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Evaluating techniques for measuring the volume of large woody debris on erosion-prone cutovers

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Abstract

Background: This study compares two remote sensing methods to a field-based line intersect sampling (LIS) method for measuring Large Woody Debris (LWD) on 27 ha of recently clear-felled plantation cutover in North Canterbury, New Zealand. The remote sensing methods tested were: 1) machine learning-based LWD detection on high-resolution orthophotography; and, 2) virtual line intersect sampling via photogrammetric point clouds.

Methods: The site was flown at 40 m above ground level with a 20 megapixel RGB camera, and 80% image overlap, achieving a ground sampling distance of 1.1 cm. The resulting point cloud and orthophoto were used for remote sensing measures, compared to the ground-based volume measure. The ground-based line intersect sampling used 28 x 50 m, slope-corrected L-shaped transects arranged in a grid pattern across the site. LWD diameter was measured at the transect intersection and used to derive volume using Van Wagner's (1968) LIS formula.

Results: The ground-based method measured a mean LWD volume of 31.0 ± 10.2 m^3/ha. The photogrammetry-based method measured a lower mean volume of 13.6 ± 3.8 m^3/ha, with an r^2 value of 0.61, indicating moderate correlation with the ground-based method. The machine learning method measured a mean LWD volume of 14 m^3/ha and had a moderately weak r^2 value of 0.39, in line with other published models. The machine learning method positively correlated with both ground-based and photogrammetric LWD volume, making it most useful for identifying high-density areas.
The ground-based method consistently returned higher volume measures. Occluded residues could not be captured by the remote sensing methods, but were positively observed in the field. Accuracy in establishing and measuring to the in-field transect remains critical also, regardless of topography challenges. Plot-wise interpretation of the orthophoto revealed 11% of field-measured pieces fell outside the transect. While challenging in steep topographies, field measures remain the only way to capture occluded volume in high-density areas.

Conclusions: Remote sensing techniques based on RGB photography offer a safer, more efficient alternative that can reliably identify high-density areas, even if the estimate is likely low. Strategic application of these methods, considering costs, benefits, and limitations, will enhance plantation owners' ability to ensure alignment with new cutover standards.

Keywords: Harvest residues; large woody debris; plantation harvesting; remote sensing.

Introduction

Since 2023, regulations for commercial forest operations in New Zealand have imposed limits on the volume of Large Woody Debris (LWD), officially termed 'residual slash', that may be left to decompose on any terrain classified as having a 'High susceptibility to erosion', or worse. The 2023 limit is set at 15 m^3/ha of 'sound' LWD (not readily broken upon mechanised extraction). This is applied to pieces of LWD greater than 2 m in length, and greater than 10 cm in diameter at the large end. Assuring alignment with Regulations therefore requires reliable method(s) of objective assessment for LWD volumes.

No methods of assessment are specified in Regulation. Several variations of Line Intersect Sampling (LIS) for LWD volumes are established in research practice. Anecdotally however, manual LWD measurement is considered impractical in the steep terrain that is common to New Zealand's highly erosion-prone sites, and so remote sensing methods offer possible alternatives.

A 2023 survey of New Zealand's forestry sector reported very high levels of remote sensing data integration into forest management processes (Manning 2023). Of the respondents, representing 74% of the national plantation forest estate, 93% used Unmanned Aerial Vehicles (UAVs) for low-altitude data collection. All respondents reported using aerial imagery for cutover mapping. Therefore, additional value may be derived from this imagery if it can also be utilised for measuring LWD volume.

Several manual and remote sensing methods for measuring residual LWD appear in literature. Line Intersect Sampling (LIS) is the most popular in research. Plotless methods may be adapted to LWD measurement. Machine learning methods that apply virtual replications of manual sampling methods, or provide full inventories using images and point clouds show promising results in research, although a wide range of accuracies have been documented, with and without true field verification.

Line Intersect Sampling

The LIS method was first developed for forestry by Warren and Olsen (1964) and then refined by Van Wagner (1968). The method was first intended for quantifying the residual saleable timber volume distributed across clearfell forestry cutovers, but has been used extensively in other applications including vegetative fuel assessments (Sikkink & Keane 2008), LWD measurement (Harvey & Visser 2022), and forest canopy gap distributions (Battles et al. 1996). LIS methods define a transect and only pieces of LWD that intersect the transect are measured. When applied to LWD volume assessments, LIS relies on several key assumptions and faces potential biases, which can impact the accuracy and precision of the results. LIS assumes:

1. The area (cutover) is a horizontal plane therefore transects must be slope-corrected for length;
2. LWD are cylindrical; and
3. LWD are randomly oriented.

The precision of an LIS assessment is related to the intensity of sampling, and the variability of LWD density across the cutover.

Pickford and Hazard (1978), Bell et al. (1996), and Karpachev et al. (2020) simulated variations of the LIS method, in virtual environments. Both Pickford and Hazard (1978) and Bell et al. (1996) showed that the advantage of a simulation approach is that potential forms of bias can be removed or added to sampling depending on what is being tested. Bell et al. (1996) focused on orientation bias, showing that L-shaped and fan-shaped plots are less susceptible.

Simulations have also been used to compare different methods with each other, particularly to evaluate the efficiency of methods. Thomaes et al. (2024) simulated full area (sample plot inventory) plots against LIS plots and determined that LIS should always be used instead of sample plot inventory when measuring LWD with diameters less than 30 cm as it reduces the workload by 67-83%. Khan et al. (2016) showed that the point-centred quarter method requires 50 plots for a relative RMSE of 25% when sampling vegetation density. In both studies, method simulations were useful for validating statistical accuracy and sampling efficiency, however could not highlight any bias caused by the practical application of the method in a given context.

Remote Sensing for LWD

Field-based measurements are "not practical" when measuring large areas (Joyce et al. 2019). Windrim et. al (2019) go further to say that manual assessments are "labor-intensive, time-consuming, and do not scale well to heterogeneous landscapes". The motivation for researchers and industry to develop various remote sensing alternatives is clear. Peng and Karimi Sadaghiani (2023) highlighted machine learning as a promising tool for quantifying LWD volumes because machine learning can analyse large datasets including high-resolution imagery of complex environments.

Davis (2017) used a statistical classification system on Unmanned Aerial Vehicle (UAV) imagery to mask areas of woody debris, understanding woody debris has a higher reflectance in the red band than surrounding ground for the site studied. Davis (2017) turned the surface area identified by the statistical classifier into a volume measurement by approximating the surface under the woody debris from the photogrammetric point cloud and applying a correction factor to represent the occluded portions of the woody debris. The predicted total woody residue volume of all plots combined fell within 16% of the manual measurement, and yielded a similar uncertainty. Volume comparisons at the plot-level usually varied by more than 50%, and up to 771%. As a site average therefore, the Davis (2017) method may be acceptable, however when isolating individual plots, the low accuracy may be operationally unhelpful.

Orthophoto-based approaches that use machine learning often take a semantic segmentation approach rather than instance segmentation, and typically use a Random Forest machine learning model. Semantic segmentation more simply looks to define a pixel in an image as being LWD, or not, while instance segmentation additionally ensures that each object (piece of LWD) is uniquely identified and masked.

Windrim et al. (2019) used the Faster R-CNN machine learning model to find individual LWD pieces from orthophotos. Processing constraints of the Faster R-CNN model at the time meant that analyses were constrained to a 600-by-600 pixel window, perhaps contributing to the low accuracy (r^2 = 0.572) of the relationship between the machine learning detection and the volume measured by manual image interpretation.

Lopes Queiroz et al. (2019) reported high accuracy with 5 cm orthophotos, achieving 93.4% completeness (the area accurately identified as woody residues) and 94.5% correctness (the area accurately identified as non-LWD). They also found that the classifier's accuracy did not improve with the inclusion of LiDAR data. Udali et al. (2024) achieved similar accuracy using a Random Forest classifier, but unlike Lopes Queiroz et al. (2019), they derived a volume measurement. The Udali et al. (2024) volume measurement was based on similar principles as Davis (2017). Despite the high accuracy of the classifier, the Udali et al. (2024) method achieved only a weak relationship for the volume, with an r^2 between 0.17 and 0.31, reporting that the instance segmentation step may have been what generated the higher accuracy for Windrim et al. (2019). Instance segmentation has therefore been demonstrated to be more accurate but requires higher-quality training data and more computational power.

The strong model performance (r^2 = 0.92) indicated by Joyce et al. (2019) is typical of measurements compared to manual annotation of remote sensing datasets. Windrim et al. (2019) also compared against manually annotated model training datasets and found the machine learning model to be very accurate (r^2 = 0.958), regardless of a comparatively small amount of training data.

A proliferation of remote sensing methods in literature with varying accuracies and limited field-based verification of outputs currently challenges the use of remote sensing data as a robust solution for New Zealand's cutover slash Regulations. Semantic segmentation methods are impractical as Regulations refer to individual piece size limits. Therefore, when considering a machine learning method paired with remote sensing imagery, additional piece separation beyond simple semantic segmentation is likely required. This study takes a steep and erosion-prone cutover site and applies manual LIS, virtual LIS and a full site inventory method with piece-separated semantic segmentation to provide a comparative analysis of methods.

Methods

Study site

The study site (Figure 1) was 27 ha of the Teviotdale block in Omihi Forest, North Canterbury. The plantation was second rotation *Pinus radiata*, harvested between November 2023, and May 2024. The stand had a final stocking of 457 stems/ha and yielded an average of 525 t/ha at harvest. Some isolated areas of windthrow were present prior to harvest. Felling was mechanised with winch-assist and extraction completed by a swing yarder/running skyline setup with a rope-operated grapple.

The stand straddled two incised gully systems. The mean terrain slope was 24° with a standard deviation of 9.5°. Underlying geology is consolidated marine sediments, with soil depths ranging from 40-60 cm in the gullies to over 1 m on the ridges (Smith 2024).

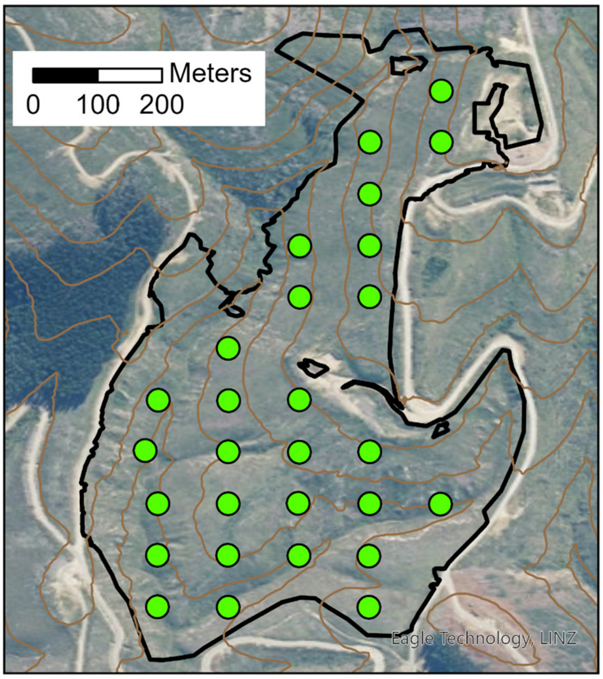

FIGURE 1: Clearfell harvest study site showing the locations of 28 plot centres measured on the ground and by remote sensing methods. Contour interval: 20 m. The northern-most plot centre is located at 172.8282° E 43.1196° S.

Ground-based procedure

Each LIS plot was approximately located in the field with a mobile phone-based GNSS mapping application. Plot centres (Figure 1) were marked clearly on the ground using a 50 cm cross shape of spray paint and subsequently recorded with a Trimble Zephyr 3 GNSS receiver. A Suunto KB-14 handheld precision compass was used to define L-shaped transect orientations (see Figure 2). Transect sides were 25 m (measured horizontally) and corrected for average terrain slope along the transect, measured using a Haglöf Vertex. The ends of the transect were marked on the ground with

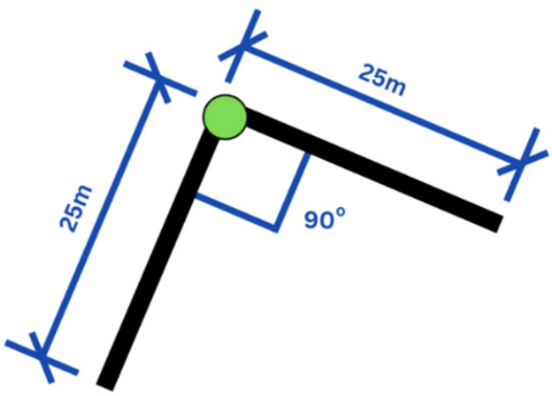

FIGURE 2: Diagram of a singular L-shaped line intersect sampling plot.

spray paint with the same 50 cm cross shape.

The transect was walked from the endpoint, towards the plot centre. LWD >10 cm diameter at the large end and >2 m long were measured in the order that they were found to intersect the transect line.

For each qualifying piece, the following measurements were recorded:

- Small-end diameter (SED)
- Large-end Diameter (LED)
- Total length
- Diameter at intersection

Qualifying LWD lengths were measured using a 30 m fibreglass measuring tape. Piece diameters were measured using callipers to the nearest 0.1 cm. The large end of each qualifying piece was sprayed with spray paint. Once the first transect line was walked back to the plot centre and every qualifying piece had been recorded, the second transect was established at a 90-degree angle from the previous and the same measurement process repeated.

Volume per hectare (m^3/ha) was calculated at the plot level using Equation 1, from Van Wagner (1968).

$$V = \left(\frac{\pi^2}{8L}\right)\sum d_i^{\,2} \qquad (1)$$

Where d_i is diameter (cm) of piece *i* at the transect intersection, perpendicular to the piece's longitudinal axis, and L is the length of the transect (m).

The total volume of pieces intersected by the transect was calculated to compare to the machine learning procedure. The volume of each piece was calculated using Smalian's formula (Equation 2):

$$V = \frac{\pi}{4}\left(\frac{SED + LED}{2}\right)^2 l \qquad (2)$$

Where V is the total volume in m^3, *SED* is the Small End Diameter (m), *LED* is the Large End Diameter (m) and l is the length of the LWD piece (m).

Remote sensing data collection and processing

Remote sensing data was collected on 28 July 2024 with the following equipment and specifications:

- Sensor: Zenmuse L1 20 megapixel RGB camera (24 mm lens)
- Height above ground level: 40 m
- Overlap between images: 80%

The PIX4Dmapper software package was used to generate a photogrammetric point cloud and an orthophoto of the cutover with a ground sampling distance of 1.1 cm. The site was flown in three parts, and the orthophotos were mosaiced together in ArcGIS Pro. The transect line of each plot was digitised by identifying the spray-painted marks in the orthophoto as shown in Figure 3.

The photogrammetric LIS procedure was completed in the virtual environment, following digitised transects. Quick Terrain Modeler (software) was used for measurement data capture, shown in Figure 4. Where pieces overlapped in the point cloud or were otherwise unclear, PIX4Dmapper software was used to interpret

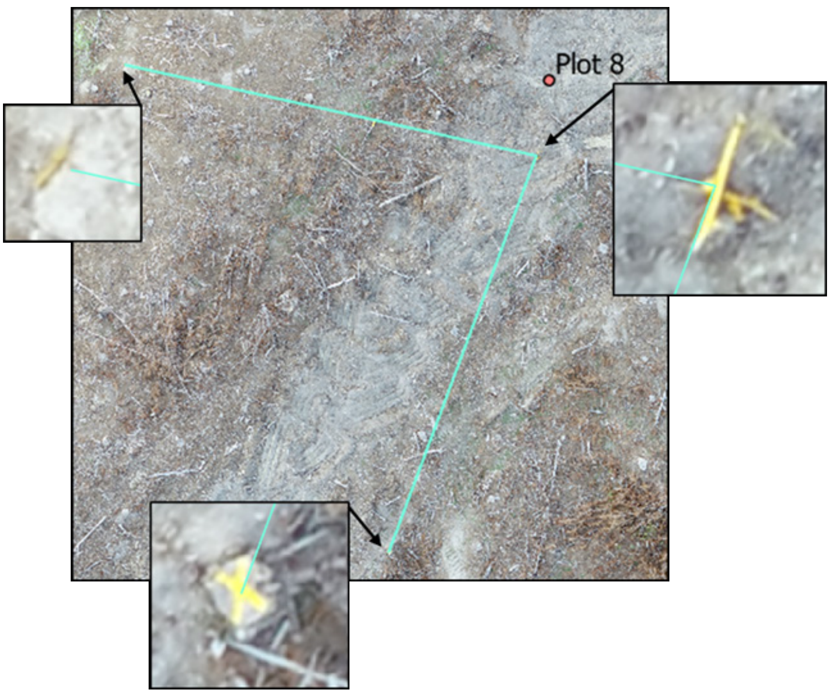

FIGURE 3: Example of locating the plot transect lines in the orthophoto from the visible spray paint, using information from the GPS measurement (red dot) and compass bearings recorded in the field.

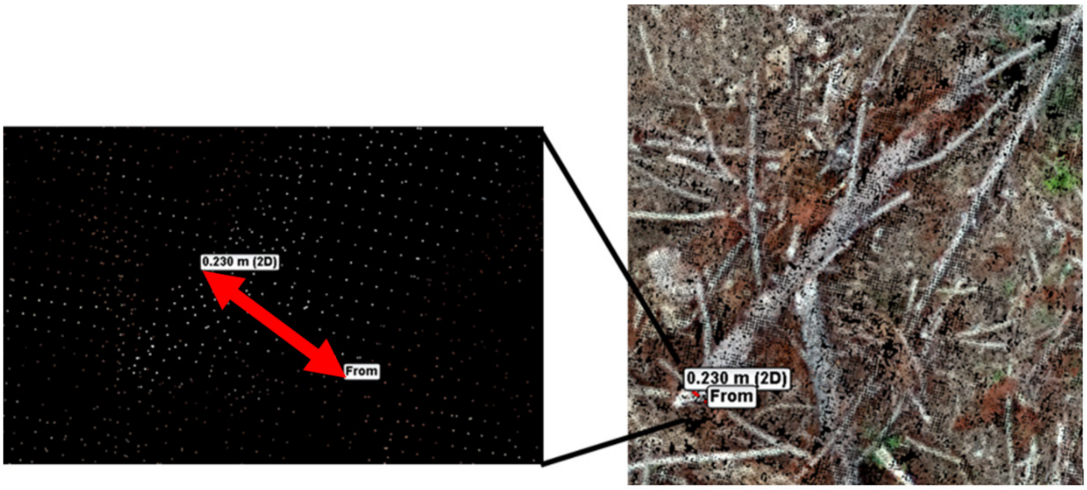

FIGURE 4: Screenshot of point-cloud based diameter measurement in Quick Terrain at two scales. The red arrow represents a stem diameter measurement of 23 cm.

the piece's location from the original aerial photographs. LWD pieces were only measured in the photogrammetry analysis if the diameter at intercept was larger than 10 cm, which due to stem taper meant some pieces with a LED greater than 10 cm were excluded. The volume per hectare at each plot was calculated with Van Wagner's equation (Equation 2).

Each LWD piece was given a piece code that enabled 1:1 analysis between the measurements for the same piece from the ground-based procedure and the photogrammetry procedure. The LWD pieces were systematically measured in order across both methods, allowing for the order in which the pieces were found within the plot and the similarities in their measurements to be used for assigning piece codes. Pieces that were recorded only in the photogrammetry procedure or recorded only in the ground-based procedure were visually analysed in the orthophoto to categorise the reason for the discrepancy, such as if the piece was partially obscured.

The machine learning-based residue detection model used in this study was developed by Interpine Innovation for commercial use. It is a semantic segmentation model based on Convolutional Neural Network (CNN) architecture that identifies all the pixels belonging to LWD within an orthophoto. The model was not trained on any part of the orthophoto from this study.

The volume of each piece was calculated based on the two-dimensional measures of the segmented polygon. The length was the longest axis through the polygon, and the average diameter was calculated as the segmented surface area divided by the length. The volume calculation assumes the log is shaped as a cylinder. Pieces with lengths greater than 2 m are then used to compute a moving average volume per hectare raster. This process involved approximating the volume of each LWD piece as at the centroid of the LWD piece, then summarising the centroids over a 10 m raster grid (100 m^2 per raster cell).

During segmentation, the orthophoto was split into tiles which produced small 'splits' where LWD pieces crossing the border of a tile were identified as two separate polygons. Although this had minimal impact on the volume raster, since the split represented a small area of the piece, it affected the comparison between the machine learning-identified pieces and the pieces measured in the field. Split pieces were combined for the comparison with the ground-based and photogrammetry LIS methods with an ArcGIS Pro ModelBuilder process (Figure 5). The minimum bounding geometry tool was used to estimate the orientation of each piece, based on the assumption that woody residues will always have straight, long axes, much longer than the width. Polygons that had an orientation (long axis) within ±5° and were <0.5 m apart were dissolved together, as shown in Figure 5.

A total of 25 plots were measured by all three methods and used for the analysis. Three plots were excluded from the analysis for falling across boundaries in the UAV flight patterns and were unable to be accurately aligned for comparison.

Results

The ground-based line intersect method measured a mean LWD volume of 31.0 m^3/ha across the cutover, which was significantly higher than the measurements from either remote sensing method (Table 1). The remote sensing methods measured a similar volume per hectare to each other, 13.6 m^3/ha for the photogrammetry and 14.0 m^3/ha for the machine learning. Both plot-based methods had large confidence intervals due to the high variation between plots.

Figure 6 details the variation that was found at the plot level. Ground-based LIS yielded the highest volume result in all but five plots. The difference between the machine learning result and the ground-based LIS results at the plot level is more variable ($\overline{\Delta x}$ = 20%, $\sigma_{\Delta x}$ = 99%) than the difference between the photogrammetry-based LIS and ground-based LIS results ($\overline{\Delta x}$ = 50%, $\sigma_{\Delta x}$ = 22%).

The difference between the ground-based LIS and the photogrammetry methods is evident in Figure 7.

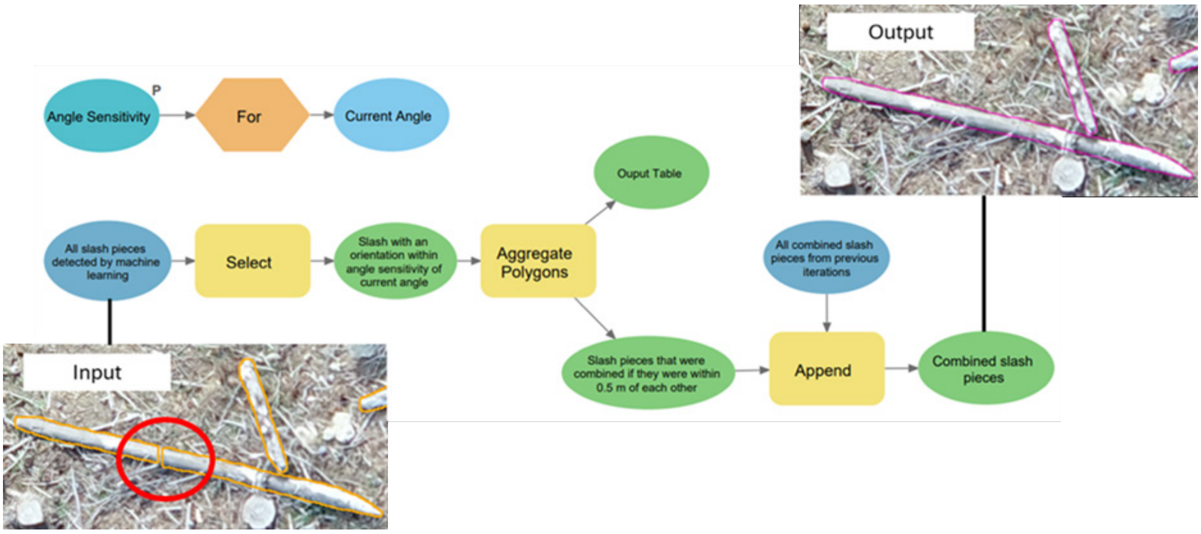

FIGURE 5: ArcGIS ModelBuilder model used to combine pieces that were at the same orientation and nearby each other. The example shows a long LWD piece that was combined at the split but not combined with the nearby piece at a different angle.

TABLE 1: Results for the cutover volume per hectare as measured by the three methods. Plot-based methods (ground-based and photogrammetry line intersect) have confidence intervals (C.I.) to represent that a sample was measured, whereas the machine learning volume surface covered the whole cutover.

Method	**Mean Volume (m^3/ha)**	**95% C.I. (m^3/ha)**	**Probable Limit of Error (95% Confidence)**
Ground-based line intersect	31.0	20.8 - 41.3	33%
Photogrammetry line intersect	13.6	9.8 - 17.5	28%
Machine learning (average of volume raster)	14.0	-	-

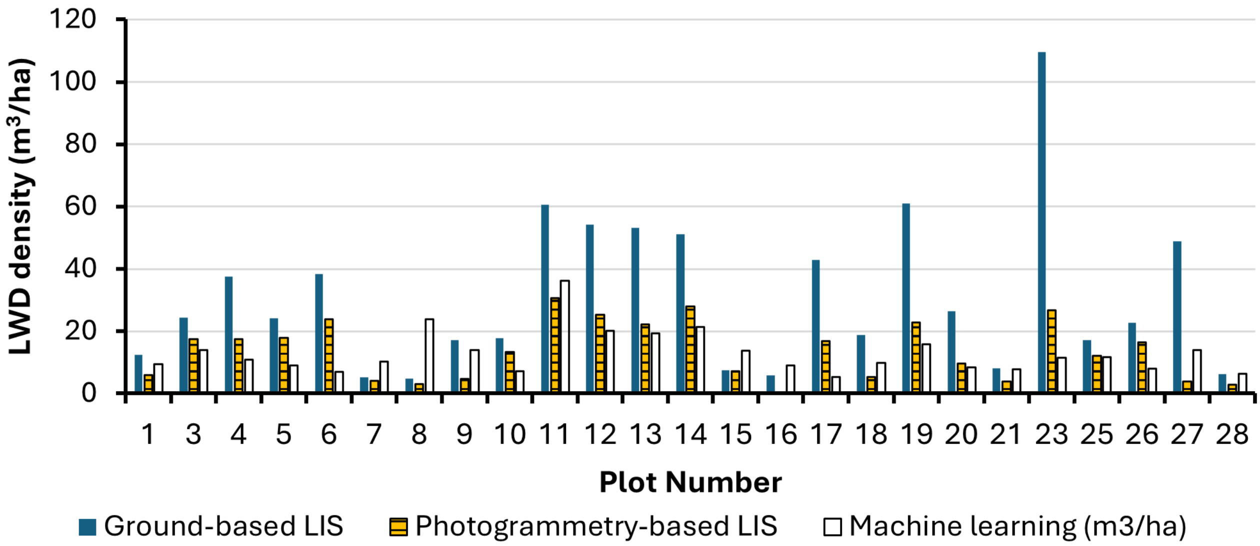

FIGURE 6: Comparison of LWD volumes found by the three methods tested at each of the 25 plots.

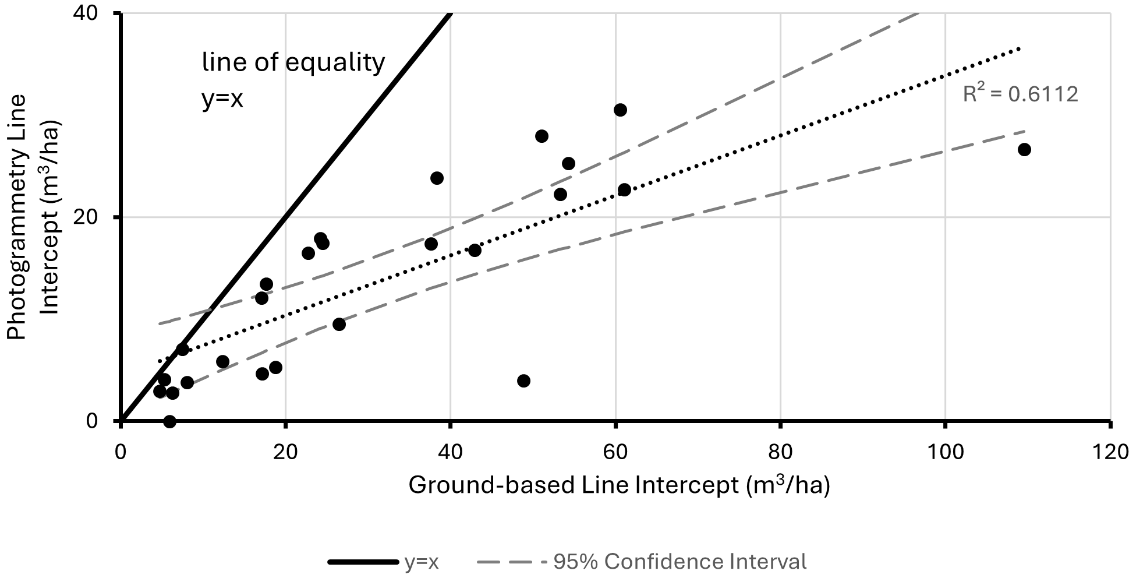

FIGURE 7: Plotwise comparison of ground-based and photogrammetry results.

The linear trend gives an R^2 value of 0.61 and a Pearson correlation of 0.78, noting however the influence of extreme values. A paired two-tail t-test of the means gives a p-value <<0.001 at $\alpha = 0.05$.

LWD pieces were measured by the ground-based LIS procedure but not detected by photogrammetry-based LIS for various reasons, as detailed in Figure 8. Overall, 119 pieces were measured in the ground-based procedure whereas 57 pieces were measured in the photogrammetry procedure across the 25 plots. No pieces were measured in the photogrammetry procedure that were not measured on the ground. LWD that was buried or partially obscured was the biggest driver for the discrepancy. LWD 'Not intersecting with the transect' (21% of pieces) highlights the difficulty in defining and maintaining accurate transects on the ground in steep terrain, and the result inflates the volume difference between methods.

The machine learning method outputs a 'wall-to-wall' volume raster, as shown in Figure 9. The areas identified as 'very high' LWD volume also showed visually high amounts of LWD in the orthophoto. This is especially relevant in the lower-most LWD cluster identified because there are no plots in that location. Note that the machine learning method was able to measure in the windthrow area, which was not sampled due to safety considerations.

Discussion

The overall underestimation of the photogrammetry method, when compared with the ground-based volume, is mostly attributed to the photogrammetry method missing LWD that were partially obscured, either by other residues, or soil. Examples of these pieces are shown in Figure 10. During the ground-based procedure,

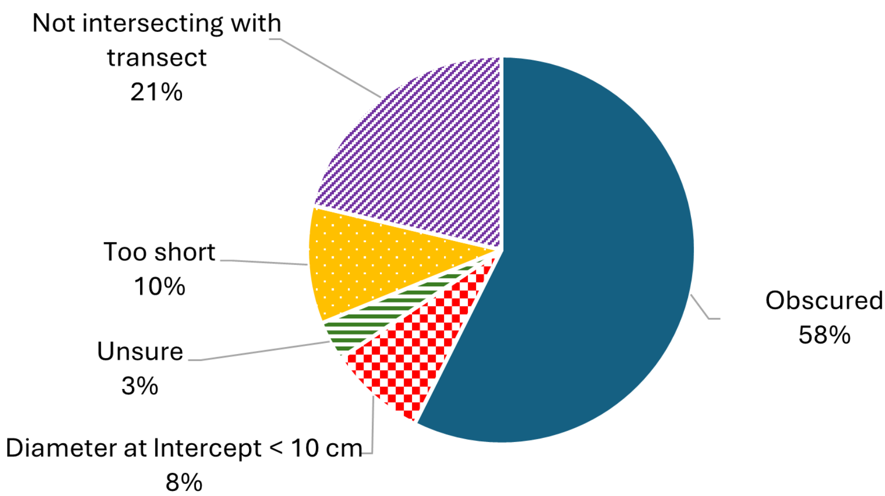

FIGURE 8: Reasons a piece was measured in the ground-based procedure, but not the photogrammetry procedure.

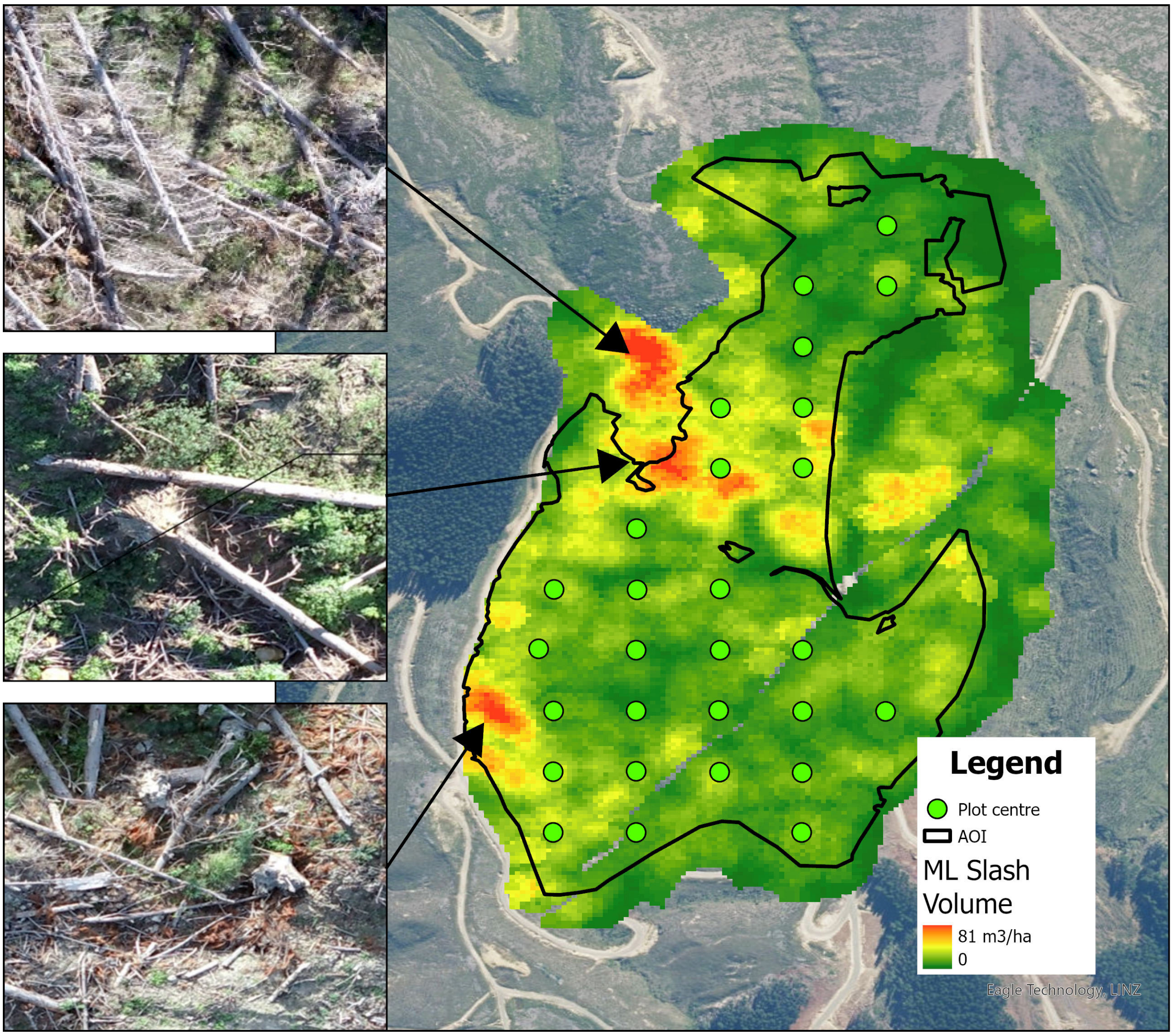

FIGURE 9: Average volume surface across the site from the machine learning LWD detection and screenshots of the orthophoto for the highest density areas identified by the machine learning.

the LWD piece was kicked at one end and the other field worker felt where the vibrations had reached to identify the full length that was buried by soil or other LWD. This yields a clear issue for optical remote sensing methods because if an object is obscured from view, it cannot be measured remotely.

LiDAR has been widely adopted in New Zealand forest operations. The data is currently used for harvest planning and road mapping (Manning 2023), with point densities used ranging from 1-25 points per square metre. LiDAR has the capability to penetrate through gaps in foliage to capture the form of the LWD on the forest floor (e.g., Joyce et al. (2019)), however laser pulses cannot penetrate through soil or solid LWD pieces. Previous studies that selected LiDAR for woody debris measurement targeted material obscured by a tree canopy. Joyce et al. (2019)'s manual annotation of a LiDAR point cloud had a stronger relationship between volume, (R^2 = 0.92) compared to this study's photogrammetry R^2 value of 0.61, likely because the average piece size targeted in the 2019 study was larger, so was more likely to be identified. While LiDAR could potentially be used to measure LWD pieces partially obscured by foliage, the cost-benefit to capture appropriate point densities, and build workflows to separate LWD returns from foliage 'noise' is yet to be established.

The photogrammetry results should be used with a clear understanding of the underestimation of the volume. The extent of this underestimation would be lower if fewer LWD pieces were obscured. The proportion missed will also increase with increasing LWD density where it is more likely a piece will be obscured by another LWD piece.

The machine learning results for this study show a moderately weak relationship between the machine learning volume and ground truth volume with an R^2 of 0.38. This is aligned with Udali et al. (2024) who found an R^2 between 0.17 and 0.31 after comparing their semantic segmentation model with ground truth volumes. By extrapolation of results, Windrim et al. (2019) with a 2 mm ground sampling distance on sample plot imagery achieved a higher R^2 of 0.59 when comparing

FIGURE 10: Examples of pieces only measured in the ground-based procedure because they are partially buried so appeared in the photogrammetry method as either too short to be measured or not intersecting with the transect line.

their segmentation workflow to field measures. The automated procedure had a bias when fitting bounding boxes to LWD and systematically overestimated volume, which required the derivation and application of a scaling parameter to correct the bias. Overall, while each study yields some positive correlation between the automated and manual methods, each study shows that more research and development on remote sensing workflows is required to rely on results as a replacement for field measures, where accuracy is imperative. Despite this, the positive relationship between ground truth volume and machine learning volume indicates that the Interpine model used in this study reliably identifies areas within a cutover that have relatively high or relatively low LWD volumes. As a 'drafting gate' therefore for isolating areas that may require field assessment, the automated method may be considered an appropriate proxy.

For machine learning, some improvement may be found by the adoption of instance segmentation as an alternative to the semantic segmentation method used. Semantic segmentation cannot identify separate pieces where they are crossed in the orthophoto and instead treats them as one piece. Instance segmentation may be more robust at identifying individual pieces and assessing each against the size standard.

The methodology used to lay out and maintain measurement accuracy for the ground-based transect needs to be refined. This is evidenced by the 21% of LWD pieces that were measured, but failed to fall under the transect line, on review of the orthophoto. Steep sites, residues and weather conditions on the day all provide hindrances to establishing an accurate transect and a solution such as a tripod-mounted compass, together with a taut wire or similar should be investigated for future ground-based measures using a similar procedure. Orthophotos should be used to quantify the precision of these other practical implementations of LIS, since the ground perspective of the precision of the line walked is misleading.

Another factor contributing to the bias in the ground-based method is the tilt of the LWD pieces. The line intersect method assumes the piece lies flat on a horizontal plane. In a complex cutover environment, many pieces are tilted vertically. In this work, 5% of pieces that were measured in the field with lengths of over 2 m were not included in the photogrammetry measurement, as from an aerial view, the two-dimensional piece length was less than 2 m. One method to address this is to apply a tilt correction factor (Van Wagner 1982). Tilt-correcting diameter measures from manual LIS would have further increased the reported volume. With the site's average terrain slope of 24°, a piece orientated in the direction of the slope (worst case scenario) would have its diameter measure adjusted by approximately +9% to account for the tilt bias.

Careful interpretation of measurement methods is particularly important on steep sites. Methods based on orthophoto interpretation, that do not rectify planar lengths to tilted (actual) length are prone to underestimating volume. While Van Wagner (1982) notes that the inclusion of tilt "is a matter of judgement", when sites are predominantly steep, the argument strengthens.

Conclusions

This study set out to investigate the comparative differences between three methods for measuring residual LWD in New Zealand's erodible cutovers.

Our findings revealed that ground-based LIS, while traditionally regarded as a reliable measurement method, was error-prone on the steep study site, when completed with basic tools. The manual LIS method measured a mean volume of 31.0 m^3/ha, significantly higher than both remote sensing methods. Analysis of orthophotos found that 11% of all LWD pieces had been mistakenly measured on the ground. This therefore justifies careful consideration of a standardised field LIS methodology that can be applied on difficult terrain, particularly if used as a means of assessing LWD volumes against regulation.

The photogrammetry-based LIS method was (on average) consistent with machine learning, measuring a mean LWD volume of 13.6 m^3/ha. Photogrammetry volume measures were lower due to the inability to accurately measure pieces partially buried in the ground, under other LWD pieces, or under foliage. Where plots had lower overall volume and fewer obscured pieces, the photogrammetry-based LIS method showed a closer, less variable relationship to the ground-based volume.

Machine learning methods demonstrated considerable efficiency in identifying areas of high LWD density across cutovers. This method also measured a lower mean LWD volume (14.0 m^3/ha), with the same tendency to underestimate total volume at the plot-level; under-reporting where occlusion occurs.

While no measurement method is without limitations, the integration of ground-based LIS, and remote sensing-based methods presents a series of solutions to the complexities of ensuring alignment with cutover residue regulations. This study contributes to the ongoing discussion on forestry practice, emphasising the need for structured, objective and reliable measurement methodologies, where regulation introduces specific quantum into standards.

Competing interests

Sam West (co-author) is an employee of Interpine Innovation Ltd; developers of the machine learning and photogrammetric cutover volume assessment methods, and providers of the methods as a specialist remote sensing service to forest owners.

Authors' contributions

HH designed the study, completed field data collection, analysed results, wrote and reviewed the manuscript. CGB designed the study, completed field data collection, analysed results, and contributed to the manuscript. CH guided study design, completed field data collection, analysed results, wrote and reviewed the manuscript. SW guided study design and analysed remote sensing data.

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