Comparison of Discrete Return and Waveform Airborne Lidar Derived Estimates of Fractional Cover in an Australian Savanna

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Abstract

The advance of commercial airborne lidar systems from discrete-return to waveform recording instruments has made repeatable estimates of biophysical variables from these different methods questionable. Using an experimental airborne waveform lidar dataset acquired in an Australian savanna, this study presents a method for the derivation of canopy/ground backscatter coefficients from waveform lidar and a comparison of discrete return and waveform approaches to the estimation of fractional cover. Despite limited validation, the results indicate that waveform estimates of fractional cover can provide consistently higher accuracy than discrete return estimates under varying survey properties. Ongoing work using raw waveform data across larger areas and 3D radiative transfer simulations aims to develop a quantitative understanding of the impact of disparate sensor and survey properties on the detection of change in vegetation structure using commercial lidar instruments.

1. Introduction

The fractional cover of woody vegetation, defined as one minus the gap fraction at a zenith angle of zero degrees, is an important description of plant canopy structure in the biophysical remote sensing and ecological literature. Crown cover projection (CCP), foliage projective cover (FPC) and leaf area index (LAI) are all a function of the spatial and angular distribution of gaps and are common canopy metrics used in mapping, monitoring and modelling applications by natural resource management agencies in Australia (Scarth et al., 2008). Field-based estimates of canopy metrics are difficult to acquire consistently over large areas and there is often insufficient resources to accurately capture the spatial and temporal variability in structure, especially for scaling up to satellite remote sensing (Asner, 2009). Airborne lidar has shown potential to enable scaling between in situ and satellite monitoring of vegetation change (Asner, 2009; Lucas et al., 2010) and also provide a viable alternative to traditional field techniques (Armston et al., 2009).

Height and directional gap fraction (one minus the fractional cover) are the only canopy metrics that can be directly retrieved from airborne lidar measurements, with other canopy metrics and above-ground biomass subsequently modelled using different expressions, combinations or spatial variance of these parameters (e.g., Ni Meister et al., 2010). Error is introduced in the estimation of canopy metrics from airborne lidar when empirical methods are applied to
different regions, sensor or survey properties than for which they were developed (Næsset, 2009). As a result, many published empirical relationships between field and lidar estimates of vegetation cover have limited wider application unless recalibrated using field measurements (e.g., Solberg et al., 2010; Armston et al., 2009; Rosette et al., 2009). The rapid advance of commercial lidar sensor technology from single discrete return to waveform recording systems has resulted in often disparate lidar datasets over time and exacerbated this problem. Long-term monitoring programs that employ lidar derived metrics, from often disparate sensor and survey configurations, need to determine if these can replicate the same change observed over space and time using direct field methods. Waveform lidar is required to validate our understanding of the impact of sensor and survey properties, especially for discrete return datasets (Disney et al., 2010; Næsset, 2009).

Methods for estimating fractional cover and related canopy metrics have been developed for discrete return and waveform lidar (Lovell et al., 2003; Ni-Meiseter et al., 2001). However no studies have demonstrated an improvement in fractional cover estimates derived using waveform data in Australian vegetation communities dominated by eucalypt tree species. Discrete return sensors typically only record intercepts, which can be interpreted as a binary measure of signal intensity. Therefore estimates of fractional cover do not account for gaps smaller than the size of the footprint (Liu et al., 2008) and only a limited number of returns above a noise threshold can be recorded. Waveform sensors digitize the entire return signal at a particular temporal sampling interval so do not suffer the same limitations. However estimates of fractional cover are sensitive to canopy/ground reflectivity and therefore the wavelength of the sensor (Ni-Meister et al., 2001). Estimates of fractional cover from both classes of lidar require ground and canopy returns to be separated, which in turn is sensitive to lidar sensor and survey properties and their interaction with canopy structure. An assessment of the relative importance of these differences on estimates of fractional cover in Australian environments is lacking.

The objective of this study was to compare waveform and discrete return estimates of fractional cover for a savanna woodland in northern Queensland, Australia. This paper presents an initial investigation of these objectives through empirical analysis of data currently available from an experimental RIEGL LMS-Q680 waveform lidar survey acquired over an existing monitoring site with repeat field and lidar measurements. These data were used to simulate coincident waveform and discrete return datasets for comparison.

2. Data and Methods

2.1 Study site

The study site is located near Charters Towers in northern Queensland, Australia, and is within the Einasleigh Uplands region at approximately 400 m elevation. This is a region of savanna and woodlands and is subject to livestock grazing. This study utilised three structurally contrasting savanna open woodland field plots (CHAT0101, CHAT0102, CHAT0103; Figure 1) that are part of a larger network of monitoring 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 dallachiana sub-dominant in the 12–20 m height canopy. Petalostigma pubescens and Maytenus cunninghamii are also occasionally present in the understorey (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 and E.
melanophloia also present. *P. pubescens* dominates a higher density understorey compared to the other two sites. The canopy at CHAT0103 (20.0230°S, 145.6029°E) was very sparse site with *Eucalyptus brownii* forming the overstorey and the occasional *Acacia salicina* and *Acacia farnesiana* in the understorey. 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.

Figure 1: CHAT0101 (left), CHAT0102 (centre) and CHAT0103 (right) near the time of the airborne waveform lidar surveys.

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-Q680 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. Multiple flying heights were designed to capture the changing footprint size and signal to noise level 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 was used in this study, as directly measured fractional cover validation data was 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.

A range of coincident measurements were collected at the three 100 m × 100 m field sites. However for the present study, estimates of fractional cover 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) and the understorey (woody or herbaceous plants less than 2 m height) using a GRS densitometer™. This instrument employed a mirror, two bubble-line levels and a centred cross-hair to project an
exact vertical line-of-sight of the sample point in the canopy to the observer. Fractional cover was then calculated as the fraction of observations that were overstorey leaf or wood intercepts.

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>
</tr>
</thead>
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<td>2010/06/18</td>
<td>2010/06/18</td>
<td>2010/06/18</td>
</tr>
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<td>RIEGL sensor</td>
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<td>LMS-Q680</td>
<td>LMS-Q680</td>
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<td>900</td>
<td>1200</td>
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<td>No. parallel flight lines</td>
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<td>3</td>
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<tr>
<td>Scan rate (Hz)</td>
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<tr>
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</tr>
<tr>
<td>Footprint diameter (m)</td>
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<td>0.23</td>
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</tr>
<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>

2.3 Processing lidar waveforms and discrete returns

At the time of this work, the data provider was unable to deliver waveform data for the RIEGL LMS-Q680 surveys. GPS time, Cartesian coordinates (easting, northing, elevation), Gaussian parameters (range, amplitude and width) and pulse parameters (scan zenith, range) produced for each return using the RIEGL RiAnalyze software were available. The Cartesian coordinates were input to a modified version of the progressive morphological filter by Zhang et al. (2003) to classify ground and non-ground returns. Discrete return datasets were generated using the Cartesian coordinates of the Gaussian peaks above the noise threshold. Pulses from each acquisition were randomly sampled to a density of 1 pulse / m² to avoid any potential differences in the height distribution of returns.

By assuming the Gaussian model captures the shape of the received waveforms \( I(t) \), as outlined by Wagner et al. (2006), the waveforms were reconstructed using the Gaussian parameters. Limited validation of the Gaussian model for the study site was performed using raw waveform data from the A1 survey (Table 1) that was only recently made available without matching RiAnalyze products. Estimates of the Gaussian parameters were derived using non-linear least-squares fitting (Levenberg–Marquardt method) to Equation 1:

\[
I(t) = \varepsilon + \sum_{i=1}^{N} A_i e^{-\frac{(t-t_i)^2}{2s_i^2}}
\]

where for each return, \( \varepsilon \) is the noise level, \( A_i \) is Gaussian amplitude, \( t_i \) is the time (or range) and \( s_i \) is the Gaussian standard deviation. Starting parameters were determined from the zero-crossings of the waveform first derivative that were above \( \varepsilon \). False returns due to “ringing” in the transmitted pulse were omitted from the starting parameters if their amplitude was less than \( \varepsilon \) plus the value from an exponential time decay function on the amplitude of earlier local maximums. The \( \varepsilon \) parameter was set to the same default constant value of 9 used by RiAnalyze (Matthew McCauley, Atlass Pty. Ltd., pers. comm.). It is also important to note that several details on the Gaussian decomposition procedure performed by RiAnalyze are proprietary knowledge and therefore exact replication was unlikely.
Examples of the transmitted and received waveforms and corresponding Gaussian model fits are shown in Figure 2. The gain for the transmitted waveform is unknown and different from the received and therefore cannot be directly used to calibrate waveforms to apparent reflectance. The RIEGL LMS-Q560 and LMS-Q680 instruments record waveform samples in 60 ns sample blocks, with recording of blocks initialised by the signal exceeding a noise threshold. The missing data between 2.5 and 6 m in the received waveform was the result of this “dead time” (RIEGL, pers. comm.). For direct comparison of the ground \(I_g\) and canopy \(I_v\) components 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.

![Figure 2: Measured (thin black line) and Gaussian model (dashed red line) transmitted (left) and received (right) waveforms from a single pulse over the CHAT0101 field plot. The waveforms are normalized by the maximum signal and the noise level is shown (dotted grey line). Three canopy returns were derived from the received waveform with peaks at heights of 8.55, 11.44 and 12.36 m above the ground.](image)

2.4 Estimation of fractional cover

Studies that have used discrete return lidar sensors typically estimate fractional cover as the proportion of returns intercepted by the canopy within a data bin (Lovell et al., 2003):

\[
P_{\text{cov}, z}(c) = \frac{\sum_{z_{\text{top}}}^{z_{\text{max}}} C_{v,j}}{N}
\]

(2)

where \(C_v\) is the number of returns from the top of canopy down to height \(z\) and \(N\) is the total number of canopy and ground returns. We assume here that all pulses are at a zenith of zero. Equation 2 was applied to two categories of discrete returns often used to calculate fractional cover: first returns only (D1) and all returns (D2).

Waveform recording instruments digitise the received waveform and, assuming single scattering only, can be separated into vegetation and ground backscatter components:
\[ I = I_g + I_v \]  

(3)

where \( I_v \) is the integrated vegetation backscatter component of the waveform and \( I_g \) the integrated ground return. Disney et al. (2006) showed greater than 80% of reflectance at the nadir hotspot is single scattered photons and since green foliage typically has low reflectance at 1550 nm, it is reasonable to assume negligible multiple scattering. Following Ni-Meister et al. (2001) and assuming the recorded lidar signal is linearly related to the receiver power, fractional cover can then be estimated from uncalibrated waveforms by:

\[ P_{\text{cov,cr}}(z) = \frac{I_v(z)}{I_v(0) + I_g \frac{\rho_v}{\rho_g}} \]  

(4)

where \( I_v \) is the integrated vegetation backscatter component of the waveform from the top of the canopy down to height \( z \). Since the returned backscatter is a function of the apparent reflectance, phase function and leaf angle distribution of canopy and ground targets as well as the gap fraction, we need some prior knowledge of the canopy/ground backscatter coefficient ratio \( \rho_v/\rho_g \) to obtain unbiased estimates of fractional cover from waveform data. Previous studies have suggested using a constant (e.g., 2 for 1064 nm; Lefsky et al., 1999), however canopy and ground properties often change between stands. Therefore a method to derive \( \rho_v/\rho_g \) from waveforms is required in order to avoid field calibration, especially in savannas where estimates of fractional cover will be most sensitive to \( \rho_v/\rho_g \) due to sparse canopies and variable backgrounds.

The canopy backscatter component of the waveform is the product of the fractional cover at the zenith of the lidar pulse and the volumetric backscattering coefficient of the canopy (\( \rho_v \)), and the ground component is the product of the gap fraction and the volumetric backscattering coefficient of the ground (\( \rho_g \)):

\[ I_v = P_{\text{cov,cr}}(0) \rho_v \]  

(5)

\[ I_g = [1 - P_{\text{cov,cr}}(0)] \rho_g \]  

(6)

where \( \rho_g \) and \( \rho_v \) are a function of the foliage angle distribution and apparent reflectance at the wavelength of the lidar. Combining Equations 5 and 6, the relationship between \( I_g \) and \( I_v \) is then linear:

\[ I_g = \rho_g - \frac{\rho_g}{\rho_v} I_v \]  

(7)

If constant \( \rho_g \) and \( \rho_v \) is assumed to extend to \( N \) pulses within a local area, estimation of \( \rho_g \) and \( -\rho_g/\rho_v \) is then a simple linear regression problem (\( y = \alpha + \beta x \)). An estimate of \( \rho_g \) is the intercept (\( \alpha \)) and \( \rho_v \) can be estimated from the slope (\( \beta \)) by \( -\rho_g/\beta \). Fractional cover is then estimated directly using Equation 4. Two waveform estimates of fractional cover are evaluated in this study: \( \rho_v/\rho_g \) derived using the method just described (W1) and with \( \rho_v/\rho_g \) set to a constant of 0.5 for 1550 nm (W2).
3. Results and Discussion

3.1 Accuracy of the Gaussian model

A very close correspondence exists between the measured and Gaussian model estimates of $I_g$ and $I_v$ (RMSE < 6; Figure 3). The error estimates were consistently higher for $I_v$ than $I_g$, but the difference is negligible. Since the canopy was sparse and the terrain flat, a large percentage of the pulses were single returns from the ground, from which returns that correspond to a Gaussian shape are to be expected. The canopy was composed of clumped scattering elements with variable leaf angle distributions, which resulted in more complex waveforms. Poor fits to a number of individual waveforms with overlapping returns $<\sim60$ cm apart (twice the temporal bin spacing of the waveform) have also been observed. However these results provide evidence that Gaussian modelling of RIEGL waveforms in a savanna environment is able to statistically reproduce received waveforms for a large number of pulses.

![Figure 3: Comparison of waveform and Gaussian model calculated $I_g$ and $I_v$. Darker regions indicate a higher density of observations. The red line is the 1:1 line.](image)

The advantages of representing the waveform in this way are: raw waveform data are not typically available for most natural resource management agencies; data volumes are greatly reduced; noise is less of an issue when interpreting reconstructed waveforms; and Gaussian distributions have well known properties. The disadvantage is that not all returns necessarily have a Gaussian shape, with this depending on interactions between the shape and duration of the transmitted pulse and vertical canopy structure; and low intensity returns may not be detected (Chauve et al., 2009).
3.2 Relationship between canopy and ground backscatter

The linear relationship between \( I_g \) and \( I_v \) is shown in Figure 4 for the A2 survey. The small footprint of the RIEGL lidar systems results in high spatial variance in the cross-section but also in the spectral properties of intercepted targets, making robust estimates of \( \rho_v / \rho_g \) difficult. For \( I_g \) each received waveform may be backscatter from an individual grass sward or a patch of bare soil between swards. For \( I_v \) each received waveform is likely to be composed of highly variable proportions of leaf and woody canopy elements (e.g., dead and foliated branches), which have different spectral properties at 1550 nm for these sites. Jupp and Lovell (2007) also highlight that small footprints also result in “speckle” due to high apparent backscatter from individual canopy elements acting as Fresnel reflectors.

Figure 4: Simple linear regression relationships between \( I_g \) and \( I_v \) at multiple simulated footprint sizes for the A2 survey at the three field plots. The estimates and uncertainty of \( \rho_v \) and \( \rho_g \) derived from this relationship are shown.

To test the effect of footprint size on estimation of \( \rho_v / \rho_g \), pseudo-waveforms were created at 1 m and 5 m footprint sizes. By integrating all waveforms within a local area and normalizing the signal by the number of pulses to simulate a larger footprint waveform, the distributions of \( I_g \) and \( I_v \) tend towards unimodal. The smallest deviation from a straight line was at 5 m footprints.
for the CHAT0101 and CHAT0102 sites. However the trend did not hold for the CHAT0103 site, as there was little remaining range in $I_g$ and $I_v$ at that footprint size because of the very sparse canopy cover. The spatial heterogeneity in grass cover was high (see CHAT0103 in Figure 1) compared to the uniform grass cover at CHAT0101 and CHAT0102, violating the assumption of constant background. The CHAT0103 site also had dark cracking soils, which resulted in the lowest $\rho_g$ value for all three sites and increased noise. For the next section fractional cover was estimated using $\rho_v/\rho_g$ calculated from the 5 m footprints.

### 3.3 Effect of survey properties on estimates of fractional cover

Vertical fractional cover profiles and $\rho_v/\rho_g$ derived from each of the lidar survey datasets for each of the three field plots are shown in Figure 5. Fractional cover estimates calculated from discrete returns (D1 and D2) are always higher (differences up to 0.2) than the waveform (W1 and W2) between lidar surveys. There is a trend of decreasing fractional cover with altitude for the discrete return estimates, which is consistent with Morsdorf et al. (2008) who used data from a 1560 nm instrument at two altitudes, but in contrast with studies that have reported little or no change in fractional cover using 1064 nm instruments (e.g., Goodwin et al., 2006). Blindness to gaps smaller than the footprint size can lead to overestimation of fractional cover (e.g., Liu et al., 2009), however low intensity returns are more common from canopy elements than the ground which can lead to underestimation of fractional cover if these returns are not separated from noise. The relative importance of these effects depends on wavelength, canopy structure and pulse energy and shape, which are difficult to separate using available measured lidar data.

The calibrated waveforms (W1) appear to be the most consistent for different ranges however $\rho_v/\rho_g$ estimates decrease with increasing range from the A2 to the A4 survey for each site. CHAT0103 is an exception as the fit between $I_v$ and $I_g$ was poor (Figure 4) and the resulting fractional cover too low. The estimation of $\rho_v/\rho_g$ may be compensating for increased noise levels in the waveforms acquired at longer ranges as the number of returns in the canopy detected by the Gaussian decomposition reduces as their amplitude falls below the noise threshold. For example the number of pulses that only have single returns from the canopy at the CHAT0101 site ranges from 38% for the A2 survey (450 m range) to 53% for the A4 survey (1200 m range). This is important as vegetation has low reflectance at 1550 nm so the waveform signal to noise ratio is quite sensitive to pulse energy and range. Another contributing factor could be that the recorded lidar signal is non-linearly related to 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., 2010).
Figure 5: Comparison of discrete return and waveform derived vertical fractional cover profiles for the three field plots at the nominal aircraft altitudes (Table 1). D1 = first returns (grey solid line); D2 = all returns (grey dashed line); W1 = calibrated waveform (solid black line); and W2 = waveform with $\rho_v/\rho_g$ set to 0.5 (dashed black line). The W1 estimates of $\rho_v/\rho_g$ are also shown.

The correspondence between field and lidar estimates of fractional cover is shown in Figure 6. The waveform estimates correspond within 5% fractional cover to field measurements compared to within 9% fractional cover for the discrete return estimates. The overestimation exhibited by the discrete return estimates correspond to results shown by other studies using a RIEGL sensor (Miura and Jones, 2010) and discrete return lidar at the same field sites (Armston...
There appears to be less scatter using the estimated $\rho_v/\rho_g$ rather than the constant of 0.5, however the magnitude of this error falls within that one might expect from binomial sampling error in the field measurements (Armston et al., 2009).

![Comparison of fractional cover estimates](image)

Figure 6: Comparison of fractional cover ($z = 2$ m) estimates derived using discrete return (D1; D2) and waveform (W1; W2) methods. The symbol indicates the source lidar survey (Table 1): square = A1; cross = A2; triangle = A3; and circle = A4. The colour indicates the field site: red = CHAT0101; black = CHAT0102; and blue = CHAT0103. The grey line is the 1:1 line.

4. Conclusions

This study has conducted a preliminary comparison of estimates of fractional cover using field, waveform and discrete return lidar methods. The waveform and discrete return lidar data were simulated using a Gaussian model, which showed a close correspondence with the waveforms. Additionally, a method to estimate $\rho_v/\rho_g$ directly from the waveform data was introduced. Provided the assumptions were satisfied and $\rho_v/\rho_g$ was estimated with some certainty, waveform methods provided more accurate and consistent estimates of fractional cover than discrete return methods under varying flying heights.

The method to retrieve $\rho_v/\rho_g$ shows promise, however a quantitative understanding of the limits on retrieval imposed by the interaction between the pulse energy, wavelength, canopy/background heterogeneity and the signal-to-noise of waveforms is required. 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 fractional cover estimation to combinations of these sensor and survey properties at a range of fractional cover levels.

Analysis of the raw waveforms is also required as the return detection and Gaussian decomposition procedure used may lead to omission of low backscatter returns. The validation
in this study was confined to a sparsely wooded savanna, however the performance of these methods to estimate fractional cover and derived metrics (FPC, LAI, CCP) are currently being evaluated over approximately fifty monitoring sites from low arid shrubland to coastal rainforest where waveform lidar have been acquired coincident with field and terrestrial lidar surveys.

Improved estimation of the fractional cover of woody vegetation using waveform over discrete return airborne lidar acquired under varying survey properties has important implications for natural resource management agencies undertaking large area land cover mapping, monitoring and modelling programs in Australia. The results from this study indicate waveform estimates of fractional cover from different flying heights are consistent, enabling comparison of estimates from different surveys over space and time and reducing the need for calibration using field measurements. In future this will 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 in Australia.

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References


