RMSE were also calculated as \( \text{RMSE} = \frac{\text{RMSE}}{\text{RMSE}_{\text{max}}} \).

### Table 1

Survey properties for the RIEGL airborne waveform lidar datasets used in this study.

<table>
<thead>
<tr>
<th>Survey</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
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<tr>
<td>Acquisition date</td>
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<td>2010/06/18</td>
<td>2010/06/18</td>
<td>2010/06/18</td>
</tr>
<tr>
<td>RIEGL sensor</td>
<td>LMS-Q560</td>
<td>LMS-Q680i</td>
<td>LMS-Q680i</td>
<td>LMS-Q680i</td>
</tr>
<tr>
<td>Nominal altitude (m)</td>
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<td>450</td>
<td>900</td>
<td>1200</td>
</tr>
<tr>
<td>No. parallel flight lines</td>
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<td>3</td>
<td>3</td>
<td>3</td>
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<td>Swath width (m)</td>
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<td>520</td>
<td>1039</td>
<td>1386</td>
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<tr>
<td>Pulse rate (kHz)</td>
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<td>200</td>
<td>150</td>
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<tr>
<td>Pulse energy (J)</td>
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<td>17.11</td>
<td>22.81</td>
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<tr>
<td>Scan rate (Hz)</td>
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<td>63</td>
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<tr>
<td>Pulse density (pulse/m²)</td>
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<td>2.10</td>
<td>1.11</td>
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<tr>
<td>Maximum zenith angle (°)</td>
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<td>30.0</td>
<td>30.0</td>
<td>30.0</td>
</tr>
</tbody>
</table>

3.2. Lidar calibration

For Lambertian extended targets orthogonal to the laser beam, the equation for the received power \( P_r(t) \) can be expressed as:

\[ P_r(t) = P_l \rho_{app} T_{\text{atm}}^2 A_r \frac{\eta}{r^2} \Phi \]  

where \( T_{\text{atm}} \) is the two-way atmospheric transmittance, \( A_r \) is the receiver aperture area, \( P_l \) is the transmitted power, \( r \) is the range to the target, \( \eta \) represents system losses (e.g. quantum efficiency), and \( \rho_{app} \) is the apparent reflectance of the target. The recorded signal is
convolved by the transmitted pulse ($\Phi$), which has a peak power of unity. Targets closer than the width of the transmitted pulse or the temporal sampling interval of the waveform digitizer (1 ns for the RIEGL instruments) are not separable.

The $\rho_{app}$ is interpreted as the reflectance of a Lambertian target filling the lidar beam and orthogonal to the pulse direction of travel that would return the same intensity as the actual target (Jupp et al., 2009). For non-Lambertian targets the $\rho_{app}$ will change with zenith angle, therefore this effect will need to be considered when interpreting derived estimates of $\rho_{app}$. We can invert Eq. (4) for $\rho_{app}$:

$$\rho_{app} = \frac{P_r(t) r^2}{P_r T_{dm} A_v \eta}$$

(5)

The system waveform recorded by the RIEGL instruments is an unknown constant fraction of $P_r$, therefore calibration is required to derive $\rho_{app}$. Wagner et al. (2006) developed a method to calibrate to the backscatter cross-section, which was adapted here to calibrate the recorded intensity of each return to $\rho_{app}$. Since the convolution of two Gaussian pulses results in another Gaussian, deconvolution is implicit in the calibration. A calibration constant (C) can be formulated by separating constant from variable terms in Eq. (5):

$$\rho_{app} = C r^2 P_r$$

(6)

where $C$ is a calibration factor to account for the parameters ($P_r, A_v, T_{dm}, \eta$) that are assumed to be constant for each acquisition. It is also assumed that $P_r$ is linearly related to the intensity recorded by the lidar receiver.

The calibration constant can then be derived from ground measurements of $\rho_{app}$ for Lambertian calibration targets that fill the lidar beam. It was not possible to set-up calibration targets at the time of the airborne surveys, therefore we used reflectance measurements of the unsealed flat road parallel to the flight line taken using an ASD FieldSpec Pro Spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA) and laboratory calibrated Spectralon® panel. A mean reflectance value of 0.39 ± 0.03 was calculated and Eq. (6) inverted to estimate $C$:

$$C = \frac{0.39}{r^2 A_{cal} s_{cal}}$$

(7)

where $A_{cal}$ and $s_{cal}$ are the return Gaussian amplitude and standard deviation for the calibration target. Estimates of C were derived for each acquisition listed in Table 1 as an average of ten pulses manually selected at the site of measurement. A more accurate calibration would have used a larger number of dedicated extended calibration targets of varying brightness (e.g. Kaasalainen et al., 2009), however the measured reflectance used to calibrate was constant for all acquisitions therefore does not impact on their comparison. The $\rho_{app}$ was then estimated for each return by substituting $A_{cal} s_{cal}$ for $P_r$ in Eq. (6).

3.3. Estimation of $P_{gap}$

Classification of ground and non-ground returns was completed using the Cartesian coordinates of each return determined by the Gaussian decomposition. These coordinates were input to a modified version of the progressive morphological filter by Zhang et al. (2003). Natural neighbour interpolation of returns classified as ground was used to predict the ground elevation at the location of each non-ground return. The height above ground of each return was then calculated as the difference of the return and ground elevations.

Discrete return estimates of $P_{gap}$ were generated using the Cartesian coordinates of the Gaussian peaks, normalised to height above ground. The review of previous research using discrete return lidar sensors found that $P_{gap}$ was typically estimated as some expression of the proportion of returns intercepted by the canopy within a data bin. Two of these expressions were tested in this study, one based on the interception of a pulse by the canopy (method D1), and another that used all returns for each pulse (method D2).

For method D1, the first returns for each pulse were aggregated and the $P_{gap}$ from above the canopy down to height $z_i$ was estimated by taking the cumulative sum and normalising by the total number of pulses ($N$):

$$P_{gap}(z) = \frac{\sum_{z_i}^{z_{max}} z_i \#Z_i}{N}$$

(8)

For method D2 a weighting ($w$) was calculated for each return as $1/n$ where $n$ is the number of returns detected for the given pulse. This method assumes that the same projected area of foliage was intercepted by each return and is similar to the first-last return weighting method presented by Lovell et al. (2003). These weightings were aggregated and $P_{gap}$ calculated according to Eq. (9):

$$P_{gap}(z) = \frac{\sum_{z_i}^{z_{max}} z_i \#Z_i w_i}{N}$$

(9)

Next we present the basic lidar equations to derive $P_{gap}$ from waveform lidar using the nomenclature of Ni-Meister et al. (2001). Assuming single order scattering only (i.e. only one interaction of transmitted photons with ground or vegetation elements), the waveform energy $R$ can be separated into independent vegetation and ground backscatter components:

$$R = R_v + R_g$$

(10)

where $R_v$ is the integrated vegetation backscatter component of the waveform and $R_g$ the integrated ground return. Disney et al. (2006) showed greater than 80% of reflectance at the nadir hotspot is single scattered photons, and Calders et al. (2013) reported that greater than 90% of large footprint 1064 nm backscatter from a dense canopy was single order scattering only. Since green foliage typically has low reflectance at the 1550 nm wavelength of the RIEGL instruments, it is therefore reasonable to assume negligible multiple scattering. Assuming the recorded lidar signal is linearly related to the received power, $P_{gap}$ can then be estimated from uncalibrated waveforms by Eq. (11) (Lefsky et al., 1999a,b; Ni-Meister et al., 2001):

$$P_{gap}(z) = 1 - \frac{\sum_{z_i}^{z_{max}} R_{ij} 1}{R_g \sum_{z_i}^{z_{max}} R_{ij} + \rho_v \rho_g}$$

(11)

where $R_{ij}$ is the integrated vegetation backscatter component of the waveform from the top of the canopy down to height $z_i$, $R_g$ is the ground backscatter integral, $\rho_v$ is the backscattering coefficient of vegetation, and $\rho_g$ is the backscattering coefficient of the ground. The $\rho_v$ and $\rho_g$ are a function of the reflectance, scattering phase function (may be defined as the ratio of observed reflectance from the actual surface area visible within the field-of-view to the reflectance that would result if the same surface area were flat and normal to the view directions over all view angles) and angular distribution of canopy and ground elements (Ni-Meister et al., 2001). $R_v$ and $R_g$ can be expressed as a function of $P_{gap}$:

$$R_v = J_0 (1 - P_{gap}(0)) \rho_v$$

(12)

$$R_g = J_0 P_{gap}(0) \rho_g$$

(13)

where $J_0$ is the transmitted pulse energy corrected for transmission losses. Ni-Meister et al. (2010) originally noted that by comparing
R_v and R_g from two spatially adjacent pulses an estimate of \( \rho_v/\rho_g \) could be expressed as:

\[
\frac{\rho_v}{\rho_g} = \frac{R_{v,1} - R_{v,2}}{R_{g,2} - R_{g,1}}
\]

The assumption here is that the two \( R_v \) and \( R_g \) observations are sufficiently different to obtain an accurate estimate in the presence of noise. For small footprint lidar a larger sample would be required to be representative of a local area. By observing that \( \rho_v/\rho_g \) can then be solved for using linear regression techniques. An estimate of \( J \) may be calculated with only an estimate of \( \rho_g \) and \( \rho_v \) set to a constant of 0.5 for 1550 nm (method data), and (to be representative of a local area. By observing that \( P_{gap} = 1 - \frac{P_g}{P_s} \), we can substitute this into Eq. (13) and rearrange to define a linear relationship between \( R_g \) and \( R_v \):

\[
R_g = J_0 J_s \frac{P_g}{P_s} R_v
\]

If assumed to be constant and to extend to \( N \) pulses within a local area, \( \rho_v \) and \( \rho_g \) can then be solved for using linear regression techniques. An estimate of \( J_0 J_s \) is the intercept (\( J_0 \) is unity for calibrated data), and \( \rho_v \) is \( -\frac{P_v}{\beta} \) where \( \beta \) is the slope of the regression line. The ratio \( \rho_v/\rho_g \) is simply \( -\beta^{-1} \).

It is also possible to remove dependency on \( \rho_v \) entirely. If we invert Eq. (15) for \( \rho_v/\rho_g \) and substitute the right hand side of the result into Eq. (11), we can simplify to:

\[
P_{gap}(z) = 1 - \sum_{z=0}^{z_{max}} \frac{R_{v,i}}{R_v} \frac{1}{1 + \frac{x_i}{\rho_g z_{max}}}
\]

With this expression, total (i.e. when \( z_i = 0 \)) canopy \( P_{gap} \) is independent of \( R_v \) as well as \( \rho_v \). It also means that waveform estimates of \( P_{gap} \) may be calculated with only an estimate of \( J_0 J_s \). For small footprint waveform lidar, an estimate of \( J_0 J_s \) can easily be calculated as the mean integral of unimodal ground returns, assuming \( \rho_g \) is constant and the mean converges to a normal distribution.

Waveform estimates of \( P_{gap} \) were calculated in this study using the Gaussian amplitudes and standard deviations for each peak. These data were scaled to \( P_{app} \) and the sum of all canopy \( (I_v) \) and ground \( (I_g) \) \( P_{app} \) calculated. \( P_{app} \) was then estimated by substituting \( I_v \) for \( R_v \) and \( I_g \) for \( R_g \) in Eqs. (11) and (15). Two waveform estimates of \( P_{gap} \) were evaluated in this study: \( \rho_v/\rho_g \) derived from Eq. (15) (method W1) using ordinary least squares, and with \( \rho_v/\rho_g \) set to a constant of 0.5 for 1550 nm (method W2).

Accuracy assessment of lidar \( P_{gap} \) methods was by comparison with transect estimates of \( P_{gap} \) with \( z \) set to 0.5 m. This was to ensure near-ground objects (e.g. litter, termite mounds, grass) did not contribute to lidar \( R_v \).

4. Results and discussion

4.1. Accuracy of the Gaussian model

The correspondence between the measured and Gaussian model estimates of \( R_v \) and \( R_g \) is shown in Fig. 2. Overall the correspondence is high for both \( R_v \) and \( R_g \), with errors ranging from 0.7% to 2.4% of the data range for all sites. The tall vegetation and sparse understory resulted in ground and canopy returns that were well separated in time. Therefore there were few overlapping returns near ground level, increasing the likelihood of Gaussian shaped returns (Ulrich and Pfennigbauer, 2011) and simplifying the separation of the \( R_v \) and \( R_g \) components. The RMSE were consistently higher for \( R_v \) than \( R_g \), particularly for CHAT0101 (28.32 compared to 13.01). The majority of scatter for all plots is above the 1:1 line, which is the result of the Gaussian decomposition procedure not fitting to the low amplitude peaks. This is because of the relatively high noise threshold (Eq. (9)) used in the peak detection, and the removal of peaks following high amplitude returns due to ringing in the receiver electronics. High amplitude peaks, which are predominantly unimodal ground returns, typically have the lowest relative error but highest absolute error due to slight deviations of the system waveform from a true Gaussian (Wagner et al., 2006).

The \( R_v \) scatter is partly explained by canopy structure as well, with CHAT0101 having the greatest canopy density and height of all three sites. The canopy was composed of clumped scattering elements with variable leaf angle distributions, which resulted in more complex waveforms. CHAT0101 had 71.5% of pulses consisting of single Returns (i.e. unimodal waveforms), compared to 87.6% and 95.5% for CHAT0102 and CHAT0103. Of pulses that intercept the canopy, CHAT0101 has 81.4% with multiple Returns, compared to 64.7% and 62.2% for CHAT0102 and CHAT0103. Therefore it was likely to have a higher proportion of overlapping Returns resulting in non-Gaussian shaped peaks (Fig. 3). The CHAT0101 site also had the highest proportion of low \( R_v \) (0–400; Fig. 2), where the error is largely determined by the reduced SNR in the waveform data (Wagner et al., 2006). The predominantly senescent grass cover was also highest at the CHAT0101 site (72.5%), compared to 54.6% and 33.9% for the CHAT0102 and CHAT0103 sites. Increasing grass volume may alter the amplitude, width and timing of ground return peaks (Wu et al., 2011), thereby causing deviation from an ideal Gaussian scatterer.

Fig. 3 shows an example of the Gaussian decomposition for an individual RIEGL LMS-Q560 waveform at the CHAT0101 site. The raw measured waveform (left panel) has a number of peaks distributed as a function of range. The second peak from the top in the raw waveform has an asymmetrical profile to which the Gaussian model is not an ideal fit. Skewed returns over vegetation have also been observed elsewhere (e.g. Chauve et al., 2009), possibly due to interactions between the shape and duration of the transmitted pulse and vertical canopy structure. For comparison, the middle panel of Fig. 3 shows the effective differential cross-section derived using Lucy–Richardson deconvolution (Lucy, 1974) with the actual corresponding system waveform. The cross-section profile shows an additional peak, highlighting additional vertical vegetation structure information not captured by the Gaussian model.

These results provide evidence that Gaussian decomposition of RIEGL waveforms in a savanna environment is able to statistically reproduce the components of received waveforms for a large number of pulses with errors less than 3% of the observed range in \( R_v \) and \( R_g \). However, it is likely that the low normalised RMSE statistics shown (0.7% to 2.4%) are site-specific and may not be replicated in other environments with dense vegetation and more complex terrain. Pulses at off-nadir scan angles (>15°) and with a larger beam divergence (or footprint size) were not assessed in this study. The interaction of sloped terrain and off-nadir scan angles with increasing lidar beam divergence will, in general, reduce the amplitude and increase the width of ground returns (Yang et al., 2011). In turn, this effect may: (i) reduce the SNR of ground returns and hence the detection of their peaks in the Gaussian decomposition, particularly in dense vegetation; and (ii) distort the shape of ground returns, resulting in deviation from a true Gaussian and making \( R_v \) and \( R_g \) difficult to separate, especially in the presence of low vegetation. Despite these potential limitations, it is reasonable to assume that waveforms reconstructed using the Gaussian model were valid for the objectives of this study, enabling comparison of \( R_v \) and \( R_g \).

4.2. Relationship between canopy and ground backscatter

Images of the total \( P_{app} \) (I), a false colour composite of the corresponding canopy \( (I_v) \) and ground \( (I_g) \) components, and canopy height from the A2 acquisition are displayed in Fig. 4 to illustrate the spatial variation in waveform \( P_{app} \) for different land covers. Pulses that intercept the canopy \( (z > 0) \) generally have lower total \( P_{app} \) than pulses that only intercept the background. This is interpreted as water
absorption at the 1550 nm wavelength of the RIEGL sensor by live foliage, although specular reflections away from the sensor field-of-view would also contribute to a reduction in received power. CHAT0103 is an exception to this contrast, with areas of dark ground exhibiting similar total $\rho_{app}$ as the canopy. The areas of low $\rho_{app}$ ground in CHAT0103 correspond to patches of exposed black clay soils (see Fig. 1). In comparison, areas of senescent grass cover exhibit higher $\rho_{app}$ similar to the ground $\rho_{app}$ observed at CHAT0101 and CHAT0102. The lower water content of senescent grasses results in a higher reflectance at 1550 nm compared to green grasses, in which case the spectral properties of the carbon content (i.e. cellulose, lignin) are more important in determining the observed reflectance (Asner, 1998). The spatial variation in $I_g$ appears uniform for the CHAT0101 and CHAT0102 sites, which is consistent with the uniform grass cover observed at these sites.

The distributions of $I_g$ and $I_p$ for pulses that have returns from only the canopy or ground, respectively, are shown in Fig. 5. The distributions of $I_g$ consist of unimodal waveforms (i.e. single returns) from the ground, and the $I_p$ distributions often consist of multiple waveform peaks distributed along the path of the pulse but with no ground return (i.e. assumed to be completely intercepted by the canopy). The mean value for the CHAT0101 and CHAT0102 sites converge to a normal distribution, and are significantly different at the 0.05 level (two-sample t-test). This supports the waveform $P_{gap}$ method assumption of constant $\rho_g$ for the CHAT0101 and CHAT0102 sites. The mean values of $I_g$ for the CHAT0103 site does not converge to a normal distribution and observations are significantly different to the CHAT0101 and CHAT0102 observations ($p < 0.05$; Wilcoxon two-sample test). This result is consistent with the non-uniform spatial distribution of $I_g$ observed in Fig. 4, which indicates that the waveform $P_{gap}$ method assumption of constant $\rho_g$ may be invalid for CHAT0103. The distributions of $I_p$ shown in Fig. 5 are highly heterogeneous. The higher relative frequency of low $I_p$ compared to $I_g$ is consistent with the higher proportion of live foliage relative to other canopy materials, but is in contrast to the normal distributions of waveform backscatter totals from a dense forest canopy reported by Wagner et al. (2008). This contrast is probably due to the relatively small number of observations (range 81–1764) coincident with the sparse tree cover in this study, and different proportions of spectrally contrasting materials.

The relationship between $I_g$ and $I_p$ for individual pulses from the A2 acquisition is shown in the top panel of Fig. 6. Visual inspection of the scatter indicates there may be a linear relationship between $I_g$ and $I_p$ where the density of observations is highest. However, the large increase in variance of $I_p$ with decreasing $I_g$ resulted in poor linear model fit using the ordinary least squares method due to heteroscedasticity. Alternative fitting techniques such as orthogonal distance regression may reduce this problem. However, the main issue is the assumption of constant $\rho_g$ and $\rho_p$. The small footprint of
the RIEGL lidar data (0.23 m at 450 m altitude) caused measurements to be sensitive to high spatial variance in the cross-section and spectral properties of intercepted targets. For \( I_v \), each received waveform may backscatter from an individual grass sward or a patch of bare soil between swards. For \( I_g \), each received waveform is likely to be composed of highly variable proportions of leaf and woody canopy elements, which have different spectral properties at 1550 nm for these sites. There are a large number of outliers with very high \( I_v \), which is also consistent with ‘speckle’ due to high apparent reflectance from individual canopy elements acting as Fresnel reflectors (Jupp and Lovell, 2007).

It is possible to reduce local spatial variance and noise in small footprint lidar data by aggregating all waveforms within a local area and normalizing the signal by the number of pulses to simulate a larger footprint waveform (Blair and Hofton, 1999). The bottom three panels of Fig. 6 shows the relationship between \( I_v \) and \( I_g \) using pseudo-waveforms created at 1 m, 3 m and 5 m footprint sizes. For footprint sizes of 3 m and 5 m at the CHAT0101 and CHAT0102 sites, the variance in \( I_v \) is constant as a function of \( I_g \), the correlation is high \((r > 0.9)\), and the values of \( \rho_v \) and \( \rho_g \) stabilise. The highly linear relationships also add weight to the argument that multiple scattering forms a negligible component of the waveform signal in a savanna environment. In contrast, the trend in variance for the 0.23 m footprint size was reversed at the CHAT0103 site because the variance in \( I_g \) increased as \( I_v \) decreased. The spatial heterogeneity in grass cover across the CHAT0103 site, as shown previously in Figs. 4 and 5, violated the assumption of constant \( \rho_g \). At footprint sizes of 3 m and 5 m, the correlation was also very low because there was little remaining range in \( I_v \) due to the extremely sparse canopy cover.

The local spatial variability of \( I_v \) and \( I_g \) has implications for the estimation of \( \rho_g \) and \( \rho_v \). If spatial variance is greatest at distances less than the footprint size then estimates of \( \rho_g \) and \( \rho_v \) represent a mixed backscatter response, which is acceptable for the estimation of \( \rho_{gap} \) if their mean values converge to a normal distribution. If spatial variance is greatest at distances greater than the footprint size (e.g. 20–30 m at the CHAT0103 site) but less than the plot size then the mean value of \( \rho_g \) or \( \rho_v \) will not converge to a normal distribution and estimates of \( \rho_g \) and \( \rho_v \) may be biased. Individual lidar returns are often a convolved response of multiple materials due to the footprint size (0.1–2 m) and range resolution (0.6–1.5 m) of current airborne systems (Mallet and Bretar, 2009), therefore \( \rho_g \) and \( \rho_v \) will not often represent the volumetric scattering properties of individual canopy elements (e.g. leaves, needles). The structure and reflectance of non-photosynthetic canopy elements can have a large effect on both tree and grass top-of-canopy reflectance properties (Asner, 1998; Verrelst et al., 2010), therefore are expected to drive spatial variation in \( \rho_g \) and \( \rho_v \) in savanna environments.

The increase in variance of \( I_v \) with decreasing \( I_g \) for individual pulses at the CHAT0101 and CHAT0102 implied that the assumption of constant \( \rho_g \) was invalid at the footprint size of the RIEGL sensor (0.23 m). Assuming single scattering only, there may be more than one slope defining the relationship between \( I_v \) and \( I_g \). To explore this idea, Eq. (15) was inverted for \( I_v \) and fitted to different quantiles \((r)\) of the \( I_v \) distribution \((r = 0.5\) is the median\) using quantile regression (Koenker and Bassett, 1978). The resulting linear fits for the CHAT0101 site are shown in Fig. 7(A) for a range of quantiles of \( I_v \). Fig. 7(B) shows the spatial distribution of pulses above the 0.75 quantile. The circled crown in Fig. 7 that almost
The estimates of $\rho_v$ are significantly different for all survey altitudes at the CHAT0101 and CHAT0102 sites, with maximum differences of 0.07 for CHAT0101 and 0.11 for CHAT0102. The estimation of $\rho_v$ is affected by the number of canopy returns detected by the Gaussian decomposition procedure, which reduces as the amplitude of individual returns fall below the noise threshold. Although the same raw intensity noise threshold was used for all acquisitions, this corresponded to the minimum observed $\rho_{app}$ ranging from 0.006 (acquisition $A_2$; −450 m range) to 0.039 (acquisition $A_4$; −1200 m range) across all sites. The implication is a large reduction in the number of returns with flying altitude as shown in earlier studies (e.g., Goodwin et al., 2006). For example the number of pulses that only have single returns from the canopy at the CHAT0101 site ranges from 38% for the $A_2$ survey to 53% for the $A_4$ survey. Since live foliage often has low reflectance at 1550 nm, partial interceptions of the lidar beam will result in returns with low SNR that are below the noise threshold. Therefore only a subset of the received waveform signal is being recorded in these cases, introducing bias into the estimation of $I_v$. Bias in $I_v$ is less likely to occur, since the ground is often an extended bright target that fully intercepts the lidar beam. Therefore the resulting ground $\rho_{app}$ is unlikely to fall below the noise threshold, and the slope of the relationship between $I_v$ and $I_g$ will change.

Vertical $P_{gap}$ profiles derived from each of the lidar survey datasets for each of the three field sites are shown in Fig. 9. The estimates of $\rho_v/\rho_g$ were calculated from the 5 m pseudo-waveforms. $P_{gap}$ estimates calculated from discrete first returns ($D_1$) are always higher (differences up to −0.15) than the weighted discrete return ($D_2$) and waveform ($W_1$ and $W_2$) profiles between lidar surveys. There is a notable trend of decreasing $P_{gap}$ with altitude for the RIEGL LMS-Q880i $D_1$ $P_{gap}$ profiles ($A_2$–$A_4$), which is consistent with Morsdorf et al. (2008) who used data from a 1560 nm instrument at two altitudes. This is in contrast with studies that have reported little or no change in $D_1$ $P_{gap}$ using 1064 nm discrete return instruments (e.g., Goodwin et al., 2006). The calibrated waveform ($W_1$) estimates of $P_{gap}$ are the most consistent for different acquisition altitudes, however $P_{gap}$ estimates decrease with increasing range from the $A_2$ to the $A_4$ survey for each site. In contrast the constant $\rho_v/\rho_g$ waveform $P_{gap}$ estimates ($W_2$) were higher than all other methods. The weighted discrete return estimates ($D_2$) are of similar magnitude to the $W_1$ estimates. However, they exhibit a greater variance for different acquisition altitudes. This suggests the use of all returns, by assuming each return intercepts the same projected target area, is accounting for much of the bias introduced by assuming that all targets that intercept the lidar beam are hard targets. The magnitude of the $A1$ (600 m altitude) $P_{gap}$ profiles are similar to the $A3$ (900 m altitude) $P_{gap}$ profiles, despite the different acquisition altitudes. There are two possible reasons for this. First, the acquisition dates are different therefore there may be some change in the true $P_{gap}$. Second, the transmitted pulse peak power of the RIEGL LMS-Q560 instrument is substantially lower than the Q680i instrument (Table 1; RIEGL, pers. comm.).

The observed bias in the $P_{gap}$ profiles as a function of acquisition altitude is dependent on the interaction of different sensor and survey properties (Goodwin et al., 2006; Hopkinson and Chasmer, 2009; Morsdorf et al., 2008; Næsset, 2009). Blindness to gaps smaller than the footprint size have been suggested to lead to underestimation of $P_{gap}$ using the $D_1$ method (e.g., Armston et al., 2008; Liu et al., 2008; Morsdorf et al., 2006). While that may be true if the SNR of waveforms is extremely high (e.g. the $A_2$ profiles in Fig. 9), these results suggest that transmission energy losses due to low intensity returns previously observed in $I_g$ exists at all bin sizes considered, therefore the assumption of constant $\rho_g$ was invalid. The estimates of $\rho_g$ calculated as the mean $I_g$ of unimodal ground returns (no spatial aggregation) shows that the values are near identical to the estimates of $\rho_g$ derived by the linear model for bin sizes 3–5 m. The implication is that the $W_1$ waveform model can calculate estimates of $P_{gap}$ from Eq. (16) without fitting Eq. (15).

The change in estimates of $\rho_g$ and $\rho_v$ with footprint (bin) size and acquisition altitude for each of the sites are presented in Fig. 8. For all survey altitudes the estimates of $\rho_v$ and $\rho_g$ stabilise at the CHAT0101 and CHAT0102 sites for bin sizes greater than 3 m. The estimates of $\rho_g$ are similar for the 900 m and 1200 m altitudes, but the 450 m estimates are significantly higher. One cause of difference could be errors in the calibration to $P_{gap}$ that would result from any non-linearity in the relationship between the recorded lidar signal and the receiver power. Other studies that have attempted to calibrate RIEGL sensors have suggested minor differences in loss of received power with range compared to that expected from theory (e.g., Reitberger et al., 2009). Future work will need to improve the calibration employed in this study. The CHAT0103 estimates of $\rho_g$ for different survey altitudes also appear to stabilise to a common value (~0.45) at bin sizes greater than 3 m. Despite this, the spatial heterogeneity entirely consists of pulses above the 0.75 quantile present to a $P_{pubescens}$ crown. This is the only individual of that species present within the plot, and has dense foliage composed of small oblate leaves. Otherwise these pulses were distributed amongst all crowns within the site. This distribution is likely to be related to: (i) specular reflectance by individual canopy elements; (ii) where targets intercept the Gaussian spatial distribution of laser energy within the footprint; and (iii) the higher reflectance and apparent projected area of boughs and stems, which is expected to be greatest towards the centre of eucalypt crowns whereas on the periphery of crowns clumps of leaves dominate (Jacobs, 1955; Lee and Lucas, 2007). These observations highlight some potential of using the $I_v$–$I_g$ feature space to define variables for classification problems, possibly in combination with estimates of $P_{gap}$ for individual waveforms.

### 4.3. Impact of survey properties

The observed bias in the $P_{gap}$ profiles as a function of acquisition altitude is dependent on the interaction of different sensor and survey properties (Goodwin et al., 2006; Hopkinson and Chasmer, 2009; Morsdorf et al., 2008; Næsset, 2009). Blindness to gaps smaller than the footprint size have been suggested to lead to underestimation of $P_{gap}$ using the $D_1$ method (e.g., Armston et al., 2008; Liu et al., 2008; Morsdorf et al., 2006). While that may be true if the SNR of waveforms is extremely high (e.g. the $A_2$ profiles in Fig. 9), these results suggest that transmission energy losses due to low intensity returns
not being separated from noise are a more important determinant of bias as a function of acquisition altitude. Other authors have also found that transmission energy losses resulting from a range of perceived causes can affect the interpretation of lidar intensity data (e.g. Hopkinson, 2007; Hopkinson and Chasmer, 2009; Korpela et al., 2012). The relative importance of these effects will depend on interactions between wavelength, canopy structure and pulse energy and shape, which are difficult to quantitatively separate using the available measured lidar data.

The $W1_{P_{gap}}$ profiles were the most insensitive to acquisition altitude, however the $P_{v}/P_{g}$ estimates decreased with acquisition altitude for the RIEGL LMS-Q680i surveys. The reduction in the SNR of waveforms resulted in higher values of the ratio $R_{g}/R_{v}$ from Eq. (11), because a higher proportion of $I_{v}$ was less than the noise threshold compared to $I_{g}$. This introduced bias in the $W2$ method results and changed the slope in the relationship between $I_{v}$ and $I_{g}$. The reason the $W1$ profiles were insensitive to these changes is because the method is only actually sensitive to the estimate of $P_{g}$, as shown by Eq. (16). Therefore if ground returns are of sufficient power to exceed the noise threshold, estimates of $P_{gap}$ will be relatively insensitive to minor transmission losses in the canopy. If ground returns are of low SNR, their detection may be improved by aggregating waveforms.
over a local area (Magruder et al., 2010). It is important to note that while total $P_{\text{gap}}$ is not sensitive to $R_v$ or $\rho_v$, the shape of $P_{\text{gap}}(z)$ profiles may be affected by $R_v$ transmission losses or non-constant $\rho_v$.

4.4. Accuracy assessment

A comparison between ground transect and airborne lidar estimates of $P_{\text{gap}}$ is shown in Fig. 10. The calibrated waveform $P_{\text{gap}}(W1)$ estimates provided the closest match to the transect estimates, corresponding to within 5% $P_{\text{gap}}$ and the highest correlation ($r = 0.93$). The greatest difference to the transect estimates was in the comparison with the first discrete return ($D1$) estimates, which were within 9% $P_{\text{gap}}$ and had the greatest positive bias at lower $P_{\text{gap}}$ levels. All other methods had negative bias, in particular the constant $\rho_v/\rho_g$ waveform ($W2$) $P_{\text{gap}}$ estimates. The weighted discrete return ($D2$) $P_{\text{gap}}$ estimates showed less sensitivity to changing acquisition height, resulting in relatively lower bias for the RIEGL LMS-Q680i acquisitions. The error in the RIEGL LMS-Q560 acquisition $P_{\text{gap}}$ estimates were more difficult to interpret here due to the limited sample size, different date of acquisitions, and different transmitted pulse peak power.

The relatively lower bias and variance in the $W1$ $P_{\text{gap}}$ estimates were due to the effect of varying transmission energy losses across a range of LMS-Q680i acquisition altitudes being subsumed into the $\rho_v/\rho_g$ estimation as previously discussed. The biased $W2$ $P_{\text{gap}}$ estimates indicated that the selected $\rho_v/\rho_g$ constant (0.5) for the $W2$ method was suboptimal, therefore optimisation is required to improve this method. However, this would introduce dependency on independent $P_{\text{gap}}$ estimates or measurements of $\rho_v/\rho_g$ for calibration, which may not be available over large areas and may change through time. The underestimation of $P_{\text{gap}}$ exhibited by the $D1$ estimates corresponds to empirical validation results shown by other discrete return studies across a range of environments and lidar instruments including a RIEGL LMS-Q560 (Miura and Jones, 2010), Leica ALS50-II (Johansen et al., 2010), Optech ALTM-3100 (Hopkinson and Chasmer, 2009), and an Optech ALTM-3025 using the same transect $P_{\text{gap}}$ measurement technique and field plots employed in this study (Armston et al., 2009). The $D2$ method is possibly a better alternative to the textitD1 method in the savanna environments considered, assuming that the discrete return lidar instrument has no ‘dead time’ between returns due to electronic delays imposed by the detector.

The range of $P_{\text{gap}}$ values sampled for accuracy assessment is quite small (~0.7–1.0), although typical for savanna ecosystems in the Einasleigh Uplands bioregion. Therefore further validation across a greater range of $P_{\text{gap}}$ levels, and a range of sensor and survey properties, would increase confidence in the interpretation of results reported here. It is also important to note that direct comparison of such results with other studies is problematic due to errors introduced by the field
measurement techniques, as these are often not acknowledged or corrected. Accordingly it is important to acknowledge that while the errors observed in this study are systematic and readily linked with known limitations of lidar sensors and algorithms, the magnitude of the errors reported in this study are close to the limits of binomial sampling error in the transect estimates of $P_{\text{gap}}$. By modelling the error of $P_{\text{gap}}$ observations acquired using the same transect method as in this study, Armston et al. (2009) indicated that this error may be up to ~0.1 at 0.5 $P_{\text{gap}}$.

The Einasleigh Uplands savanna woodland study site restricted the accuracy assessment to open canopies on flat terrain, and to small footprint airborne lidar acquisitions with near-nadir scan angles. Additional accuracy assessment of the W1 model for dense canopies and sloped terrain is required, as different challenges are likely to emerge. The previous modelling of large footprint airborne lidar systems has indicated that the impacts of increasing LAI, off-nadir scan angles, footprint size, and $\rho_v/\rho_g$ over sloped terrain are interdependent and can all lead to $R_v$ and $R_g$ being indistinguishable (Yang et al., 2011). However, the small footprint and narrow pulse width of commercial waveform airborne lidar systems are likely to minimise this effect. The interaction between terrain slope and scan angle in high LAI canopies are also expected to reduce the frequency and SNR of ground returns for both small and large footprint systems. This may: (i) reduce the local range of observed $R_v$ and $R_g$, hence cause problems in fitting the W1 model; and (ii) increase error in lidar $P_{\text{gap}}$ derived LAI estimates, which are sensitive to noise in low values of $R_g$ (Tang et al., 2012).

In savanna ecosystems, temporal variation in leaf fall from semi-deciduous understorey species, grass green-up and senescence, and changes in vegetation and soil moisture in response to rainfall may all contribute to changes in $\rho_v/\rho_g$. This is due to changes in the relative importance of water content and plant cellulose/lignin content on observed 1550 nm lidar $\rho_{\text{app}}$ (Asner, 1998). In different eco-systems such as deciduous broadleaf or boreal forests, leaf fall and snow fall may cause similar temporal variation in $\rho_v/\rho_g$. It is anticipated that the method presented here to estimate $\rho_v/\rho_g$ will detect such
seasonal changes and estimates of $P_{\text{gap}}$ will remain unbiased, provided the validity of the constant $\rho_v/\rho_g$ assumption persists within sites and other effects (e.g. detector saturation; transmission losses) are minimised. However, as shown for the CHAT0103 site, within-site spatial variation in $\rho_v/\rho_g$ may be a considerable source of error in estimates of $P_{\text{gap}}$ and derived canopy structure parameters. Current work is examining the assumption of constant $\rho_v/\rho_g$ more generally, and how $\rho_v$ and $\rho_g$ estimation might be constrained or used as a source of information to infer changes in physiological condition (e.g. senescence) as well as canopy structure.

5. Conclusions and future work

The aim of this study was to investigate if waveform lidar data can improve the estimation of $P_{\text{gap}}$ from airborne platforms compared to discrete return lidar data. This study focused on waveform and discrete return datasets reconstructed from Gaussian decomposition of RIEGL waveforms. The Gaussian model was able to statistically reproduce the canopy and ground waveform integrals with errors of less than 3%. This allowed a controlled comparison of waveform and discrete return estimates of $P_{\text{gap}}$. However, the impact of missing low SNR returns was evident in all the results presented. Advancing the quantitative analysis of measured lidar waveforms requires access to raw waveform data and disclosure by commercial lidar instrument manufacturers of details on the sensor and survey properties that are required to model transmission losses. Disclosure of all survey and sensor properties will only lead to greater understanding and use of these data, and more commercial opportunities.

A waveform $P_{\text{gap}}$ model was presented that solved for $\rho_v$ and $\rho_g$. The model was found to fit observed waveform data in cases where the assumption of constant $\rho_v$ and $\rho_g$ were satisfied. This study showed that spatial heterogeneity in $\rho_v$ and $\rho_g$ was scale-dependent (footprint size) and its impact on the model fitting could be minimised by spatially aggregating waveforms to footprint sizes of 3–5 m. If spatial variance in $\rho_g$ is greatest at distances greater than the footprint size but less than the plot size, then the mean value would not converge to a normal distribution and the assumptions of the $W1$ model were violated. In this case, a more complex waveform model where $\rho_v$ and $\rho_g$ are not assumed to be constant is required. Such a model will likely require an additional constraint to invert, such as an additional waveband for unmixing $\rho_v$ and/or $\rho_g$ components or locally weighted model fitting to relax the assumption of spatially constant $\rho_v$ and/or $\rho_g$. This is the subject of current research.

The estimates of total $P_{\text{gap}}$ using the $W1$ model were relatively insensitive to minor transmission losses in the canopy resulting from increased acquisition altitude, in contrast to other methods of estimating $P_{\text{gap}}$ from waveform and discrete return lidar data. This was because the $W1$ model was shown to only be sensitive to the estimates of $R_g$ and $\rho_g$, which were readily estimated using small footprint waveform lidar in savanna woodland environments. The method to retrieve $\rho_v/\rho_g$ is therefore a significant advance in methods to directly retrieve $P_{\text{gap}}$ from small footprint waveform lidar. This has important implications for the accuracy of canopy structure parameters that may be modelled using directional gap probability theory (e.g. LAI), since models may be transferable between waveform lidar datasets acquired using different instruments without the need for ground calibration. In the future, reduced field calibration requirements may lead to a reduction in operational costs as well as uncertainty in reference lidar products used for the calibration and validation of satellite imaging products over large and remote areas.

Validation of lidar $P_{\text{gap}}$ using transect measurements found the $W1$ waveform $P_{\text{gap}}$ method produced the best matching estimates, corresponding to within 5% $P_{\text{gap}}$. Total $P_{\text{gap}}$ estimates calculated from discrete first returns ($D1$) were always greater (differences up to −0.15) than all other discrete return and waveform methods, which is consistent with published work. The use of all returns ($D2$ model), by assuming each return intercepts the same projected target area, showed indications of being less sensitive to bias caused by footprint size. It may be applicable to discrete return sensors with minimal sensor dead time between returns. A limitation of the validation of all methods was the small sample size, therefore testing over a greater range of sensor, survey and canopy structure configurations in different environments and seasonal conditions should be a focus of future research. We suggest that the waveform method presented in this study also be tested using data acquired by other waveform lidar instruments currently in operation (e.g. Asner et al., 2007).

An approach to the direct retrieval of $P_{\text{gap}}$ using airborne waveform lidar data has been demonstrated for a savanna woodland environment. However, a generalised understanding of the limits on retrieval imposed by interdependent sensor and survey properties such as pulse energy, footprint size, scan angle, wavelength, and the SNR of waveforms; and their interaction with surface topography, canopy structure, and the spatial distribution of canopy/background materials is still lacking. This will require 3D radiative transfer simulation experiments (e.g. Disney et al., 2010) as measured experimental data are not available to establish the joint sensitivity of $\rho_v/\rho_g$ and $P_{\text{gap}}$ estimation to combinations of these sensor and survey properties for different canopy structure configurations.

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