Tree counts from airborne LiDAR

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Abstract

The purpose of this report is to inform the New Zealand forest industry of test results for a new tree counting system, discuss the potential for inventory applications, and identify future developments. The new methodology utilises calibration counts, made either on the ground or on an image, to obtain accurate estimates of total tree counts for forest stands. The method also provides a measure of error, which has been used to evaluate test results. Accuracy of tree counts was evaluated on two image types for a number of stands of varying stockings and ages from two contrasting sites. The effect of two different image-processing operators and two different tree detection algorithms were also evaluated.

Results showed that overall the tree count error with LiDAR images was 6% with the ground calibration method and 11% with the image calibration method. The increased error of image calibration method is due to operator subjectivity in image interpretation and LiDAR images were found to give better accuracy than orthophotos. There was no effect of stand age, stocking, image-processing operator or tree detection algorithm on accuracy, indicating the tree counting system is robust. The reduction in operator input of the new system has increased automation and accuracy. Future work will focus on improving tree counting accuracy and developing inventory applications.

Introduction

New remotely sensed data are creating a revolution in forest inventory. A combination of new technologies, increased computing power and novel processing methods are opening up new possibilities. LiDAR is a notable example, currently being evaluated and adopted by the local forestry sector using very effective area-based analysis (ABA). To address some issues with ABA, such as difficulty in estimating stocking, we have been developing an alternative approach based on the detection of individual trees from LiDAR. In this paper we present results of accuracy tests for a new tree counting system and discuss options for its use in forest inventory.

Conventional inventory

Conventional forest inventory in New Zealand is based on sampling. Typically bounded circular plots are used, but refinements such as stratification and the use of double sampling with tally plots are also often implemented. The basis of this approach is the estimation of stand level measures from multiplication of plot means by stand area. This approach has been used successfully for decades. Experience has shown that plot sampling rates of 1–5% by area are sufficient to realise a PLE (probable limits of error) of 10% (Goulding & Lawrence, 1992). However, it is worth noting that any error in stand area is usually ignored when estimating stand totals and, depending on the state of the stand records, this can be large.

Airborne LiDAR for inventory

The use of airborne LiDAR for forest inventory is a relatively recent development internationally and locally, with a useful introduction and outlook for the New Zealand scene given in an earlier article (Adams et al., 2011). A notable early local example was the use of LiDAR in a double sampling approach with ground plots for the national inventory of carbon stocks in the Land Use and Carbon Analysis System (LUCAS). The approach used here was to fit regression models to estimate carbon stocks from LiDAR metrics (Beets et al., 2011, 2012). This is an example of ABA of LiDAR, an approach widely used to describe forest stands, which can provide estimates of variables of interest with fewer ground plots than would be used in conventional inventory and offer cost savings, dependent on the cost of the LiDAR.

Individual tree inventory

There is another approach to inventory that can reduce ground measurements and potentially offer cost savings – individual tree inventory. In conventional inventory, outlined earlier, measures made in ground plots are scaled to the stand level by multiplying by stand area. In a tree-based inventory, measures made on individual trees are scaled to the stand level by multiplying by the number of trees in the stand. The potential benefit of this approach is that far fewer trees need to be measured to characterise a stand to a given level of confidence (PLE), thereby making significant cost savings. There are two base requirements for individual tree inventory: an accurate estimate of tree count; and procedures to select and measure single trees. In both cases robust, efficient methods are required to make operational use a reality.

Tree-based analysis (TBA) is an alternative approach to ABA of LiDAR, and it may be used to meet the tree counting requirement for individual tree inventories. TBA is commonly referred to as individual tree crown (ITC) analysis in the scientific literature. This approach has been widely researched internationally, but operational methods have remained an elusive goal. The international research has spanned decades, beginning with attempts to detect individual trees in aerial photographs, later in satellite images, and most recently in LiDAR data. Obtaining an accurate tree count, useful for a number of potential operational uses, is one of the reasons tree detection is being so avidly researched around the world.

Counting trees is difficult

Future Forests Research Ltd (FFR) initiated a project to develop individual tree inventory, targeted for use in woodlots where conventional inventory would be inefficient or infeasible, but also with potential cost savings for larger stands. Initial research showed promising results using the TIMBRS software with aerial photographs (Culvenor, 2002; Goulding et al., 2009). By 2010 variability of image quality in aerial photographs was identified as an issue affecting tree counting and near infrared (NIR), normalised difference vegetation index (NDVI) and QuickBird satellite images were being investigated to reduce these effects. In 2011, canopy images derived from LiDAR were evaluated and it soon became evident this could be the breakthrough required in image quality (Pont et al., 2012a).

In addition to image quality, another significant issue affecting tree counting was the amount of time-consuming and subjective operator input required to carry out the process. Most tree detection methods require smoothing to be applied to input images. The degree of smoothing applied has a strong effect on the number of trees detected, but this critical input is typically a best guess by the operator. These issues were also being echoed in the international research literature. LiDAR was beginning to be identified as the remote sensed imagery of choice for tree detection, and subjective inputs or choice of tree detection algorithm were seen as major barriers to the development of robust, accurate methods (Kaartinen et al., 2012; Larsen et al., 2011; Vauhkonen et al., 2011).

A new methodology for tree detection

With LiDAR images and the TIMBRS tree detection algorithm (Culvenor, 2002), attention was focused on reducing subjectivity in the process and applying statistical methods to obtain a measure of certainty on estimates of tree count. A framework was developed to combine these elements into a new approach called calibrated tree detection. A detailed description of the method and initial evaluation results are given in Pont et al. (in press). Figure 1 illustrates the main steps carried out in the new tree detection process.

A key feature of the method is the use of calibration counts to reduce subjectivity in the process. Two alternative methods of making calibration counts are used:

- In the ground calibration method, tree counts are made by field crew of trees falling inside circular calibration plots in the stand
- In the image calibration method, counts of tree-tops are made by the image processing operator within circular 'virtual plots' drawn on the image.

Figure 2a shows an example of a virtual plot on the image with blue dots indicating the tree-tops selected by the operator. Tree detection carried out by an algorithm lies at the heart of the process, but it is the use of calibration counts that ensures accurate counts are obtained.

The calibration counts are used at three distinct steps in the process, each reducing the amount of subjective inputs. The only subjectivity remaining in this new process is the determination of calibration counts on images when the image calibration method is used. Figure 2b shows an example of the results of the tree detection process on an image.

In evaluating the tree counting methodology there are a number of important factors to be considered. We wanted to quantify the effects of image type (i.e. LiDAR image versus aerial orthophotos), calibration method (i.e. ground-based versus image-based), tree detection algorithm and operator on accuracy. The new methodology provided estimation of the variance associated with tree count, which was used to generate a measure of error (root mean square error or RMSE) to evaluate these factors.

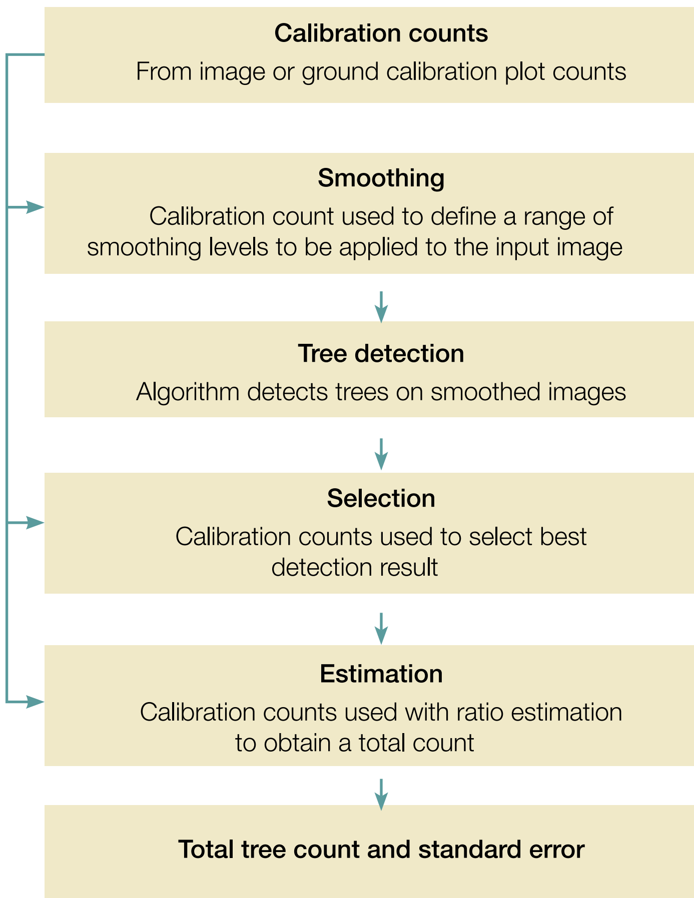

Figure 1: The main processes in the tree counting methodology

Tree counting accuracy was evaluated using images and ground data collected in *Pinus radiata* D. Don stands from two North Island forest sites representing a range of ages. Aerial LiDAR data was converted into raster images suitable for tree counting with a pixel size of 0.5 m using the Fusion tool *CanopyModel* (McGaughey & Carson, 2003). In the first study at Site A, orthophotos (0.4 m pixel size) and aerial LiDAR (pulse density 8.1 last returns per square metre) for four stands on relatively flat terrain were used.

In the second study at Site B, only aerial LiDAR (pulse density 5.4 last returns per square metre) was evaluated for seven stands on steep terrain. At both sites ground and image calibration plots were established in stands loosely following conventional inventory practice: circular plots on a grid with random origin and orientation to obtain at least a 1–2% area sample; and plot area chosen to obtain a nominal 20 trees per plot. The characteristics of the four Site A and seven Site B stands are given in Table 1.

Tree counting accuracy

LiDAR images from both sites were used to evaluate the effect of calibration method and operator on accuracy. Error was quantified using root mean square error expressed as a percentage of the total count. Ground and image calibration gave errors of 5% and 10%, respectively, at Site A and 6% and 11%, respectively, at Site B as shown in Figure 3. Tree count accuracy was not affected by operator or calibration method at either of the two sites.

Table 1: Characteristics of test stands

Forest site	Stand	Age years	Area ha	Stocking stems ha-1	Plot size ha	Plots no.
A	1	7	37.97	826	0.02	20
	2	17	89.28	341	0.04	26
	3	32	45.60	219	0.08	47
	4	32	59.21	204	0.06	38
B	1	13	34.93	417	0.05	14
	2	14	8.31	383	0.05	10
	3	21	27.62	517	0.04	18
	4	22	46.00	467	0.04	23
	5	21	21.08	417	0.05	21
	6	26	46.57	400	0.05	14
	7	25	25.25	383	0.05	13

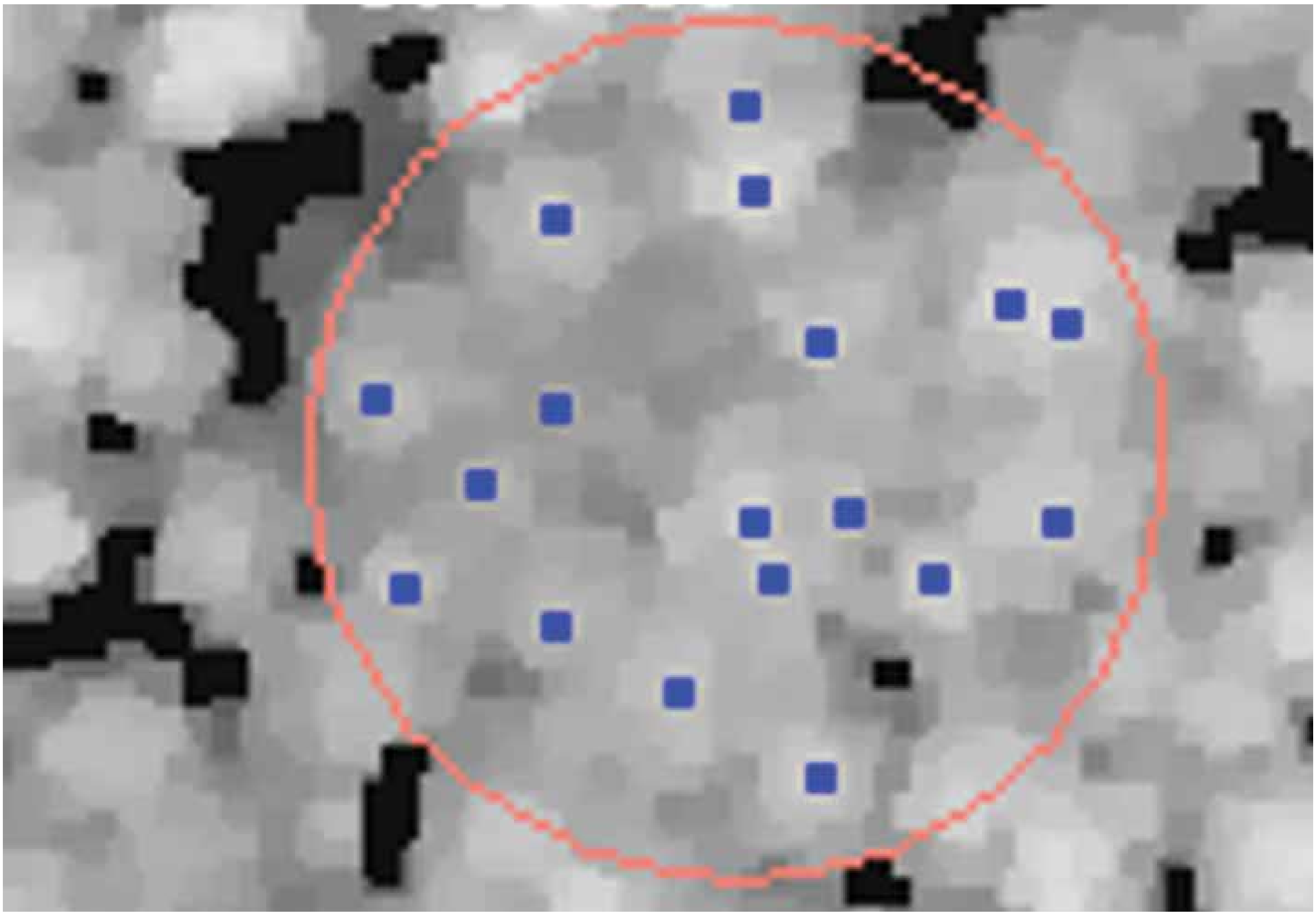

Figure 2a: Region from LiDAR image for Stand 4 at site B showing the input image with an image calibration plot marked on the image in red and operator digitised tree-tops in blue

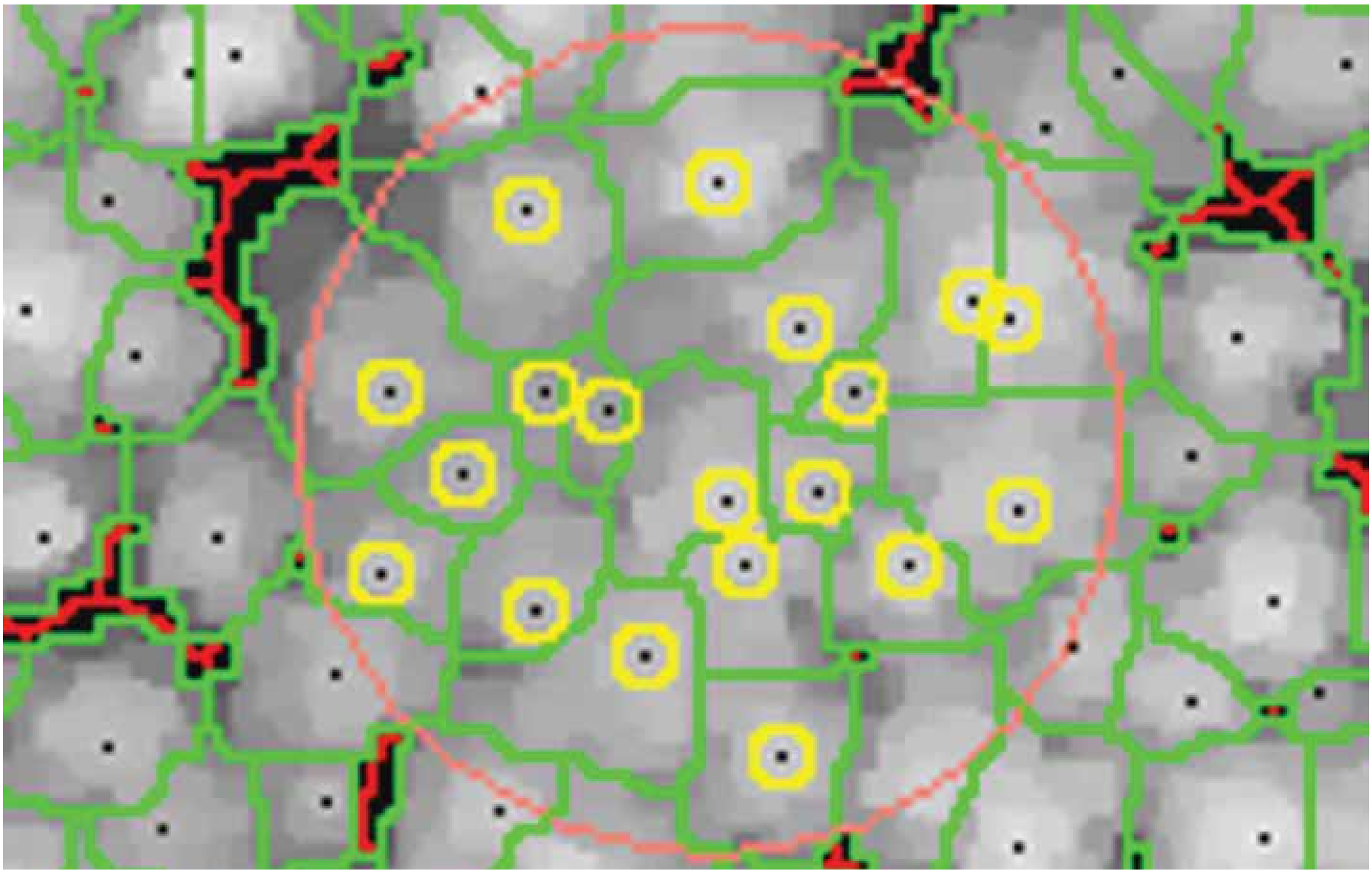

Figure 2b: Region from LiDAR image for Stand 4 at site B showing tree-tops detected by the algorithm in black and those inside the calibration plot circled in yellow. Delineated crown boundaries are in green and extents of tree growing spaces are in red

At Site A, tests showed tree counting based on LiDAR imagery gave superior results compared to orthophotos with both ground and image calibration methods. Orthophotos were affected by various lighting issues, such as shade, which confused both the human eye and the computer algorithms, particularly affecting the image calibration method. LiDAR images did not have these lighting issues as they do not rely on sunlight. Instead the emitted laser pulses uniformly illuminate the target. Because of this, interpretation by operators and tree detection algorithms was greatly improved.

Site A results also showed no significant difference between the TIMBRS and an alternative tree detection algorithm, based on the watershed method, with differences in root mean square error of only 0.03% for ground calibration and 0.34% for image calibration. Recent international tests concluded that tree detection algorithms were a key determinant of accuracy, and that algorithms performed best when applied to forest types they were developed for. In those studies counts were often being carried out on a range of forest types, more complex than our even-aged single species forests. However, our study did cover a wide range of stand ages, which still represents considerable variation in crown size and shape.

Our results indicate that the new methodology presented here allows the effects of tree detection algorithm and operator on accuracy to be minimised. The ground calibration method applied to LiDAR images gave accurate estimates of tree count (within 6%) independent of stand age and stocking at two contrasting sites, for two operators. Image calibration is a highly desirable alternative to ground calibration as it avoids the costs and risks associated with installing the ground calibration plots. Error with image calibration was within 11% for LiDAR images, which might be acceptable for some applications.

Reduced subjectivity

Operational methods for tree counting from images are recognised as difficult to achieve. International research shows that bias, largely due to operator inputs, and difficulty in quantifying error on operational-sized areas are barriers to progress. The new methodology developed in this project has provided practical and effective solutions to these issues. The use of calibration plots was the key to addressing subjectivity. Using ground calibration effectively eliminated subjectivity, while image calibration restricts subjectivity to operator interpretation of the images. Operator interpretation was also significantly improved by using LiDAR images. Reducing operator input not only reduced subjectivity, but also the image-processing time through increased automation of the process.

Error is quantified

Another key feature of the methodology was the provision of a measure of error, which is an important

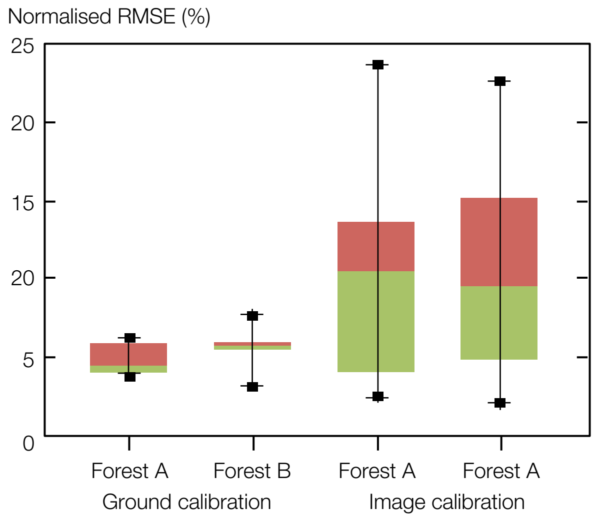

Figure 3: Error on tree count, root mean square error as a percentage of total count for the two forest sites, and the two calibration methods

feature in operational use to provide confidence intervals on estimates. However, it will also be of huge benefit in the ongoing development of tree detection research. The methodology provides the means to quantify error using simple ground plots, applicable to any forest type. Such a cost-effective approach will also allow evaluation of more and larger test areas. This practical error measure could accelerate development of tree detection research by providing the critical tool to quantify algorithm and methodological improvements.

A robust method

Accuracy was only very slightly lower at Site B, despite notably lower LiDAR pulse return density and more complex terrain. Both of these factors would be expected to reduce accuracy, but the effect was only minor and we can observe that a LiDAR pulse density of five pulses per square metre is sufficient for tree counting, even on steep terrain. No significant effect of operator or stand age (stocking) was observed on accuracy in this study. However, experience has shown us that older stands are most difficult to obtain accurate counts on, while stands that have just been thinned and with clearly defined canopies are the simplest for tree counting. Evaluation of more extensive data sets will help quantify differences in tree counting accuracy across stand age, but it does seem the effect is not large.

Use in operational inventory

An accurate tree counting method is a significant achievement, but the original question of how to provide an efficient, accurate and cost-effective assessment of woodlots, or larger areas, still requires definitive answers. Tree counts derived from an image alone would have practical application in producing stocking maps, useful for assessing establishment and for planning and evaluating thinning operations. However, for mid-rotation and pre-harvest inventory additional ground data, such as diameters and stem quality cruising, will probably be required. In that case it may be quite feasible to incorporate measurement of ground calibration plots as part of the inventory workflow while in the stand. In this way the higher accuracy of the ground calibration method (6%) can be taken advantage of.

There are a number of options for incorporating tree counts within an inventory system. One approach is to implement single-tree inventory, requiring selection of individual trees for ground measurement. This could be done by selecting trees at random from the tree detection results. Unfortunately GPS error under canopy, often of the order of 5 m or more, will make it difficult to reliably locate those trees on the ground (Wing & Eklund, 2007). A further issue is that single-tree inventory would increase the relative overhead of navigation and set-up/pack-down time to take tree measurements. To address this single trees might be measured more efficiently in 'clusters' such as plots or transects, but more research is required to find the right balance between statistical benefits and practical ground procedures (Gordon & Pont, in press). Tree counts might also be incorporated into more complex inventory systems such as double sampling.

Future work

The measure of error provided by the methodology will assist further development of the tree counting process. LiDAR data can be artificially thinned and the effect on error used to define the minimum LiDAR pulse density required for tree detection (Watt et al., 2013). Further research should also examine the size and numbers of calibration plots required to achieve a desired level of accuracy with the methodology. Accuracy of ground calibration (6%) might be improved if calibration plot locations were more accurate because GPS error under canopy is contributing to the final error on tree count.

The higher error of the image calibration method (11%) was due to subjectivity in operator interpretation of images. Orthophotos are affected by a number of issues related to lighting; one example is the tops of tree in gullies completely disappearing in large areas of shadow. LiDAR images are substantially better than orthophotos in this respect, but there is still difficulty in interpretation of the larger complex crown shapes in older stands. The crowns of small trees can merge into or be hidden by other crowns, and large branches growing out from larger crowns such as on edge trees can appear as separate trees. While we are unlikely to completely eliminate these problems, there may be opportunities to develop image creation and operator training to reduce errors in interpretation. The cost benefits of being able to carry out tree counting solely on images make this a desirable goal for ongoing development.

There is new research underway to apply the tree detection methodology to obtain tree level crown metrics from the LiDAR with the potential to improve the accuracy of estimates obtained with area-based methods. A pilot study also showed the potential to estimate standing tree stiffness from tree level crown metrics extracted from LiDAR after tree detection (Pont et al., 2012b).Those metrics are derived from analysis of the shape of the crown as delineated by the tree detection process as shown in Figure 2b.

Now that we have demonstrated a viable tree detection system the challenge is to identify and develop applications for New Zealand forest management. However, we must take into account the bigger picture. New technologies in the form of tripod mounted and hand-held terrestrial LiDAR units, photogrammetric scanning techniques (Morgenroth & Gomez 2014), and unmanned aerial vehicles (UAVs) are rapidly emerging. Such tools also show considerable promise for applications in forestry and increase the scope of the challenge, which will require the fusion of basic science and forestry knowledge to forge successful solutions based on the opportunities they offer.

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