A threshold insensitive method for locating the forest canopy top with waveform lidar

Steven Hancock a,c,d,1,⁎, Mathias Disney b,d, Jan-Peter Muller c,d, Philip Lewis b,d, Mike Foster e,2

1. Introduction

Accurate biophysical parameters are essential for understanding the Earth’s systems and modelling future climate (Hurtt et al., 2010). Space and airborne lidar has been shown to be a useful tool for characterising vegetation (Dubayah & Drake, 2005; Hofton et al., 2000; Lefsky et al., 2005; Morsdorf et al., 2009; Rosette et al., 2009; Wagner et al., 2008). It is possible to make entirely physical measurements of canopy height, vertical structure and canopy cover with lidar (Dubayah & Drake, 2005). Such physical measurements allow a globally consistent dataset. Other methods (synthetic aperture radar and passive optical) require site specific calibration (Sarabandi, 1997) or models with prior information (Myneni et al., 2002) to derive the same information.

Whilst lidar cannot directly measure leaf area index and biomass, which are the traditional biophysical variables used in dynamic vegetation and climate models, there have been advances towards making use of parameters that can be directly measured into biophysical models (Hurtt et al., 2004), reducing the potential for introducing errors.

All instruments suffer from their own limitations. For lidar the literature reports a consistent underestimate of canopy height when using physical methods (Hyde et al., 2005; Lefsky et al., 2002, 2005; Morsdorf et al., 2008) referred to this as the “well known underestimate of tree height by lidar”. Some have suggested correcting for this with site specific calibration (Rosette et al., 2008), though it is then no longer a direct and physical measurement. This paper will present some reasons for this bias and suggests a simple method for removing a component of it.

Lidar have the unique ability to make direct, physical measurements of forest height and vertical structure in much denser canopies than is possible with passive optical or short wavelength radars. However the literature reports a consistent underestimate of tree height when using physically based methods, necessitating empirical corrections. This bias is a result of overestimating the range to the canopy top due to background noise and failing to correctly identify the ground.

This paper introduces a method, referred to as “noise tracking”, to avoid biases when determining the range to the canopy top. Simulated waveforms, created with Monte-Carlo ray tracing over geometrically explicit forest characteristics, are used to test noise tracking against simple thresholding over a range of forest and system characteristics. It was found that noise tracking almost completely removed the bias in all situations except for very high noise levels and very low (<10%) canopy covers. In all cases noise tracking gave lower errors than simple thresholding and had a lower sensitivity to the initial noise threshold. Finite laser pulses spread out the measured signal, potentially overriding the benefit of noise tracking. In the past laser pulse length has been corrected by adding half that length to the signal start range. This investigation suggests that this is not always appropriate for simple thresholding and that the results for noise tracking were more directly related to pulse length than for simple thresholding. That this effect has not been commented on before may be due to the possible confounding impacts of instrument and survey characteristics inherent in field data. This method should help improve the accuracy of waveform lidar measurements of forests, whether using airborne or spaceborne instruments.

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1.1. Lidar measurements

Fig. 1 illustrates how space and airborne lidars measure forest biophysical parameters. A laser emits a short pulse of light with some beam divergence (which controls the footprint) towards the ground. This reflects back from the various objects within the footprint whilst a detector co-aligned with the laser measures the returned energy split by time (which is equivalent to range). A plot of light amplitude against range is referred to as a "waveform". Features of this waveform can be used to identify the start of the canopy top and the ground, giving a direct measure of canopy height and allowing the vertical structure of the canopy to be determined.

Lidars can either measure the complete returned energy profile, known as "waveform lidar", or a set of ranges from it, known as "discrete return lidar". These discrete returns are typically the first and last return, allowing canopy height to be extracted after filtering to determine the ground position or a number (typically between five and twenty (Lim et al., 2003)) of returns from various points throughout the waveform. Discrete lidars are historically and currently the most abundant and have been shown to give useful measures of forest structure (Coops et al., 2007), though waveform airborne lidars are becoming more common. With discrete lidars the user only knows the ranges provided by the instrument and no further processing to determine the canopy start is possible. Because of this and because all past spaceborne lidars were full waveform, the rest of this paper will focus on waveform lidar.

There will always be background noise in returned waveforms and error care must be taken to ensure that the lidar estimate of canopy top range is not affected by this noise. The simplest way is to set a threshold and take the first signal return above this as the canopy top. The threshold can be set from the statistics of a portion of waveform known to be empty (for example two hundred metres above the ground); typically the mean plus three to five standard deviations is used (Chen, 2010). This is susceptible to extreme values in the background, potentially leading to premature triggering and nonsensical estimates of canopy height. Using the cumulative energy threshold rather than instantaneous amplitude to set the threshold should be more robust to extreme noise values (Hofton et al., 2000). For this method an amplitude threshold is set as above. The total energy in the waveform above this threshold is then calculated. The cumulative waveform energy above the noise threshold is calculated and the point at which it rises above some fraction of the total (typically 1% to 2% (Hofton et al., 2000)) taken as the signal start. This will be referred to as "simple thresholding" for the rest of this paper.

In order to avoid premature triggering the threshold must be set high enough to make the possibility of that happening insignificant and so some energy of the true waveform will always be lost, leading to an overestimate of range to the canopy top and so an underestimate of canopy height. This is illustrated in Fig. 2. Chen (2010) found that the optimal threshold could vary between three and five standard deviations between sites and so a threshold insensitive method would be a great advantage for a global, physically based product.

This is not the sole cause of the reported underestimate of canopy height but it is a contribution that should be avoided. In addition to this there may be issues with understory vegetation leading to an underestimate of the range to the ground. This paper will not dwell on ground errors or review methods proposed to determine the ground position as this is a very different problem and is discussed in detail in Hofton et al. (2002), Wagner et al. (2008), and Hancock (2010).

1.2. Noise tracking

It should be possible to avoid the bias due to losing the signal start in noise by using the full waveform information. Taking the bin in which the cumulative energy above the threshold reaches 1% of the total as a starting point (we can be certain that the signal from the canopy has started by that range, but not by how much it has been overshot) tracking back along the raw, unthresholded signal until the instantaneous amplitude is equal to or lower than the mean noise value provides a point that is as equally likely to be an underestimate as an overestimate, giving an unbiased result. This is referred to as "noise tracking" and is illustrated in Fig. 2.

This method was alluded to and briefly tested in Disney et al. (2010) and first presented in Hancock et al. (2008), at least in the context of lidar for forestry within the authors’ knowledge. This approach would not be possible with discrete return lidar as the necessary information is not recorded. A similar method may be employed by discrete return lidar manufacturers but the precise nature of how a particular instrument return is generated is commercially confidential (Næsset, 2009; Disney et al., 2010).

This paper aims to carry out a thorough comparison between the noise tracking method and the more traditional simple thresholding.

2. Method and tools

The error caused by the truncation of the signal start during noise removal is typically of the order of 1 m (Mallet & Brear, 2009; Morsdorf et al., 2008), though this depends on footprint size, range resolution,
signal to noise ratio (and so altitude) and canopy structure. Experiments using ground data to validate estimates from real lidar data suffer from geolocation mismatches and errors in the ground “truth” (Harding & Carabajal, 2005), along with other effects this leads to reported errors of up to several metres (Rosette et al., 2008). These other effects will obscure an effect as subtle as truncation due to noise, making it very difficult to test preventative methods. It is possible to avoid these obscuring errors by using realistic computer simulations to reveal the underlying processes (Lewis, 1999).

2.1. The simulator

A Monte-Carlo ray tracer with fully geometrically explicit forest models was used here. The concept of Monte-Carlo ray tracing is given in Disney et al. (2000). The ray tracing library, based upon the ray tracer described in Lewis (1999), was adapted to simulate a lidar with any system characteristics. Monte-Carlo ray tracers are very computationally expensive but make far fewer assumptions than faster, more abstract methods such as turbid media models (Ni-Meister et al., 2001; North, 1996). This avoids the need for “effective parameters” that can hide physical effects (Widlowski et al., 2005). They are too complex for inverting measured data but are useful tools for exploring the processes.

All comparisons between this ray tracer and real signals performed so far (direct comparison of solar signals and indirect comparison of lidar signals) suggest that the simulated signals are accurate (Disney et al., 2010, 2006). The earlier ray tracer (“drat”), which used the same library of functions used here, has taken part in the RAMI exercises (Pinty et al., 2004; Widlowski et al., 2007) and shown to agree well with the models thought to be most accurate. This ray tracer now forms part of the “surrogate truth” used by RAMI to test all other radiative transfer models against (Widlowski et al., 2008). Therefore as the simulator used in this investigation uses the same underlying computer functions as “drat” it is thought to produce realistic lidar signal simulations.

A more comprehensive validation would be very hard to perform due to the complexity of forest canopies (Bréda, 2003); it would be hard to know whether any differences between real and simulated signals were due to errors in the radiative transfer model or subtle differences in the vegetation model. To the authors’ knowledge such a comparison has never been performed with vegetation canopies.

2.1.1. Forest models

Sitka spruce forest models were used in this study. It is likely that these will be a hardest case scenario as conifers tend to have more pointed tops and so weaker initial returns than broadleaved canopies. The creation of these models, in which the three dimensional location, orientation and optical properties of every tree, branch, twig and pine needle are explicitly defined, has been described in detail in Disney et al. (2006), Disney et al. (2010) and Hancock (2010).

Five unique Sitka spruce trees were created for each of five age classes (with heights of around 3 m, 9 m, 12 m, 20 m and 25 m). Every part of the tree was described as a separate geometric primitive. These trees were randomly arranged on flat planes of soil with different densities, ground slopes and mixtures of ages to create forests with very different canopy structures and a range of canopy covers (from sub 10% to 99.999%). Fig. 3 shows some diagrams with examples of simulated waveforms and Fig. 4 shows histograms of canopy height (maximum within a 30 m plot), canopy cover (within a 30 m plot) and ground slope of the simulated waveforms. Obviously there will be some correlation between height and canopy cover and so the full range of covers is not necessarily available for all canopy heights. Around a third of forest models were mixed age, but this does not mean that one third of all waveforms contained a mixture of tree ages due to heterogeneity at the plot scale.

The Prospect model was used to create a leaf reflectance and transmittance spectrum (Jacquemoud & Baret, 1990) whilst the soil spectrum was created with the model of Price (1990). The bark spectrum was taken from the LOPEX database (Hosgood et al., 1994).

2.1.2. Noise

Noise was included in the waveforms using the equations and values described in Hancock (2010, section 4.1.3), which are based on the equations of Balsavias (1999). Noise was based upon the number of signal photons recorded, assuming a constant mean background light level and taking photon statistics into account. Background noise was added as a random number drawn from a uniform distribution at each range bin (always positive). Photon statistic noise was drawn at random from a normal distribution at each range bin and could cause an increase or decrease in amplitude, truncating at zero if the result was negative. Ray tracing is computationally expensive and so noise was applied after simulation of the ideal (noise free) signal, allowing different levels of noise to be applied to a single simulation. Fig. 5 shows a waveform with three different levels of noise added for a mixed age canopy. By altering a random number seed different sets of noise of the same level can be applied. This allows multiple “measured” waveforms to be created from each noise-free simulation.

Without knowing the characteristics of a particular instrument the level of noise is arbitrary. Signal photon counts given in this paper should be taken as a relative noise level rather than an absolute with physical meaning. A range of values were covered to explore the relative differences. The phrase “signal photons” will be used throughout the rest of this paper but this does not have a strictly physical meaning.

2.1.3. Laser pulse

All lasers emit pulses with finite lengths (Balsavias, 1999). The recorded waveform will be blurred by convolution with the pulse and this could override the benefits of noise tracking. Most lidar pulse shapes can be described by a Gaussian (such as NASA’s ICES at and LVIS (Hofton et al., 2000)). See Fig. 6 for an illustration of a Gaussian pulse. Lidars used for forestry typically have pulses between 2.04 m (TopEye II (Wagner et al., 2006)) and 5.07 m long (LVIS (Hofton et al., 2000)) where length is the point at which the laser energy drops below 1/e2 of its maximum (illustrated in Fig. 6). Wagner et al. (2006) accounted for the blurring caused by a laser pulse by adding half the pulse length to the canopy top range and it may be the case that this is all that is needed and noise tracking is unnecessary for real lidars. This should be tested.

It would be computationally efficient to make a single trace of a scene then convolve with the pulse before analysis, however this would not create a fully realistic waveform. The recorded waveform is
digitised into discrete range bins and the exact location of an object within a bin is lost. Therefore after simulation we would need to assume that all elements were in the centre of a range bin. This will not always be the case and so the pulse shape was convolved with each return before binning. This adds to the computational expense but ensures that artefacts that may affect realism are not added.

The canopy top error can be given in terms of a distance or as a fraction of the first return energy truncated. Signal shift as a fraction of first return energy is illustrated for a 2.36 m long pulse in Fig. 6. In the example the detected start is 0.24 m in front of the true position. All the laser pulse to the left of this has been lost in the noise and so the remains of the first return contain 66% of the total energy.

2.2. Experimental design

It was hypothesised that using a simple thresholding scheme, such as the cumulative energy threshold, would lead to a consistent overestimate of range to canopy tops and so contribute to an underestimate of canopy height. Tracking back through the noise should reduce this bias, though it may also lead to an increase in the spread of errors. This hypothesis was tested using simulated waveforms created with the tools described above. Various factors thought to affect the accuracy of signal top measurements were explored and both noise tracking and simple thresholding tested. In all cases the noise threshold was the mean background plus three standard deviations.

A lidar optimised for measuring forests was simulated. The recently cancelled DESDynI was used as a template and so all simulations had a 30 m footprint, 12.5 cm range resolution and a 1064 nm laser (Dubayah et al., 2008). Initially an infinitely short laser pulse was used to avoid the obscuring effects a finite pulse length would introduce. Once the underlying processes had been identified the analysis was repeated with a 5 m long laser pulse (point at which amplitude drops to $1/e^2$ of its maximum).

A total of 6673 infinitely short laser pulsed waveforms were simulated with the forest properties given in Fig. 4. A total of 725 waveforms with 5 m pulses over the same range of forest models were available.

Previous tests have shown that, for this noise scheme, measuring 10,000 signal photons will ensure that noise does not limit the accuracy of lidar estimates (Hancock, 2010, section 4.1) and this is thought to be an achievable value (Foster, 2008). Accuracy from waveforms with fewer signal photons may be limited by noise whilst those with more should be similar to those with 10,000 signal photons. Preliminary experiments and Section 3.2 confirmed this was the case. Therefore a high noise (2000 signal photons) and a low noise (10,000 signal photons) case will be used for the rest of the investigation.

2.2.1. Canopy cover

Canopy cover is likely to control the strength of the initial return and so have an effect upon inversion accuracies. The analysis was repeated, separating the results by canopy cover for both an infinitely

![Waveform for uniform mature on a slope](image1)

![Uniform mature on a slope](image2)

![Waveform for uniform young](image3)

![Uniform young](image4)

Fig. 3. Illustrations of some of the range of forest models used with accompanying simulated, noise-free waveforms.
short and 5 m long pulse and a low (10,000 signal photons) and high noise (2000 signal photons) case.

2.2.2. Noise dependence
Most lidar systems vary the instrument gain from shot to shot as they pass over surfaces with different reflectances (Harding & Carabajal, 2005). This ensures that the full dynamic range of the detector is used and avoids saturation, however it will tend to cause varying signal to noise levels. Therefore having a robustness to different noise levels will be an advantage. We would expect noise tracking to be more robust to changing noise levels than simple thresholding.

Both methods were applied to all waveforms for a range of noise levels. Initial results suggested that the canopy's vertical structure was important to the signal inversion and so the analysis was repeated, separating out to uniform aged and mixed age canopies.

Spreading the signal out with a 5 m pulse is likely to increase the sensitivity to noise. This was explored by repeating the inversions with a 5 m pulse for a range of noise levels. Canopies below 10% cover were left out of all analysis in this section.

2.2.3. Laser pulse length
A laser pulse duration will not necessarily remain constant throughout the instrument's life (Schutz et al., 2005) and so it would be advantageous to have a method in which the shift due to a laser pulse is directly proportional to its length. The canopy top error was found over all forests with pulse lengths every 50 cm between 50 cm and 10 m.

Each laser pulse length required a separate simulation and so fewer waveforms were available for these experiments (around 300 for each of the twenty pulse lengths). These came from the same forest models used in Fig. 4 and had the same DESDynl like characteristics. Canopies below 10% cover were left out of the analysis.

2.2.4. Threshold sensitivity
The noise threshold used above is an arbitrary value and any threshold will be similarly arbitrary. We would expect simple thresholding to be very sensitive to this value whilst noise tracking should be more robust as it only uses the threshold as a starting point. The sensitivity of both methods was tested for a range of noise thresholds using infinitely short laser pulses at a high (2000 signal photons) and low (10,000 signal photons) noise level. This was repeated with a 5 m laser pulse. Canopies below 10% cover were left out of the analysis.

3. Results
Throughout this paper errors are given in terms of estimated range between the lidar and the canopy top. A positive error is an overestimate of range which will lead to an underestimate in canopy height, a negative error will lead to an overestimate of canopy height. Fig. 7 shows a histogram of signal start range error for four hundred separate inversions of a single waveform with an infinitely short pulse. It can be seen that all estimates with the simple thresholding gave a positive range bias of around 1.25 m and so an underestimate in canopy height. Tracking back through the noise greatly reduced this bias, creating a roughly normal distribution of
errors around 0 m. Simple thresholding gave a mean error of 1.1 m whilst noise tracking gave −7.8 cm (the RMSE was 17.5 cm for noise tracking and 1.1 m for simple thresholding). The spread of errors was larger with noise tracking than simple thresholding (standard deviation of 24 cm for noise tracking compared to 5 cm for simple thresholding), thus for a single waveform simple thresholding gave a more consistent, though wrong, estimate. This smaller spread only holds for individual waveforms and noise levels. When averaged over a range of waveforms and noise levels, simple thresholding has a similar or greater spread in estimates than noise tracking, with the additional bias and so noise tracking seems to be the superior method. This behaviour was typical of all individual waveforms examined.

We would expect convolution with a laser pulse to shift the detected start towards the lidar (a negative distance error) and if this is not the case (i.e. no or a positive error) then more than half of the first return has been lost in noise. Fig. 8 shows the same histogram over the same canopy as Fig. 7 with a 5 m long laser pulse. It has roughly the same shape as the infinitely short pulse case. Simple thresholding gave a mean error of 59 cm with a standard deviation of 7 cm and an RMSE of 59 cm. Noise tracking gave a mean error of −90 cm with a standard deviation of 34 cm and an RMSE of 90 cm.

At first glance it would seem that simple thresholding has performed better than noise tracking, but it should be remembered that we expect the signal start to be shifted towards the lidar by the pulse and so a negative error. The standard laser pulse correction of adding half the pulse length to the signal start (Wagner et al., 2006)

Fig. 4. Histograms of properties of the contents of the 6673 30 m footprints within the Sitka spruce forest models used.

Fig. 5. A waveform with different levels of noise added. The footprint contained a 21.4 m tall canopy, had a canopy cover of 81% and was on flat ground. An infinitely short laser pulse was used. The ground is at a range of 600 m.

Fig. 6. Illustration of laser pulse length and signal shift as a fraction of pulse energy.
would not work for the simple threshold case. Noise tracking may still be the superior method and subsequent sections will examine this in more detail.

3.1. Canopy cover dependence

Fig. 9 shows the mean range to canopy top error with bars showing one standard deviation of that error for all simulated waveforms with an infinitely short pulse. In all cases the noise tracking method had a much lower bias than simple thresholding. In addition the spread of errors across all waveforms was slightly lower for the noise tracked case. Fig. 7 shows that the spread for a single waveform was much greater for noise tracking than for simple thresholding; that this is not the case when taking all canopies into account shows that noise tracking produces more consistent results from canopy to canopy.

Waveforms over canopies with covers below 10% showed larger errors in both cases. Such sparse canopies are not classed as forests (Hansen et al., 2002) and it is likely that these footprints contain only parts of tree crowns and so we should not worry that either method struggles with the weak returns from these cases. These will be ignored in further analysis. For all canopies above 10% cover the noise tracking method was within one standard deviation of the truth and the error noticeably decreased between the high (2000 signal photons) and low noise (10,000 signal photons). A slight bias (around 30 cm) in the noise tracked method was apparent in the high noise case, though this was far lower than the bias in the simple thresholding method. Both methods showed a slight reduction in error with increasing canopy cover, though for noise tracking it started near zero and the change in error was less than the spread of those errors. This is to be expected as higher canopy cover forests are likely to have more intense returns from the canopy top which are in turn less likely to be lost in noise. Along with this will be a correspondingly weaker ground return and so canopy height accuracies will not necessarily increase.

Fig. 10 shows the canopy top errors for a 5 m laser pulse against canopy cover. A canopy cover dependence is apparent in the simple thresholding results that were not in the infinitely short pulse case (Fig. 9). Whilst the results from noise tracking showed more variation than for the infinitely short pulse case, no real trend with canopy cover was visible and so it should be possible to get more consistent results after correction for the signal start shift with noise tracking. The greater variation is probably due to the spreading and so weakening of the first return caused by a laser pulse, making it more likely to be lost in background noise.

Fig. 7. Histogram of signal start errors with and without noise tracking for four hundred sets of noise on a single waveform with an infinitely short laser pulse, all equivalent to 5000 signal photons. The canopy was 12 m tall with 73% cover and on flat ground.

Due to the large errors of canopies with covers below 10% errors these were left out of all subsequent averages over all waveforms.

3.2. Noise dependence

Fig. 11 shows the mean signal start range error along with its standard deviation against noise level for an infinitely short laser pulse. It can be seen that noise tracking consistently gave a lower bias than simple thresholding and also a smaller spread of errors. However both lines showed a similar noise dependence (that is the rate of change of error with noise level), both flattening out around 5000 signal photons. The decrease in bias from the high noise level to the asymptote was of the same magnitude in both cases (around 90 cm). This asymptote shows that a signal level of 10,000 will ensure that inversion accuracy is not limited by noise.

Therefore for the average over all canopies noise tracking does not seem any more robust to changing noise conditions than simple thresholding, which is slightly surprising. It still gave estimates with much lower biases at any given noise level, but the error changed with noise at the same rate as it did for simple thresholding. To see whether this was the case for individual waveforms and the effect was being hidden within the variance for the group average, the experiments were repeated for two individual cases.

Fig. 12 shows the noise dependence for a vertically spread canopy, such as that shown in Fig. 2 and an initially dense canopy, such as that shown in Fig. 2, both with infinitely short pulses. We would expect that the errors will be larger for the vertically spread canopy, due to the weaker initial return and so the greater chance of it being lost in noise. This appeared to be the case. For both waveforms noise tracking gave a lower bias than simple thresholding at all noise levels and seems to reach a more constant value than simple thresholding, for which the bias continues to decrease above 10,000 signal photons. This suggests that the expected increased tolerance of noise tracking to noise was hidden within greater variance in Fig. 11 and so noise tracking would seem to be more tolerant to changing noise levels for individual cases, particularly for vertically spread canopies, as expected. The experiment was repeated for all vertically spread canopies (those with a range of tree ages in the footprint).

For the vertically spread canopies (results not shown) there was a greater difference between the error above 5000 signal photons to that below than for the average over all canopies for both methods, showing that vertically spread canopies are more affected by noise than others. Both methods still showed a similar noise dependence, though noise tracking had smaller errors in all cases. The errors for simple thresholding over vertically spread canopies were much greater than for the...
average of all cases (Fig. 11), showing that spread canopies are the hardest to accurately measure with lidar. Therefore it would seem that for the average over many canopies, noise tracking is not significantly less dependent on noise level than simple thresholding, though for certain canopies it may be. However it does give lower errors in all cases and in particular performs better for vertically spread canopies, where a weak initial return must be found.

Fig. 13 shows signal start error as a distance and a fraction of first return energy truncated for a 5 m pulse averaged over all canopies against noise level. It can be seen that both methods showed a noise dependence up to 5000 signal photons. Above 5000 signal photons the mean error changed by around 50 mm to 7 mm with every 1000 signal photon step with simple thresholding whilst for noise tracking the change was 82 mm to 22 mm for each step. So purely in terms of the dependence of the error on changing noise there is no great advantage with either method. However the errors for noise tracking are more directly related to the laser pulse length than they are for simple thresholding.

When repeated for only vertically spread canopies (results not shown) the two methods showed exactly the same noise dependence and so the slight difference between the two methods in Fig. 13 would seem to be due to canopies with strong initial returns. In these cases the initial return was much greater than background noise so that simple thresholding will always pick up the same point, with a bias from using the cumulative energy rather than absolute amplitude. In the presence of a laser pulse, the error for noise tracking will depend more upon the background noise (though only causing an error of a few centimetres). Whilst using the cumulative energy adds a bias it is still better than an instantaneous amplitude threshold, which would be very sensitive to premature triggering caused by spikes in the background signal.

3.3. Laser pulse length

Fig. 14 shows the canopy start error against laser pulse length for the low and high noise cases, as a distance and also as a fraction of first return energy before the detected start. In Fig. 14 the errors for simple thresholding were generally positive (until pulse lengths of 10 m or 7 m depending on noise level, Fig. 14(a) and (c)) and so the detected signal start was after the true start. In these cases a distance should be subtracted from the range rather than added to get the true signal start. For noise tracking this was rarely the case and a more stable relationship between signal start shift and pulse length was apparent. As a fraction of the first return energy truncated, noise tracking gave a remarkably consistent signal shift whilst simple thresholding did not settle to a constant until very long pulse lengths in the low noise case and never really settled in the high noise case. The errors became more spread in terms of energy truncated at lower pulse lengths for noise tracking because, for a narrower pulse, a small step (one range bin) will give a larger energy step than for a longer pulse.
At first glance it would seem that simple thresholding gave the lowest bias for very long pulses (Fig. 14(a) and (c)). However it should be remembered that we expect the laser pulse to shift the signal start and so cause a negative error, as can be seen for the noise tracking case. Attempting to correct these signal start estimates by adding a fraction of the known pulse length (Wagner et al., 2006) would lead to large positive errors (and so underestimates of canopy height) in the simple thresholding case but lead to accurate results for noise tracking.

The results suggest that simply adding half the pulse length to the range to a canopy top will not correct for the start shift when using simple thresholding. Noise tracking is not made redundant by laser pulse length and gives results that will be easier to correct for a start shift than simple thresholding. The very slight increase in noise sensitivity in the presence of a laser pulse is more than made up for by a more predictable bias in terms of pulse length and a smaller spread in errors.

3.4. Threshold sensitivity

For the low noise case (10,000 signal photons) and an infinitely short laser pulse, noise tracking showed very little dependence on threshold, the error varying by 5.6 cm between thresholds of one and ten standard deviations (results not shown). Simple thresholding showed more of a dependence, but the error only varied by 30 cm between these bounds.

The greatest difference for an infinitely short laser pulse is apparent in the high noise case (2000 signal photons, results not shown). Neither method showed much sensitivity for a threshold of up to three standard deviations, but after this the noise tracking error increased by 20 cm over five standard deviations whilst for simple thresholding the error increased by 45 cm over the same range. Therefore in the presence of high noise, noise tracking was far less sensitive to the choice of threshold than simple thresholding.

These experiments were repeated for two individual canopies, one with elements spread vertically and the other with a dense top and so strong initial return. Fig. 15 shows that the greater sensitivity to threshold of simple thresholding was even more apparent for individual waveforms, particularly for the vertically spread canopy. Simple thresholding even showed a threshold dependence in the low noise case.

These were repeated for a 5 m pulse (results not shown) and other than the offset caused by broadening of the signal (dealt with in Section 3) no differences to the above results and conclusions were apparent. Therefore it seems that noise tracking is indeed less sensitive to the choice of threshold than simple thresholding in all cases.

4. Conclusions

We have introduced a method for removing bias from lidar estimates of canopy top position, referred to as “noise tracking”. This relies on full waveform lidar, which is becoming more prolific on airborne platforms and interest in a future satellite mission remains high (National Academy of Sciences, 2007). The method has been tested over a range of Sitka spruce forest canopies, from very sparse (sub 10% cover) to almost complete closure (99.999% cover), 3 m to 25 m tall and uniform aged and vertically heterogeneous stands over different ground slopes with a range of laser pulse lengths and compared to “simple thresholding”.

This study has used simulated data throughout. This offers the advantages over real data of giving a perfect knowledge of the truth and complete control of all parameters; a virtual laboratory. This avoids many of the complications that can obscure subtle effects in real data, such as the particular properties of the instrument and survey characteristics. The validation work carried out so far on the ray tracer (Disney et al., 2006; Pinty et al., 2004; Widlowski et al., 2007) and a visual comparison with returns from lidars such as LVIS (Hofton et al., 2002) give no reason to believe that there is any deficiency that would affect the signal start detection method tests

performed here. The absolute signal photon count or canopy cover values may not correspond exactly to real measurements, but their relative behaviour will be accurate.

In all infinitely short laser pulse cases, simple thresholding gave a positive bias (and so an underestimate of canopy height), as has been reported in the literature. In the presence of high noise (2000 signal photons), noise tracking gave a small bias (much smaller than with simple thresholding) and in the presence of low noise (10,000 signal photons) gave hardly any bias at all. Surprisingly the two methods showed a similar noise dependence when averaged over all canopies. This is thought to be due to simple thresholding’s more consistent results (though always biased) over initially dense canopies, balanced out by poorer performance over vertically spread canopies for both methods. When applied to only vertically heterogeneous

Fig. 13. Mean signal start error against noise level for a 5 m pulse for all canopies above 10% cover. Each waveform was inverted forty times at each noise level. Bars show one standard deviation over all waveforms.

Fig. 14. Mean signal start error against pulse length for all waveforms above 10% canopy cover. Each waveform was inverted twenty times. Bars show one standard deviation over all waveforms.

canopies, simple thresholding showed a little more noise dependence than noise tracking, but not so different as to give a clear advantage to either method.

In the presence of low noise (more than 10,000 signal photons) noise tracking and simple thresholding were equally insensitive to the choice of noise threshold for the average over many canopies. However, in the presence of high noise (2000 signal photons) noise tracking showed much less sensitivity and so accuracy should not be affected by the choice of an arbitrary threshold when using this method. It would be possible to tune the threshold to remove the bias of the simple method, but this tuning would be site specific (Chen, 2010) and so unsuitable for a global product.

When used with lasers with a finite pulse length we would expect the signal start to be shifted upwards. Noise tracking showed this and gave results which were more directly related to pulse length. Simple thresholding showed the opposite, requiring a correction to be subtracted from the range to canopy tops. That this has not been commented on before may be due to the obscuring errors inherent in real data.

In the presence of a 5 m pulse (the longest of any current canopy lidar) the error from simple thresholding showed a dependence on canopy cover that was not apparent in the infinitely short pulse case. Noise tracking did not show this dependence. This difference between the vertically spread case and the global average must have been caused by the weak leading edge of the laser pulse getting lost in background noise, an effect that is more likely with weaker initial returns and so lower canopy covers. In addition, when sensitivity to noise level was tested with a 5 m laser pulse, noise tracking showed slightly more dependence than simple thresholding, but only very slightly. It is felt that this slight increase in sensitivity to noise is more than made up for by a decreased sensitivity to canopy cover, noise threshold, a decrease in the bias and a more direct relationship to laser pulse length.

Thus noise tracking performs far better than simple thresholding when used on weak initial returns, whether through vertically spread canopies or convolution by a laser pulse and so should help reduce the bias reported in lidar estimates of canopy heights. It performs no worse over canopies with strong initial returns. These findings agree with those of Disney et al. (2010).

Whilst the simulations focused on large footprint spaceborne lidar, the noise tracking method will be equally applicable to any footprint size and so airborne lidar. The smaller the footprint the less vertically spread a canopy is likely to be within a given waveform, therefore the bias from simple thresholding may be lower than for large footprint signals. However noise tracking will give a lower bias in all situations (see Disney et al., 2010 for a discussion of the impact of footprint size).

The method needs to be tested on real data before it can be said to perform better for certain. However with real data confounding errors would make it impossible to examine the signal start truncation in as much detail as has been possible here and so this was not attempted in this study.

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Fig. 15. Mean signal start error against noise threshold level for individual waveforms with an infinitely short pulse. The waveform has been inverted fifty times at each threshold level. Bars show one standard deviation over all waveforms.

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