Investigation of methods to measure residual slash volume in New Zealand’s erodible cutovers

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Abstract

Slash mobilisation during extreme weather events, such as Cyclone Gabrielle, poses significant environmental risks and undermines the social license of New Zealand's forestry industry. In response, the National Environmental Standards for Commercial Forestry introduced regulations to limit the residual slash volume on erodible cutovers to no more than 15 m^3/ha. There is significant interest in adopting remote sensing technologies for slash measurement in New Zealand's forestry sector to meet these requirements in an efficient way, whilst addressing safety concerns on steep terrains.

This study compares two remote sensing methods to the established ground-based line intersect method on a recently harvested cutover. The methods selected are machine learning-based slash detection and manually annotating line intersect plots in a photogrammetry point cloud.

The ground-based line intersect method measured a mean slash volume of 31.0 ± 10.2 m^3/ha, which included 11% of pieces that did not actually intersect the transect line when viewed in the orthophoto. This was due to the difficult terrain which led to bias to overestimate volume in the ground-based line intersect method.

The photogrammetry line intersect method measured a lower mean slash volume of 13.6 ± 3.8 m^3/ha, with an r^2 value of 0.61, demonstrating moderate correlation with the ground-based method. However, this method only measured 48% of the pieces measured on the ground, with 58% of these omissions due to pieces being partially buried in the ground, under other slash pieces, or under foliage, which is a limitation of remote sensing on complex terrains.

The machine learning method measured a mean slash volume of 14 m^3/ha, and had a moderately weak r^2 value to the ground-based volume of 0.39, which was in line with other published models. The machine learning method had a positive correlation with ground-based and photogrammetry slash volume, so it is most useful for identifying high slash density areas.

The results indicate that while ground-based methods are still necessary for accurate slash measurement in high-density areas, remote sensing techniques like photogrammetry offer a safer, more efficient alternative for lower-density zones. Incorporating these technologies can improve the management of slash in erodible areas, reducing the risk of mobilisation during extreme weather. Strategic application of these methods will also strengthen the forestry industry's compliance with regulatory standards and its social license to operate.

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Introduction

Slash mobilisation significantly impacts communities and ecosystems, underscoring the urgent need for improved forest management. Edwards (2023) highlights the implications of slash, stating that it “endangers lives, cuts off communities and wrecks infrastructure”. In particular, the Tairāwhiti and Wairoa districts have experienced considerable devastation post Cyclone Gabrielle as discussed by Mathias (2023). In response, the National Environmental Standards for Commercial Forestry (NES-CF) has been updated to limit the volume of slash allowed to be left on the cutover. An accurate assessment of residual slash is required to ensure that the volume limits in the NES-CF are not exceeded. Therefore, the purpose of this project is to identify the most appropriate method for determining residual slash volume for New Zealand’s forestry sector. The following literature review highlights the need to verify the utility of remote sensing methods. This report then outlines these methods, details how they were tested, and presents the results, focusing on their practicality, accuracy, and defensibility.

Definitions

Slash

Slash can be defined as coarse and fine woody debris, produced from commercial forestry activities, encompassing everything from small branches to entire trees (Visser, 2018). This woody material results from trees that have been harvested, pruned or thinned in a plantation forest (Greater Wellington, 2023). Slash is also referred to as harvest residues or woody debris.

Erosion Susceptibility Classification

The Erosion Susceptibility Classification (ESC) separates land into four classes of erosion risk: low (green), moderate (yellow), high (orange) and very high (red) (Ministry for Primary Industries, 2017). The ESC was developed specifically for land in plantation forests based on the New Zealand Land Resource Inventory and Land Use Capability database, which is for pastoral farming (Ministry for Primary Industries, 2017). The ESC takes into account:

- Probability of severe rainstorm events in the four to seven years after harvest
- Erosion processes present at the site, for example gullying or land sliding
- Strength of rock type
- Surface steepness

However, the ESC does not take into account the severity of consequences to downstream values and does not include the vegetation cover at the site (Ministry for Primary Industries, 2017).

National Environmental Standards for Commercial Forestry

The NES-CF are regulations established under the Resource Management Act 1991 to provide a consistent nationwide framework for managing commercial forestry activities (Ministry for Primary Industries, 2024). The NES-CF sets technical standards, methods and requirements to ensure that commercial forestry activities are conducted in a manner that either maintains or enhances environmental quality. This includes measures to protect water quality, soil health and biodiversity. By providing a uniform set of regulations, the NES-CF simplifies the planning and operational processes for commercial foresters, reducing compliance costs and increasing regulatory certainty. The NES-CF helps ensure that forestry practices are sustainable and environmentally responsible by setting consistent, enforceable standards nationwide.

Impacts of slash mobilisation

Slash mobilisation has profound effects on communities and forest ecosystems that go well beyond the confines of forestry operations (Ministerial Inquiry into Land Uses in Tairawhiti and Wairoa, 2023). The repercussions range from exacerbating environmental disasters to undermining social trust. These repercussions of slash mobilisation require an immediate, research-driven response.

The Coromandel, Wairarapa, Hawke's Bay and Tairāwhiti are regions with large areas of commercial forest that have experienced the detrimental effects of slash mobilisation for a long time (Madden-Smith, n.d.). For decades, destruction has been brought on by catastrophes such as the 1988 Cyclone Bola and more recent cyclones Gabrielle and Hale, underscoring the critical need for changes in forestry management techniques (Mathias, 2023). In particular, coastal areas have seen significant slash deposition, affecting tourism and posing safety risks. The aftermath of slash deposition following severe weather events has required costly clean-up efforts to repair infrastructure.

Environmental degradation is one of the most obvious consequences of slash mobilisation. Untreated gully sedimentation and mishandled forestry operations have caused severe damage to riverbeds, beaches, and waterways (Ministerial Inquiry into Land Uses in Tairawhiti and Wairoa, 2023). Elevated water levels and significant flooding events have magnified the problem as flowing water collects debris, obstructing waterways and creating dams that trigger additional flow upon release (Mathias, 2023). This degradation of natural habitats not only harms biodiversity but also jeopardises ecosystems' ability to provide vital functions, such as flood mitigation and water filtration.

Social license

In addition to causing environmental damage, the consequences of slash mobilisation have left communities feeling vulnerable and disconnected (Ministerial Inquiry into Land Uses in Tairawhiti and Wairoa, 2023). The Ministerial Inquiry into Land Uses report describes the impacts of slash with strong emotive language to highlight the social aspect of this issue. The weight of woody debris, including slash, has damaged roads, fences and bridges, and the impacts of slash mobilisation have extended to social dynamics, especially in communities where forestry is a source of income (Mathias, 2023). The loss of social license due to poor practices and inadequate regulatory oversight is a pressing concern for the forestry sector (Wallace, 2023). As forestry practices have come under investigation, communities face not only environmental challenges but also economic uncertainties. These events have also posed economic losses to forestry companies, prompting the need for sustainable forestry practices to ensure long-term viability. The breakdown of trust amongst stakeholders highlights the necessity of working together to find a holistic, evidence-based solution to comprehensively address slash mobilisation issues. Fostering transparent communication, engaging stakeholders, and respecting cultural values are crucial for achieving a solution (Beban et al., 2023). Restoring social license and building a harmonious relationship between people and their environment are paramount to the success of affected communities (Ministerial Inquiry into Land Uses in Tairāwhiti and Wairoa, 2023).

Changes to the NES-CF

Due to the significant impacts of slash mobilisation on both environmental and social fronts, reforms have been put in place within New Zealand's legislative system. The NES-CF have imposed changes to encourage more sustainable forestry practices (Resource Management (National Environmental Standards for Commercial Forestry) Amendment Regulations 2023). More stringent guidelines around slash management have been implemented with the goal of mitigating the negative effects of slash mobilisation during extreme weather events. These amendments, in regulation 69, are as follows:

69 (5) On orange zone and red zone land (as described in regulation 63(2)(b)), slash from harvesting that is sound wood must be removed from the cutover, unless it is safe to do so, if it has –

- (a) a length of over 2m; and
- (b) a large-end diameter (LED) of over 10cm.

69 (6) However, residual slash may be left on the cutover.

69 (7) In this regulation,

residual slash means a quantity of the slash required to be removed under sub-clause (5) not exceeding 15m^3 per hectare of the cutover

sound wood means wood that can be safely lifted using harvesting equipment and transferred to a landing without degradation or breaking up.

Literature Review

Understanding the volume of slash left on a cutover post-harvest is essential for effective management. It is implied in New Zealand's regulatory standards that a measurement of slash volume is required to assess compliance. Therefore, this literature review summarises current methods for measuring slash volume and highlights key uncertainties associated with these techniques. The context for applying these methods in New Zealand's erodible cutovers is presented. This information is then used to guide the research direction required to address these uncertainties.

Current methods for measuring slash

Line intersect method

The line intersect sampling method involves defining a line and measuring pieces of residual slash that cross this line. The line intersect sampling method was first developed by Warren and Olsen in 1964 and then presented by Wagner in 1968. The line intersect method was first developed for merchantable volume assessment but has been used extensively in other applications including slash measurement in New Zealand steepland cutovers by Harvey and Visser, (2022). This method relies on several key assumptions and faces potential biases, which can impact the accuracy and precision of the results. Understanding these factors is crucial for implementing or modifying procedure manuals to ensure reliable data collection and analysis.

Assumptions and bias

The line intersect method assumes that the measurement area is completely flat, however; it is rare for a forest to exhibit such characteristics. To correct for this, it is necessary to apply a slope correction factor after data collection or adjust the transect line length during the data collection process to account for the actual slope. This ensures that the volume of harvest residue is accurately represented in a horizontal map area (Herries, 2014).

The method assumes that all pieces of slash occur horizontally. If pieces are tilted, their probability of intersecting the sample line decreases, potentially leading to an underestimation of the actual volume. Wagner (1982) developed a correction factor for the issue, which can be calculated as $1/_{\cos(h)}$, where h is the angle of tilt from horizontal. The correction is minor at low tilt angles but can become significant at higher angles (Herries, 2014).

While the line intersect method assumes logs are cylindrical, non-cylindrical shapes do not introduce bias but do reduce precision (Wagner, 1982). Increasing sampling intensity can help to offset this reduction in precision (Wagner, 1982). Wagner (1982) suggested taking two diameter measurements to better represent the cross-sectional area of harvest residue, while Bate et al. (2009) recommended measuring logs at the LED and the intersecting point for a more precise volume.

The line intersect method also assumes that slash pieces are randomly oriented. However, in practice, slash often aligns in specific directions due to wind throw or logging practices like cable logging or skidder operations. This orientation bias can be difficult to detect but significantly affects the accuracy and precision of the measurements (Herries, 2014). To mitigate this bias, it is advisable to design sample layouts that counteract directional tendencies, such as using right-angle, L-shaped transects (Bell et al.,1996).

Studies have shown that non-random orientation (clumping) of slash decreases the precision of line intersect method assessments (Tansey, 2014). Bell et al. (1996) and Wagner (1968) demonstrated that an equilateral triangle layout with 25m segments is the most unbiased method. However, a right-angle (L-shaped) transect layout, which is quicker to install, is nearly as accurate (Sutherland, 1986). Despite this, the non-random orientation of slash pieces can still significantly reduce the precision of volume estimates (Wagner, 1982). Non-random distribution of slash causes a bias to underestimate slash volume (Tansey, 2014). While adjustments have been made to correct for other biases, a correction factor for slash clumping has not been explored (Tansey, 2014; Wagner, 1982).

Precision

Precision of the line intersect method is typically measured using the standard error of individual line segments. This provides a range within which the true volume is expected to lie. The standard error depends on the length of the sampling line and the density of the slash. To double the precision, it is necessary to quadruple the sampling effort (Pickford and Hazard, 1978). Therefore, determining the appropriate sampling length involves balancing the estimated volume of slash remaining on-site with the required precision of the measurements.

In summary, while the line intersect method is widely used and practical, its effectiveness hinges on addressing inherent assumptions and potential biases. By enhancing the sampling design and applying the necessary corrections, more accurate and precise measurements of residual slash can be achieved.

Other ground-based methods

Sample plot inventory refers to methods where every piece of slash is measured in a defined area of interest, such as a 10 m by 10 m square. This technique is typically only used to measure small woody debris or as a comparison for remote sensing methods, described in the evaluating methods section. Sample plot inventory for slash measurement is not popular, as supported by Bailey (1969), who found that the line intersect method was 70% faster while maintaining the same level of accuracy.

Plotless methods refer to methods that do not have a constant area of interest between sampling locations, and as a result, these methods are typically faster (Mitchell 2023). Plotless methods are common in other vegetation density measurements, such as population density and basal area (Bitterlich, 1984; Mitchell, 2023).

Few studies have used plotless methods for measuring woody debris, with the exception of Gove et al (2001). Gove et al. introduced a method using a "relascope," where a log was counted if it appeared longer than the relascope held at arm's length, with calibration of the device allowing for estimation of slash volume per acre. While Beasom & Haucke (1975) found the point-centred quarter method to be the most accurate for measuring vegetation density compared to other plotless methods, they did not evaluate the relascope approach. The point-centred quarter method focuses on identifying the nearest object to a sampling point and measuring the distance (Mitchell 2023). This process is then repeated for each of the four quarters, providing a different strategy for assessing density (Mitchell 2023).

Overall, alternative ground-based measurements have shown efficient volume density sampling in other vegetation sampling. The point-centred quarter method has high potential as a method for quantifying slash due to its focus on volume density and the advantage of not needing to set up a plot beyond defining the plot centre. However, no practical application of the point-centred quarter method in slash measurement has been reported. A trial of the point-centred quarter method is required to understand if this method is a useful measurement method in slash management.

Remote sensing methods

Field-based measurements of coarse woody debris (CWD) become impractical when measuring large areas, as noted by Joyce et al., (2019). Overcoming this problem has motivated researchers and companies to develop and validate various remote sensing techniques. Relevant terms used in the studies are set out in Table 1. Studies did not explore the thresholds or circumstances where remote sensing slash measurement would be preferable, however a variety of remote sensing approaches have tackled the question of measuring woody debris. Remote sensing data, either LiDAR or optical such as orthophotos or photogrammetry point clouds, is processed using manual, statistical, or machine learning techniques. Peng & Sadaghiani (2023) highlight machine learning as an effective tool for quantifying woody biomass because machine learning can analyse large data including high-resolution imagery of complex environments such as forest cutovers.

Table 1: Explanation of remote sensing terms.

Term	Definition
Remote sensing	Gaining information at a distance from the subject.
Unmanned Aerial Vehicle (UAV)	Colloquially called a drone (Davis, 2017).
Orthophoto	Aerial imagery corrected for topographical distortion (Davis, 2017).
Photogrammetry	Overlapping orthophotos used with Structure from Motion to produce a 3D surface (Davis, 2017).
LiDAR	LiDAR is an active remote sensing technique that stands for Light Detection and Ranging. It is also known as laser scanning and produces a 3D point cloud (Manning, 2023).
Machine learning	Artificial Intelligence-based applications that identify patterns in data with minimal human intervention (Peng & Sadaghiani, 2023).
Semantic segmentation	Semantic segmentation is when pixels are marked as either slash or not slash, but there is no distinguishing between different slash pieces.
Instance segmentation	Instance segmentation is a step further than semantic segmentation, where individual slash pieces are identified.

Automated annotation in remote sensing methods

Davis (2017) used a statistical classification system on UAV imagery to mask areas of slash, since slash has a much higher response in the red band than surrounding ground. This method is unlikely to be applicable to all sites, as it relies on a substantial colour contrast between the ground and the slash. The method also cannot distinguish between fine woody debris, which explains other studies' choice to employ machine learning algorithms (e.g., Shokirov et al. (2021), Udali et al. (2023), and Windrim et al. (2019)). Davis (2017) then turned the surface area identified by the statistical classifier into a volume measurement by approximating the surface under the slash from the photogrammetric point cloud and applying a correction factor to represent the parts of the slash not seen by the UAV. Davis predicted the total volume within 16% of the ground-based measurement and with similar uncertainty. However, the volume predicted at each plot was inaccurate, usually by over 50% and up to 771%, which questions the reliability of the method. Davis (2017) did not segment individual pieces of slash, making it impossible to differentiate between their lengths. Therefore, it remains uncertain how the classifier would perform in more complex environments.

Windrim et al. (2019) used the Faster R-CNN machine learning model to segment each individual slash piece from orthophotos. Processing constraints of the Faster R-CNN model mean that only a 600 by 600 pixel window (2 m on the ground) could be processed at once, perhaps contributing to the low accuracy ($r^2 = 0.572$) of the relationship between the machine learning detection and the volume measured at each plot. Interpine Innovation (2022) reports the development of a machine learning based segmentation of slash for commercial purposes, but has not reported a verification of accuracy.

All other orthophoto-based, UAV-based approaches that use machine learning take a semantic segmentation approach rather than instance segmentation, and typically use a Random Forest model. Queiros et al. (2019) reported high accuracy with 5 cm orthophotos, achieving 93.4% completeness (the area accurately identified as slash) and 94.5% correctness (the area accurately identified as non-slash). They also found that the classifier's accuracy did not improve with the inclusion of LiDAR data. Udali et al. (2023) achieved similar accuracy for their Random Forest classifier, but unlike Queiros et al. (2019), Udali et al. then derived a volume measurement. Udali et al. (2023)'s volume measurement was based on the same principles as Davis (2017) described earlier. Despite the high accuracy of the classifier, Udali et al. (2023) 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 may be more accurate but requires higher-quality training data and more computational power, so the choice of model architecture will depend on the priorities of the situation.

LiDAR is more costly than photogrammetry, but can penetrate the forest canopy, so it was used by Joyce et al. (2019) to measure CWD under a forest canopy. The woody debris pieces were manually mapped in the LiDAR point cloud after filtering out points classified as ground, shrub and canopy. Only 23% of CWD was identified in the LiDAR point cloud, but the pieces represented 50% of the total volume. Importantly, the relationship between the volume measured and the true plot volume was very strong ($r = 0.96$). Shokirov et al. (2021) used a Random Forest classifier on their UAV LiDAR data to classify CWD, achieving a moderate relationship for volume with $r^2 = 0.70$. Studies such as Windrim et al. (2019) and Shokirov et al. (2021) also tended to overestimate the volume of slash pieces due to an overestimation of the diameter of pieces.

Manual annotation in remote sensing methods

Joyce et al. (2019)'s strong relationship between the remote sensing derived volume is typical of manual annotation of remote sensing measurements. Windrim et al. (2019) also tested the volume measurement achievable by manually annotating the surface of the slash piece and found this very accurate (r^2 = 0.958). Interpine Innovation (2021) has reported manually manipulating a photogrammetry point cloud to conduct line intersect plots, which is presented as equivalent to the ground-based version of line intersect sampling, although a verification has not been published. Studies that cover manual annotation of remote sensing methods have not evaluated the time cost-effectiveness compared to ground-based measurement in the context of slash measurement.

Overall, remote sensing methods have very little consistency in the approaches used and accuracy achieved, which are barriers for New Zealand's forest industry to implement the methods. The inconsistency and varying accuracy prevent the sector from justifying the reliability of these methods. Existing methods show high volume accuracy when the slash pieces are segmented manually, but low accuracy when the slash is identified through a machine learning approach. Many existing methods are based on semantic segmentation rather than instance segmentation. Semantic segmentation is impractical in this context, as the model can only confirm that a slash piece meets regulatory size requirements when the segmented area is free from overlap with other slash pieces.

Evaluating Methods

Other studies used techniques like simulations and comparison to an established method when evaluating their methods. Computer programs can generate random slash distributions and measure the volume thousands of times for a given sampling technique. This strategy is used mostly when evaluating ground-based methods. Proposed remote sensing methods were more likely to be evaluated by comparing them to an established method, also known as ground truthing.

Simulations

Revised: Pickford and Hazard (1978), Karpachev et al. (2019), and Bell et al. (1996) simulated variations of the line intersect method, as replicating the required sample size on the ground would be impractical and costly. 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 to this bias. Pickford and Hazard (1978) chose to iterate their simulation 15,000 times for each population, although within 700 iterations the expected value of residue volume (absolute error) and sample variance stabilised.

Simulations have also been used to compare different methods with each other, particularly to evaluate the efficiency of methods. Thomaes et al. (2023) simulated full area (sample plot inventory) plots against line intersect plots and determined that the line intersect method should always be used instead of sample plot inventory when measuring diameters less than 30 cm, since it reduces the workload by 67-83%. Khan et al. (2016) showed that the point-centred quarter method requires 50 plots for an accurate measure when sampling vegetation density. Simulations of methods are useful to justify statistical validity and sampling efficiency, but cannot evaluate bias caused by the practical application of the method in a given context.

Comparison to an established method

Both Windrim et al. (2019) and Davis (2017) compared their remote sensing methods to sample plot inventory, measuring every slash piece in a 10 m by 10 m square. This restricted the method Davis (2017) was able to undertake: the plots were too small to cover the full length of many slash pieces, therefore Davis did not individually segment each slash piece. However, Windrim et al. (2019) trained their machine-learning algorithm to identify partially covered slash pieces. Windrim et al., (2019) plotted the field measurement against the drone-based method and computed an r^2 value to show the relationship between the two methods. The analysis of an r^2 value allowed a better comparison of the accuracy and precision between the methods.

'Wall-to-wall' remote sensing models have more application when assessing volume across the landscape, as opposed to models confined to plot areas. Joyce et al.'s (2019) study produced a wall-to-wall with a grid size of 60 m and conducted a line intersect plot within some of these grids. Udali et al. (2019) also compared their method to the line intersect method, but at the overall volume level. Udali et al. (2019) chose to compare total volume because they could not line up slash at specific plots since their method was a semantic segmentation of slash rather than an instance segmentation of individual slash pieces.

A critical step in comparing two methods is making use of a Global Navigation Satellite System (GNSS) for the position of the areas measured to make sure the methods are measuring the same slash pieces. Both Windrim et al. (2019) and Davis (2017) precisely GNSS referenced the plots measured on the ground to fly the same areas for their remote sensing method. Shokirov et al. (2021) went a step further to mark the location of every piece of CWD in their field plots. Shokirov et al. (2021) and Davis (2017) successfully achieved an accuracy of within 3 m using differentially corrected GPS. In contrast, Windrim et al. (2019) opted for a centimetre-accurate receiver, likely because they segmented individual pieces of slash, resulting in smaller areas of interest to align (Garmin, n.d.).

The validity of the study relies on the quality of the method used for comparison; if the comparison method is flawed or unreliable, it undermines the evaluation of the proposed method. Previous studies that measure harvest residues most commonly use a variation of the line intersect method, which is detailed in handbooks for assessing fire fuel load (Brown 1974).There are extensive studies quantifying the assumptions, bias and accuracy of the line intersect method. Therefore, the ground-based line intersect method is the most defensible method currently available and a good option to compare alternative methods to.

Context from the New Zealand forestry sector

Steep slope safety concerns

Orange and red ESC zones may pose additional safety risks to workers conducting ground-based plots, compared to those working on flat terrain. Measuring ground-based plots on steep slopes increases the risk of sprain and strain injuries, which were found to be the most common injuries resulting from steep slope logging in the US (Rosecrance & Lagerstrom, 2018). Forest workers consistently identify slope steepness as a major risk factor for injuries (Rosecrance et al., 2017), however, Weinbrenner et al. (2021) found that it is the high level of concentration and therefore increased stress that causes injuries in difficult terrain. Either way, the studies point to reducing ground-based work on steep cutovers to reduce injuries among New Zealand's forestry workers.

Uptake of remote sensing technologies

Every respondent in Manning's 2023 survey of New Zealand's forestry sector reported using aerial imagery. The companies represented 74% of New Zealand's plantation forest estate (Manning, 2023). Of these companies, 93% used UAVs, which is a dramatic increase from no companies specifically using UAVs in the 2013 survey (Morgenroth & Visser, 2013). This represents a significant shift in remote sensing technology use and indicates high motivations to uptake UAV-based monitoring and measurement. All respondents in 2023 reported using aerial imagery for cutover mapping (Manning, 2023). Therefore, respondents might find additional value in this imagery if it can also be utilised for measuring slash.

Although all companies acquired aerial imagery, only 48% processed this imagery into photogrammetric point clouds (Manning, 2023). The barriers to use of aerial imagery, beyond orthophotos, were identified as no perceived benefits and lack of staff knowledge (Manning, 2023). This suggests that more research into remote sensing measurement methods is required. Insufficient staff knowledge and training were also significant barriers to the adoption of AI methods such as machine learning (Manning, 2023). Only 30% of respondents used AI, although more companies indicated plans to use AI (Manning, 2023). Therefore, it seems that the use of AI in New Zealand's forestry sector is still in its infancy, making an analysis of the capabilities of AI-based models, such as machine learning, a valuable addition to current research.

LiDAR had the largest progression in uptake, increasing from 17% in 2013 to 70% in 2018 and reaching 93% in 2023 (Gouw et al., 2020, Manning, 2023). However, this increase is due to open data portals, and only two forestry companies surveyed in 2023 regularly collect their own LiDAR data (Manning, 2023). Cost and staff knowledge are barriers when using LiDAR beyond surface products, therefore, LiDAR is unlikely to be preferred over UAV imagery when taking a regular measurement of slash volume (Manning, 2023).

Summary

Several methods for measuring residual slash appear in the literature, however further research is required to confidently select the most appropriate method for residual slash measurements in New

Zealand's erodible cutovers. The methods in the literature can be summarised into the following categories:

- Ground-based
    - Sample plot inventory (defining an area of interest)
    - Line intersect and variations (defining a line of interest)
    - Plotless (defining a point of interest)
- Remote sensing
    - Orthophotos
    - Photogrammetry
    - LiDAR

Of these, the line intersect method is the most popular and well-researched, therefore it can be used as an established method to compare other methods with. With further research, plotless methods may be adapted to slash volume density measurement, with the point-centred quarter method showing high efficiency in quantifying vegetation density. Machine learning applied to orthophotos and the photogrammetry implementation of the line intersect method are promising measurement techniques. However, LiDAR has not demonstrated significant added accuracy to justify the additional costs for forestry companies, especially in areas where the canopy does not obstruct visible light. Remote sensing methods require further validation since they are inconsistently applied across literature and show a wide range of accuracy.

New Zealand has strong incentive for remote sensing slash measurement on cutovers due to safety concerns and the opportunity presented by high UAV uptake across forestry companies. The methods chosen by the forestry sector in New Zealand will be selected based on which methods allow companies to assess compliance against the NES-CF. This means the method needs to be able to measure the length and diameter of individual slash pieces, which most of the published remote sensing methods cannot do. Furthermore, both ground-based sampling and UAV-based sampling require significant time to undertake. Visual guides would be a practical resource so that an approximate initial assessment can determine whether further slash must be removed before compliance is assessed.

Objectives of Project

Regulators have introduced limits to the volume of residual slash permitted in red and orange ESC zones. The objective of this project is to investigate methods of measuring residual slash volume in New Zealand's erodible cutovers and compare factors relevant to defensibility and practicality. The methods will be trialled on a recently harvested cutover in an orange or red ESC zone.

A method is defensible if it is:

- Accurate, precise, repeatable, and preservable
- Compliant with safety standards

A method is practical if it:

- Is feasible on steep slopes such as the slopes in orange and red ESC zones
- Efficiently measures residual slash per hectare within a practical timeframe
- Uses equipment and knowledge readily available to the forestry sector

Scope

The need for a clear definition and well-defined scope arises from the complex nature of residual slash management. Specific boundaries are established below to concentrate on the most relevant and impactful aspects of slash measurement. This will ensure that the results are both practical and applicable in real-world forestry operations and enable a more precise exploration of the selected methods. This considered, certain related topics have been deliberately excluded from the scope of this project to maintain a focused and manageable research project. The exclusions are listed below then expanded on in the rest of this section:

- Measuring harvest residues in slash piles
- Determining whether a piece of residual slash is sound wood
- Methods to recover residual slash on the cutover

This project concentrates on methods that are designed to quantify slash distributed across the cutover, rather than slash that has been collected and piled. Slash piles already have established methods to measure their volume and are more likely to be visibly over 15 m^3/ha. For the purposes of this report, slash switches from being distributed slash (that will be measured) to a slash pile (that will not be measured) which occurs when slash is piled on top of other slash pieces such that the lowest layer is mostly obstructed from view. This happens when slash is pushed into piles by machinery. Slash may accumulate in piles at the bottom of gullies; however, best practice guidelines generally discourage accepting this as a method for long-term slash storage. Therefore, this project will not be looking at methods to measure harvest residues in slash piles.

Additionally, this project scope does not include an evaluation of methods to determine whether a piece of residual slash is sound wood. In this approach, slash pieces that show visual signs of decay will not be recorded as residual slash volume. However, proposing a rigorous method to define sound wood criteria will be left to future guidance by regulators or further studies.

Methods to recover residual slash on the cutover will also not be examined. Recovery methods are more focused on operational procedures and logistics rather than measurement. These methods would involve strategies and techniques for collecting and removing residual slash from the cutover area for utilisation or disposal. These exclusions allow for a concentrated focus on developing precise and accurate methods for measuring residual slash in forestry.

Methods

Overview

Two remote sensing methods were compared to the ground-based line intersect plots as the 'ground truth'. The two remote sensing methods were: conducting the line intersect method by measuring slash pieces in a photogrammetric point cloud, and running a machine learning algorithm to identify slash pieces in an orthophoto. The ground-based plots were marked with spray paint to match plots between the ground measurements and remote sensing measurements. Further details of these methods are described in the sections below.

Initial investigation of the point-centred quarter method

An initial investigation was undertaken to compare the ground-based line intersect method and the point-centred quarter method. McLeans Island, located within a green ESC zone, was chosen as a nearby study site due to its recent harvesting. After completing several plots for each method, it was concluded that the point-centred quarter plots were not optimal. These plots required significantly more walking across the cutover, with frequent backtracking to determine which slash piece was closest to the plot centre for each quarter. The full study was to be carried out in steeper terrain, so the practical challenge identified with point-centred quarter plots would only be exacerbated, reinforcing the preference for line intersect plots.

The point-centred quarter method also measured fewer pieces of slash per plot on average. This means plots would have more variation between them and therefore requires more plots to get the same confidence on total slash volume density. As found in the literature review, Khan et al. (2016) discovered that the point-centred quarter method required at least 50 plots for an accurate measure when sampling vegetation density. Given that the point-centred quarter method was not more practical than the line intersect sampling, the point-centred quarter plots were not investigated further.

Site selection

The requirements for a site to meet the objectives of this project are:

- The site was recently harvested, and
- The site is in an orange or red ESC zone.

To find a suitable site, the forest loss raster from the Global Deforestation Watch was intersected with the ESC orange and red zones from the Ministry for Primary Industries in ArcGIS Pro, as shown in Figure 1. The closest site to Christchurch was identified as the Teviotdale block in Omihi forest.

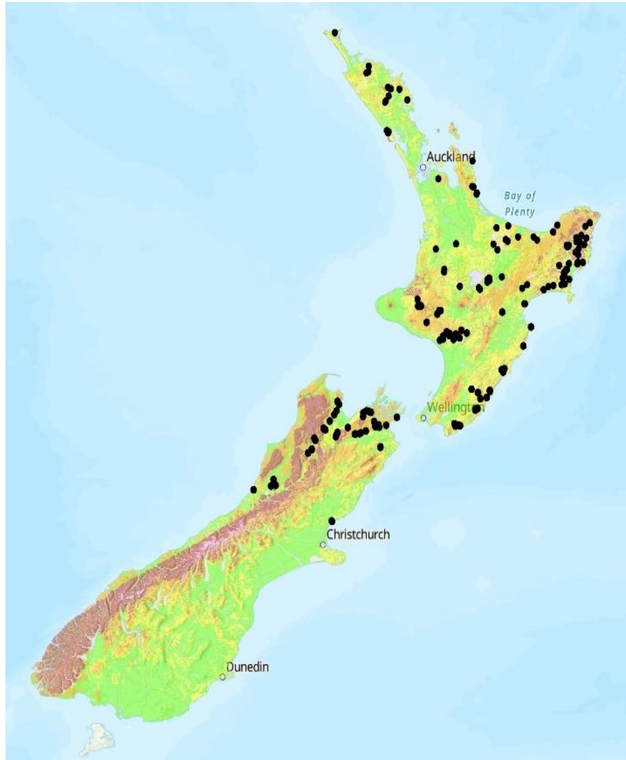


Figure 1: Potential sites (black dots) identified over the ESC zones. Data from Ministry for Primary Industries (2022) and Hansen/UMD/Google/USGS/NASA, accessed through Global Forest Watch.

Site information

The Teviotdale block in Omihi forest is a 27 ha, second rotation *Pinus radiata* block, which was harvested between December 16, 2023, and April 24, 2024. The harvesting was completed using winch-assisted felling, with a 2-stage swing yarder/stem truck extraction to a centralised processing skid (Smith, 2024). It had a final stocking of 457 stems per hectare and a harvest volume of 525 t/ha.

The terrain consists of two main gully systems that flow southward and empty into the Pacific Ocean. The site is primarily underlain by sandstone bedrock, with soil depths ranging from 40-60cm in the gullies to over 1 m on the ridges (Smith, 2024). Slopes vary from moderate to extremely steep (Figure 2). It is important to note that there were areas of windthrow in some parts of the block, visible in Figure 3. However, the plots that were initially situated in the windthrow were excluded due to safety concerns.

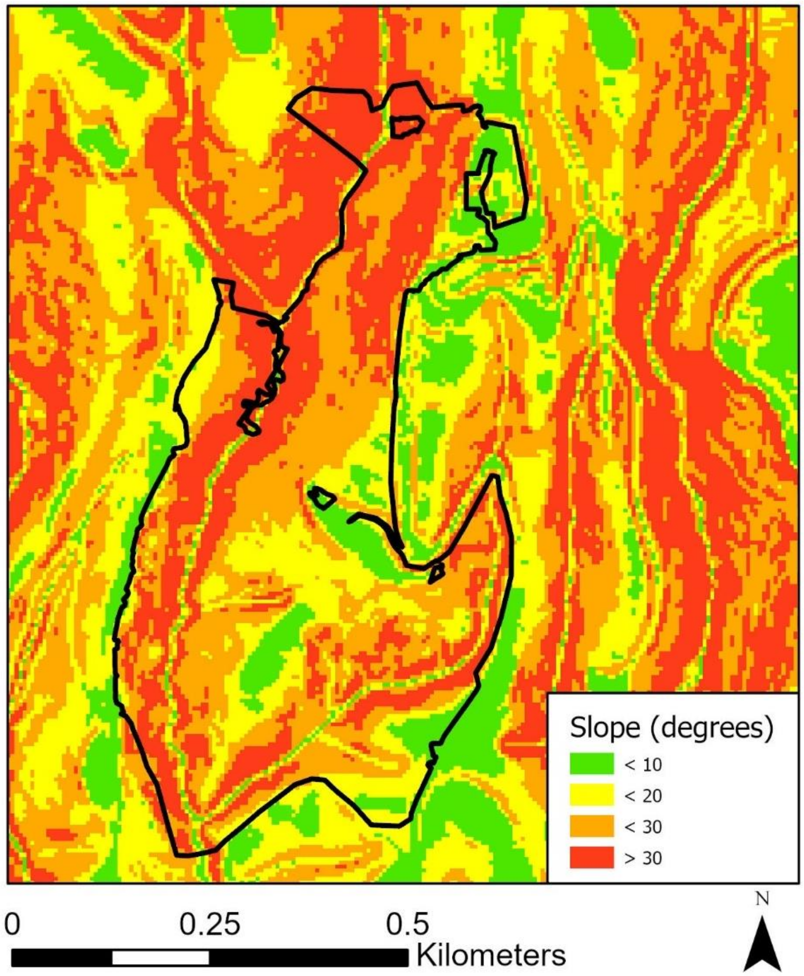


Figure 2: Slope map for Teviotdale site.

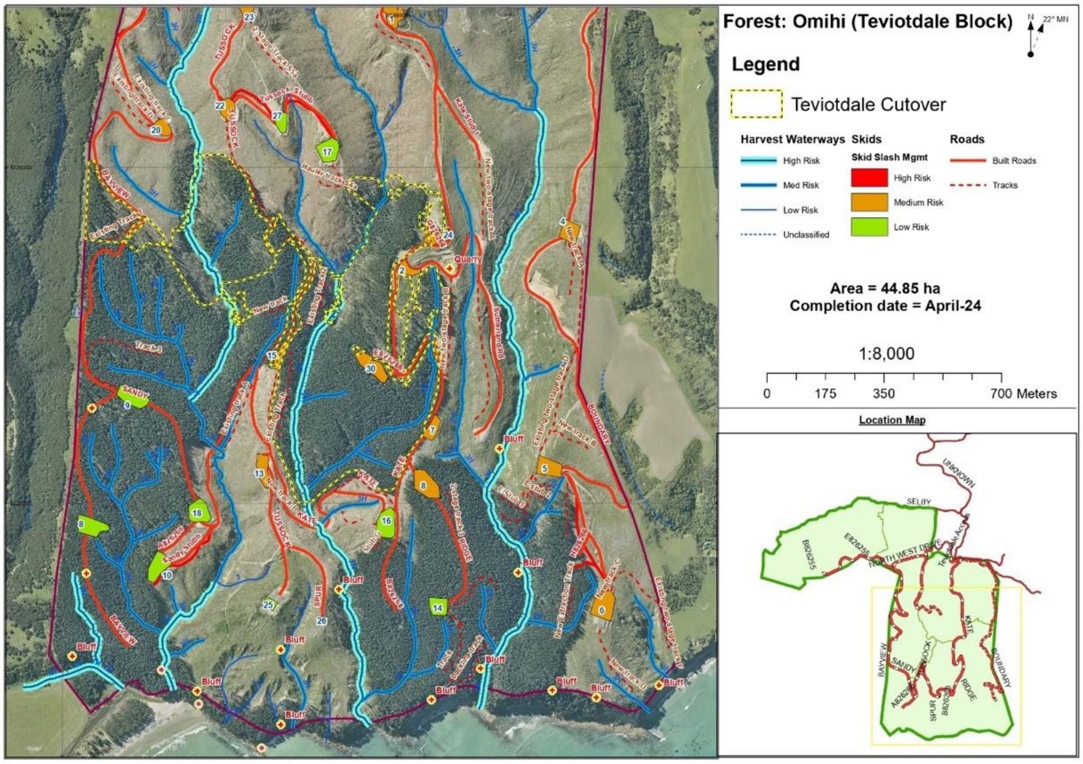


Figure 3: Harvest map of Teviotdale site (yellow dashed line surrounds the study area) with areas of windfall visible.

Sampling method

While this study was concerned with a comparison between methods, the aim of each method application was to get a total volume for the whole cutover. Therefore, it was still necessary to measure enough plots to evaluate the total volume and confidence interval of the estimate. Theoretically, with the line intersect method, the size of the area to be sampled is irrelevant; the precision of the total volume measurement depends only on the variability of the material being sampled (Wagner, 1982). Warren and Olsen (1964) found that the required total length of the sampling line was dependent on the expected total volume.

The expected volume for this study was set at 15 m^3/ha. This was to ensure that the expected accuracy sits around the NES-CF threshold value. To achieve a 25% probable limit of error at a 95% confidence interval, the standard error must be set at 1.91 m^3/ha. In Warren and Olsen's 1964 study, the equivalent situation presented is 200 cu. Ft./acre with a standard error of 30 cu. Ft./acre, which requires 72 chains of sampling lines. The factors of this study mean the volume is overestimated and the variation underestimated when compared to Warren and Olsen, so the required total length of the sampling line will be estimated at 100 chains, or 2000 m.

For this study, plot locations were positioned using an 80 m by 80 m grid, excluding any plots that fell within 25 m of the harvest boundary. Initially, 40 plots were evenly distributed across the Teviotdale site, however, due to practical constraints such as windthrow, gullies, safety concerns and drone malfunctions, only 28 plots were measured across all three methods as seen in Figure 4. Each plot had a sample line length of 50 m (two 25 m transects). The orientation of the first transect was determined by a randomly generated number between 0 and 360 to represent the bearing from north. The second transect was 90 degrees clockwise from the first transect orientation.

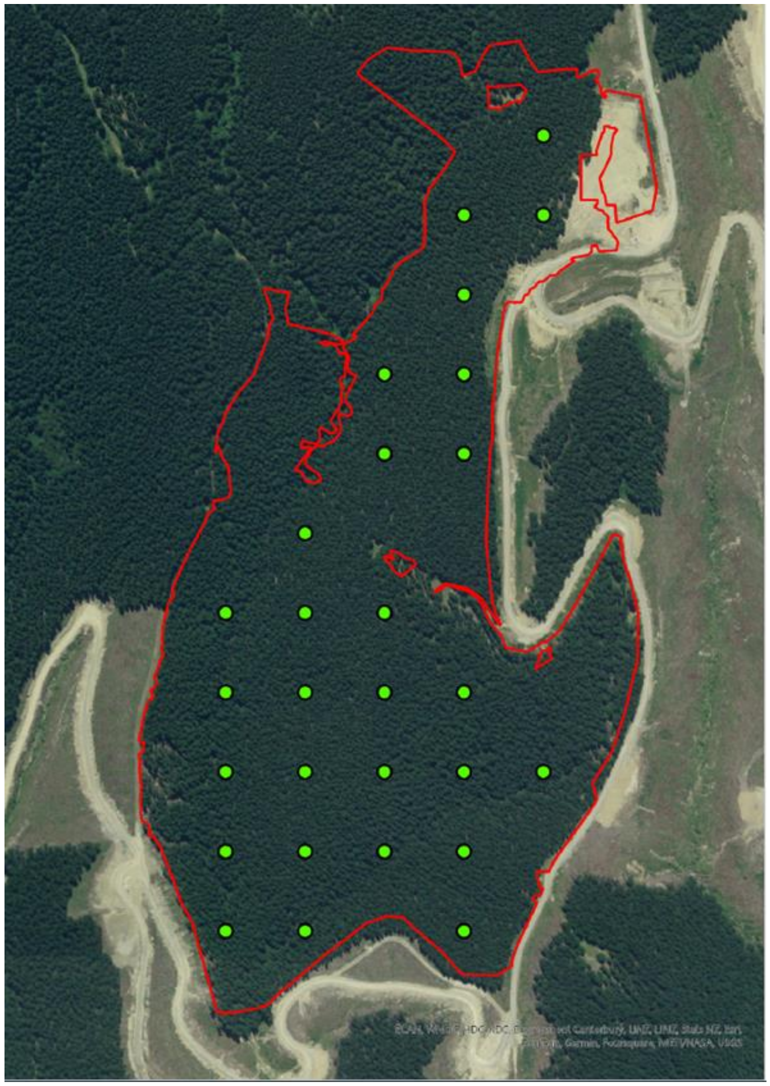


Figure 4: Locations for ground-based line intersect plots. The plot locations represent the corners of the L-shaped line intersect plots.

Ground-based procedure

Each plot was located using a georeferenced PDF of Figure 4 on Avenza Maps running on a consumer-grade GPS. The plot centre was marked clearly using a 50 cm cross shape of spray paint. A transponder on a 120 cm pole was placed in the centre of the spray-painted area. A Suunto KB-14 hand precision compass was used to find the designated transect orientation. This direction was followed for 25 m on horizontal ground, or longer as determined by the slope correction factor, in equation 1 (Brown, 1974). The compass was then used to confirm the direction, and the vertex was used to obtain an initial distance and slope back to the plot centre. The slope value was determined using a look-up table based on equation 1 to estimate the distance required on the ground to achieve 25 m after slope correction. The initial direction and distance were used to refine the endpoint of the transect line, then a final distance and slope measure was taken with the vertex and recorded. The end of the transect was marked with spray paint following the same 50 cm cross shape.

$$\sqrt{1+\left(\frac{percent\ slope}{100}\right)^2} \tag{1}$$

A direct line was walked from the endpoint of the transect line towards the plot centre. The slash pieces were measured in the order that they were found to intersect the transect line, starting from the endpoint of the transect.

Each piece was initially assessed to see if it met the size requirements: a LED greater than 10 cm, and a length over 2 m. The piece was also firmly kicked as an indicator of soundness, with the plan to record any damage inflicted.

For each qualifying piece, the following measurements were recorded:

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

The length was measured using a 30 m tape measure. The SED, LED and diameter at point of intercept with the transect line were measured using callipers to the nearest 0.1 cm. After all required measurements were undertaken, the LED of the piece was generously sprayed using spray paint. Once the transect line was walked back to the plot centre and every eligible piece had been recorded along the transect line, the second transect was walked at the determined 90-degree angle from the original transect, creating a plot shape represented in Figure 5. The same process used to locate the endpoint and measure the slash pieces was repeated for the second transect.

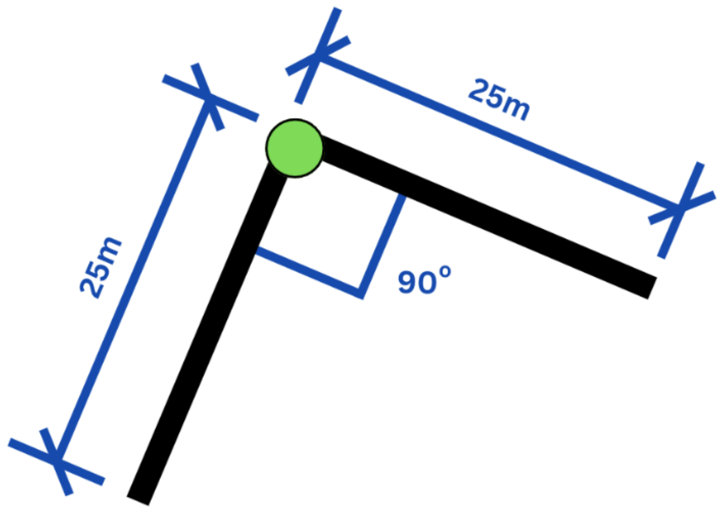


Figure 5: Diagram of a singular plot location with two 25 m intersect lines.

The geographical coordinates of each plot centre were recorded with a Trimble Zephyr 3 Rover GNSS receiver. A total of 45 position readings were taken in the field, then differential correction was applied for a final precision of 10 cm.

After the fieldwork had been completed, the volume per hectare of the slash pieces was calculated using equation 2, which is derived from Wagner (1968).

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

Where V is the volume per unit area in m^3/ha, d_i is piece diameter at intersection (cm), and L is the length of the sample line (m).

The total volume of pieces measured at each plot was calculated to compare to the machine learning procedure. The volume of each piece was calculated using Smalian's formula (equation 3)

$$V = \frac{\pi}{4}\left(\frac{SED + LED}{2}\right)^2 l \tag{3}$$

Where V is the total volume in m^3, and l is the length of the slash piece.

Drone data collection and processing

The block was flown on 28 July 2024 (3 months after harvest) with the following specifications:

- Drone: DJI Matrice 300 RTK
- Sensor: Zenmuse L1 20 megapixel RGB camera (24 mm lens)
- Height above ground level: 40 m
- Overlap between images: 80%

- Speed: maximum 2 m/s

PIX4Dmapper was used to create a photogrammetry point cloud and an orthophoto of the block with a ground sampling distance (spatial resolution) of 1.1 cm. The block was flown in three parts, and the orthophotos were mosaiced together in ArcGIS Pro. The transect line of each plot was identified using the spray paint in the orthophoto to manually digitise the line walked on the ground as shown in Figure 6.

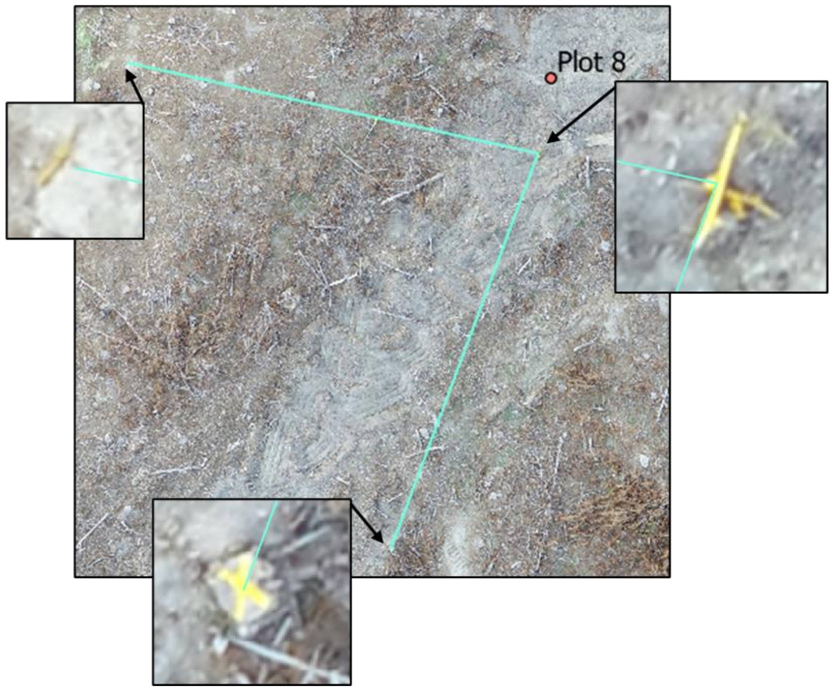


Figure 6: Example of locating the plot transect lines in the orthophoto from the visible spray paint, using information from the GPS measurement (red dot) and compass bearings recorded in the field.

Photogrammetry procedure

The photogrammetry procedure, conducted by Interpine, followed the ground-based procedure, measuring the same attributes of each slash piece. At each plot, the point cloud was buffered to 20 m on either side of the transects identified from the orthophoto. The lengths and diameters of each piece intersecting the transect line, visible in the point cloud, were then measured in Quick Terrain Modeler, shown in Figures 7 and 8. The 2D length was measured because the statistical basis for the line intersect method assumes the logs are flat on the ground. Attributes such as bug holes or visible deterioration that indicate rot were also recorded for each piece. Where the point cloud had overlapping pieces or otherwise unclear pieces, PIX4Dmapper (Figure 9) was used to understand the piece's location from the original drone photos. The volume per hectare at each plot was calculated the same as the ground-based procedure, with equation 2.

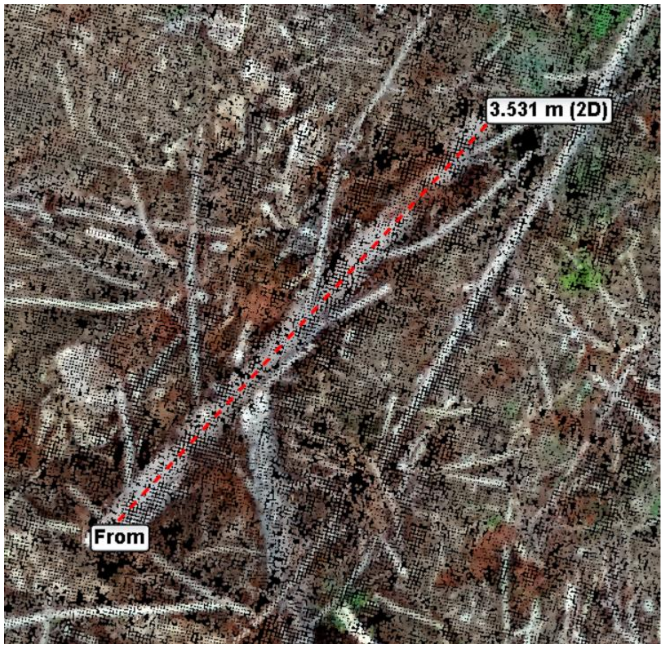


Figure 7: Screenshot of length measurement in Quick Terrain Modeler.

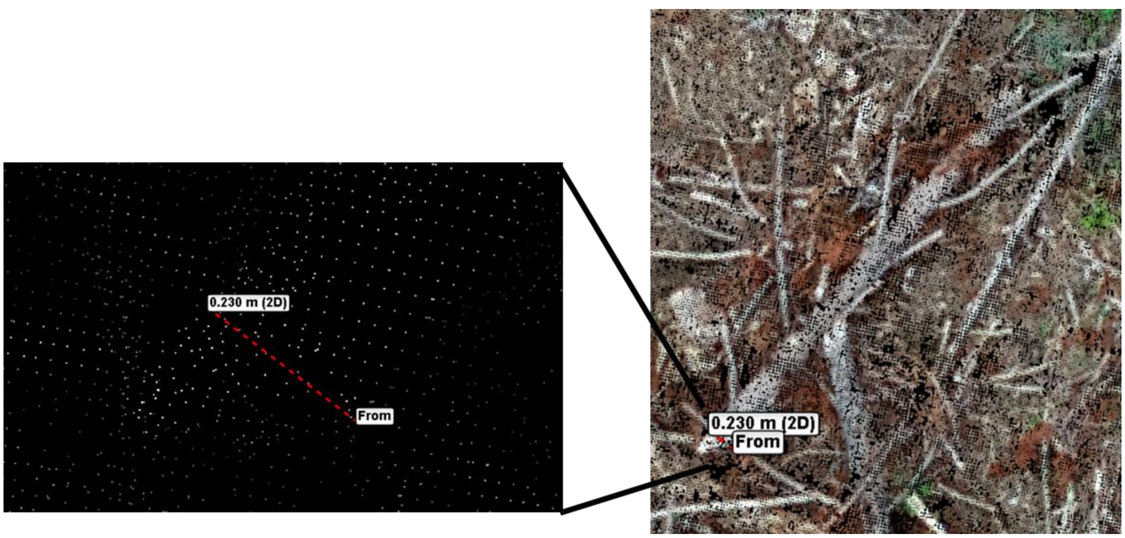


Figure 8: Screenshot of diameter measurement in quick terrain at two scales.

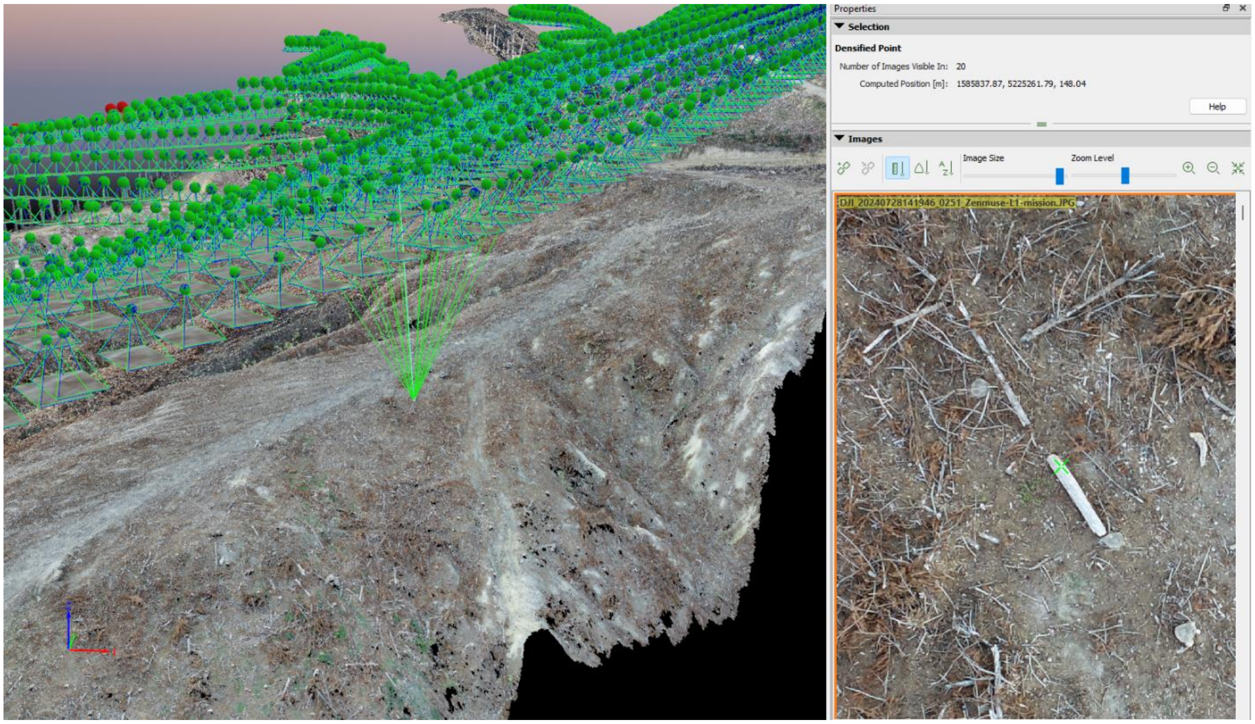


Figure 9: Screenshot of PIX4Dmapper showing the point cloud, locations of the drone photos (green prisms) and the drone photos that have the example slash piece visible (right panel).

Each piece was given a piece code that enabled analysis between the measurements for the same piece from the ground-based procedure and the photogrammetry procedure. Each piece was 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 method or recorded only in the ground-based method were visually analysed in the orthophoto to categorise the reason for the discrepancy, such as if the piece was partially buried.

Machine learning procedure

The machine learning slash model used in this study was developed for commercial purposes by Interpine Innovation. Therefore, the model was not trained on any part of the orthophoto from this study. It is a semantic segmentation model that identifies all the pixels belonging to large slash pieces within an orthophoto. The model is based on a Convolutional Neural Network architecture. Due to processing constraints, only 640 by 640 pixel tiles could be processed at a time. As a result, the orthophoto is divided into tiles, which are later stitched back together.

Interpine's training data was from a range of cloud patterns and lighting conditions. The flight height for data used in the model was between 80 – 120 m. Utilising a DJI Zenmuse photogrammetry camera, this produced training data with pixel resolutions between 1 and 2.5 cm. The training data was taken between 2 to 6 weeks post-harvest and was manually annotated by Interpine, including partially obstructed pieces. During model development, the volume of training data reached a level where additional data did not significantly improve the evaluation metrics. The metric used to evaluate performance against test data was Intersection over Union (IoU), calculated as shown in Figure 10. The IoU exceeded 0.80.

$$\text{IoU} = \frac{\text{Segmented Image} \cup \text{True Image}}{\text{Segmented Image} \cap \text{True Image}} =$$

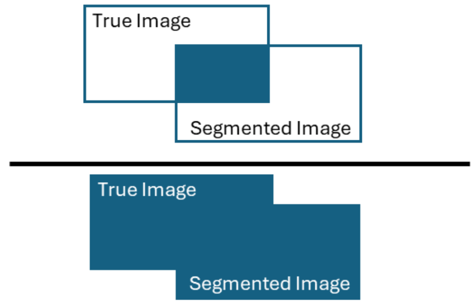


Figure 10: Illustration of intersection over union calculation to evaluate image segmentation models.

The volume of each piece was calculated based on the polygon segmented. The length used was the longest length of an axis through the polygon, and then the width was calculated as the surface area divided by the length. This estimates the width as the width of a rectangle of equal length and surface area. This method was chosen because the machine learning algorithm can pick up branches coming off the main slash piece, but the method does not significantly increase the width when these smaller branches are present. Therefore, the width is a good approximation of the average diameter. The width was used as the diameter to calculate the slash piece as a cylinder.

Interpine created an average surface raster using the volume of identified slash pieces with lengths greater than 2 m. This process involved approximating the volume of each slash piece as at the centroid of the slash piece, then summarising the centroids over a 10 m by 10 m grid. The centroid of the grid was used as points to interpolate between the volumes, using kriging. This resulted in a volume surface showing the moving average of the volume per hectare across the cutover.

During the tiling process, small 'splits' occurred where slash 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 slash and the slash measured on transect lines. In this comparison, only the slash intersecting the line was included, so a piece split halfway along its length would have only half of it captured. To address this, these split pieces were combined for the comparison with the ground-based and photogrammetry line intersect methods.

A model in ArcGIS Pro Model builder was created to combine polygons that had an orientation within 5 degrees of each other and were less than 0.5 m apart, shown in Figure 11. The minimum bounding geometry tool was used to estimate the orientation of each slash piece, based on the assumption that slash pieces will always have a straight, long axis much longer than the width. As shown in Figure 12, this approach would identify the orientation based on the longest axis of the slash piece even if it had a branch.

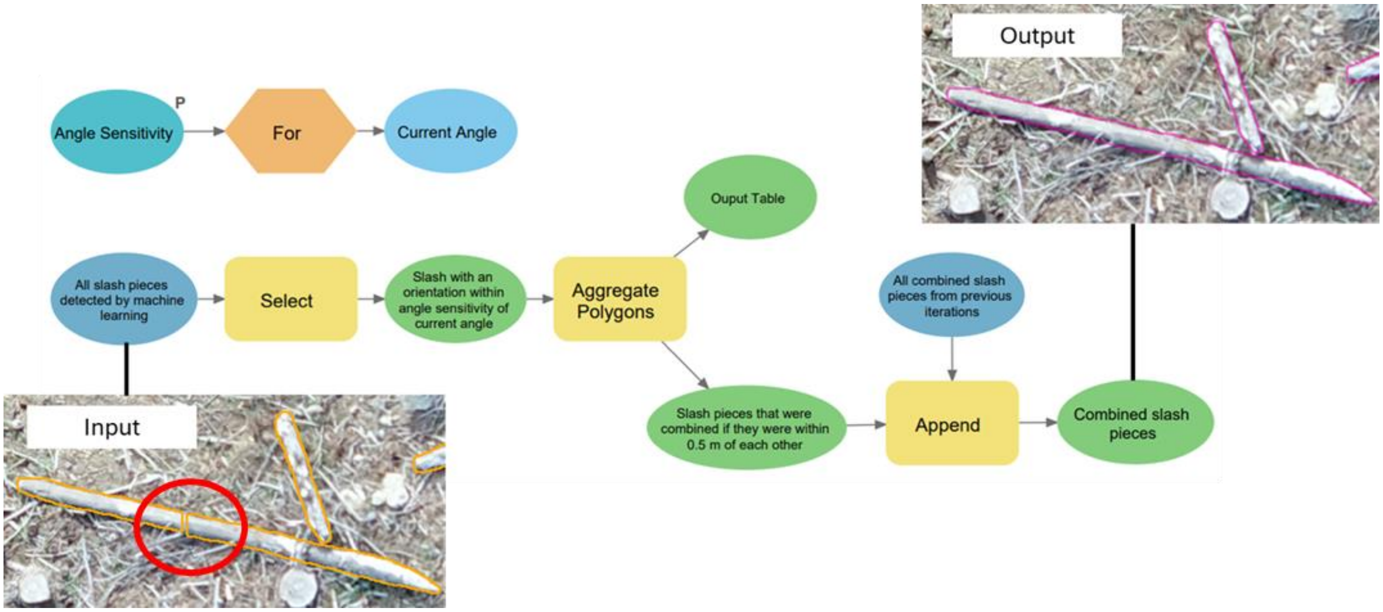


Figure 11: ArcGIS ModelBuilder model used to combine pieces that were at the same orientation and nearby each other. The example shows a long slash piece that was combined at the split but not combined with the nearby piece at a different angle.

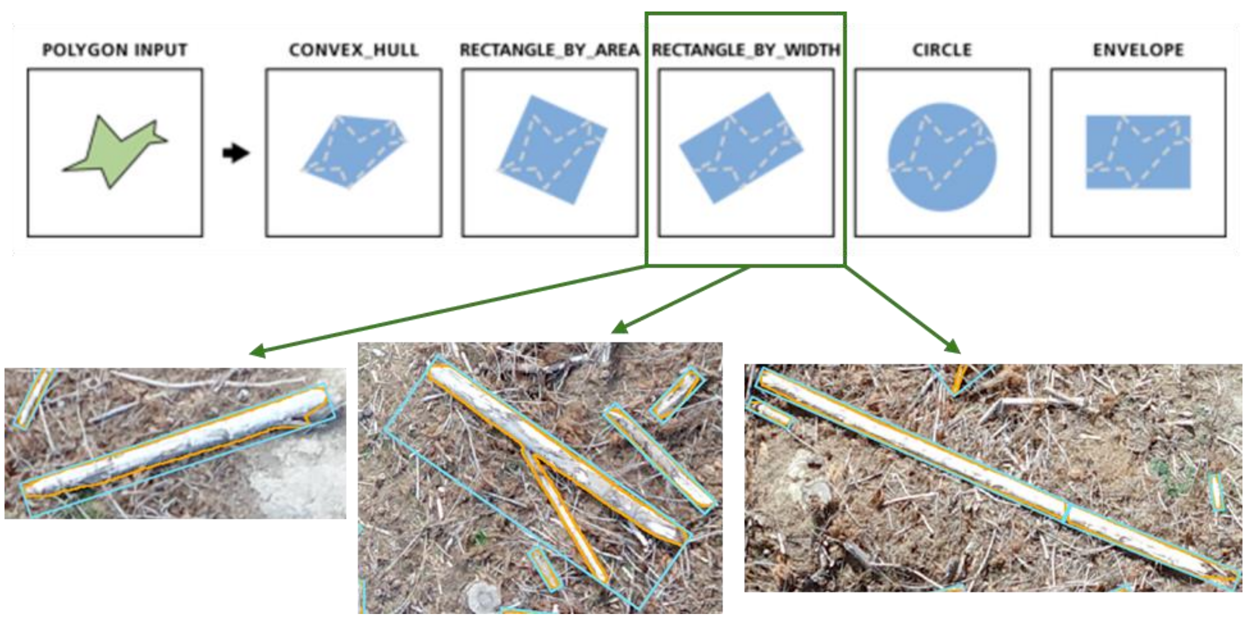


Figure 12: Illustration and examples of the Minimum Bounding Geometry tool. The top figure was adapted from the Minimum Bounding Geometry Documentation (ESRI, n.d.).

Comparison was done on a plot scale by adding the volume of each piece whose polygon intercepted with the transect line.

A total of 28 plots were measured by all three methods, then 25 plots were used in the analysis. There were 3 plots (plots 2, 22, and 24) that fell across boundaries in the flight pattern and were excluded from the analysis. This was because the ground-based and photogrammetry-based transect lines were unable to be accurately aligned for these particular plots.

Results

The ground-based line intersect method measured a mean slash volume of 31.0 m^3/ha across the cutover, significantly higher than either remote sensing method (Table 2). The remote sensing methods measured a similar volume per hectare to each other, 13.6 m^3/ha for the photogrammetry and 14.0 for the machine learning. Both plot-based methods had large confidence intervals due to the high variation between plots. The 33% PLE achieved was less precise than the predicted 25% PLE, since 25 plots were used rather than the original study design of 40 plots. When applying the same prediction method to 25 plots instead of 40, the predicted PLE is 32%, aligning with the actual PLE achieved.

Table 2: 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 to represent that a sample was measured, whereas the machine learning volume surface covered the whole cutover.

Method	Mean Volume (m^3/ha)	95% Confidence Interval (m^3/ha)	Probable Limit of Error (at 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	-	-

Photogrammetry results

Figure 13 compares the volume of residual slash per hectare obtained using ground-based and photogrammetry-based line intersect methods across 25 plots. The photogrammetry method always reported a lower volume than the ground-based method. Figure 13 displays significant variability in slash volume and discrepancies between the two techniques, as well as across plots. Plot 23 had the highest volume of slash measured by the ground-based method, at 109 m^3/ha. In contrast, plot 11 had the third highest measurement of slash volume by the ground-based method, but the highest volume of slash measured by the photogrammetry method at 60 m^3/ha. However, plots such as 7, 15 and 26 show relatively close measurements between the two methods, reflecting better detectability of slash on the ground for plots of lower volume.

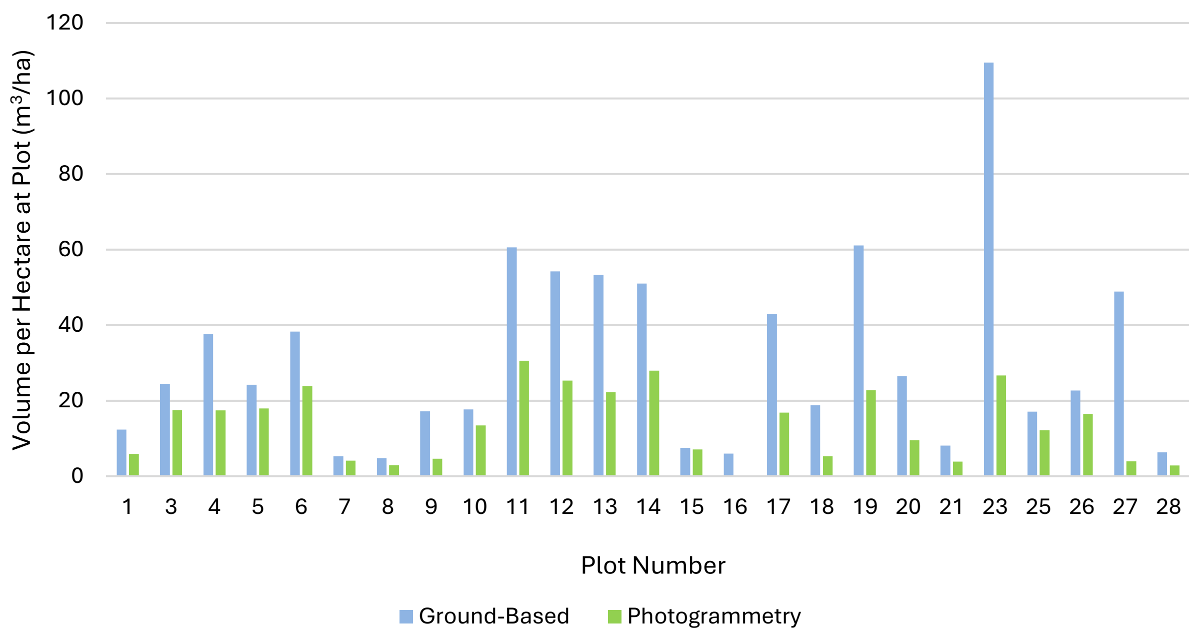


Figure 13: Total plot volume comparison between ground-based and photogrammetry line intersect methods at each plot.

Figure 14 displays the same volume per hectare at each plot for both the ground-based and photogrammetry-based line intersect methods as a scatter graph to quantify the relationship between methods. The r^2 value is 0.61, showing a moderate strength relationship between the photogrammetry and ground-based line intersect methods. The positive trendline indicates that as ground-based measurements increase, photogrammetry measurements also tend to rise, but not as sharply. Although a linear trend line is shown on the graph for the relationship, photogrammetry measurements of lower volume plots are closer to the ground-based measures than in plots with higher slash density. The line of equality (y = x) on the graph provides a reference for this comparison, with points generally falling below the line. This pattern highlights a consistent underestimation by photogrammetry compared to the ground-based approach.

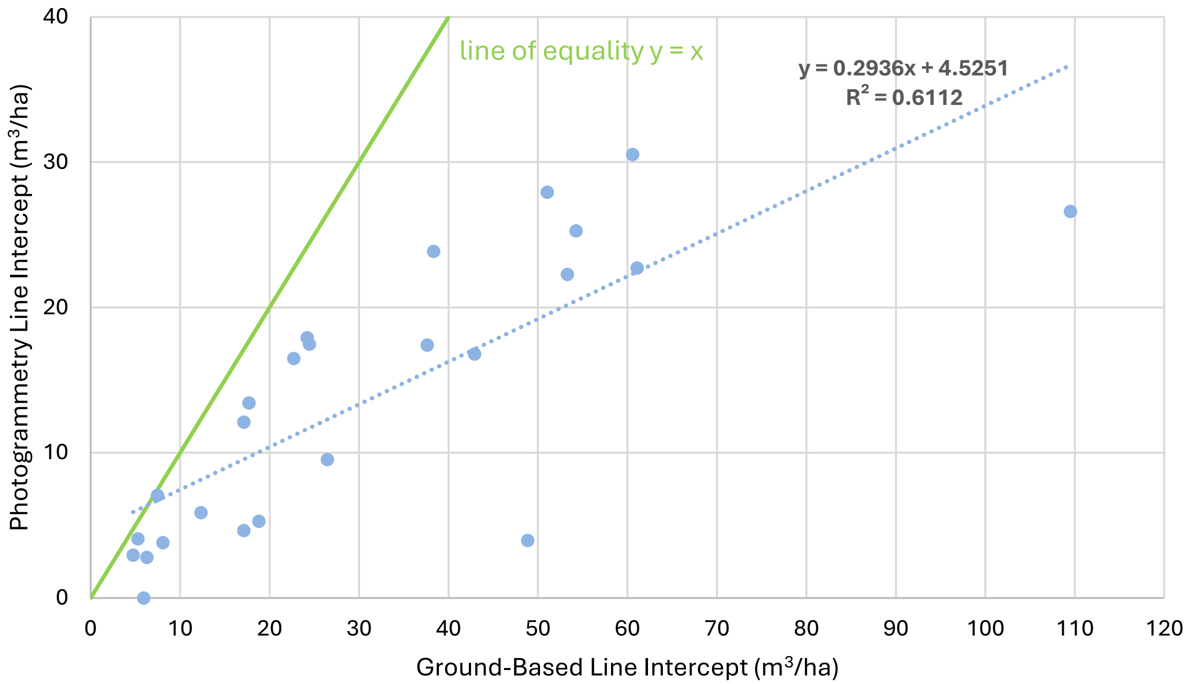


Figure 14: Relationship between ground-based and photogrammetry line intersect methods volume per hectare at each plot.

Figure 15 compares ground-based and photogrammetry piece length measurements, revealing a strong correlation between the two methods with an r^2 value of 0.86. This indicates that photogrammetry is generally effective at estimating piece lengths. However, the trendline, with the equation y = 0.8473x + 0.4642, suggests a consistent underestimation by photogrammetry, as the slope is less than 1. Most pieces that deviate from the ground-based measurement by more than 1 m are underestimated by the photogrammetry measurement, suggesting that the largest source of discrepancy in length measurement was when the full length of the slash piece could not be seen in the imagery.

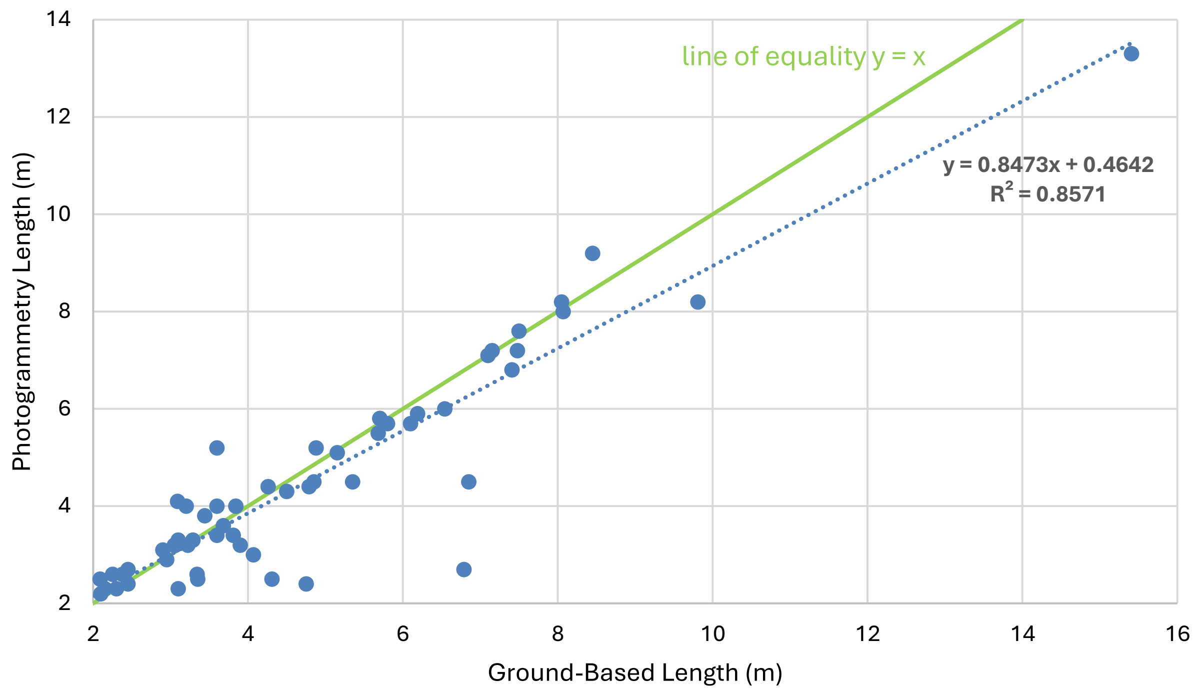


Figure 15: Relationship between ground-based and photogrammetry measurements of piece length.

Figure 16 illustrates the relationship between ground-based and photogrammetry measurements of piece SED. The data shows a moderate to strong positive correlation between the two methods, as indicated by an r^2 value of 0.68. The trend line equation y = 0.6751x + 1.4558, suggests that photogrammetry consistently underestimates SED in comparison to ground-based measurements, with the slope being less than 1. Most points lie below the line of equality (y = x), confirming this trend of underestimation.

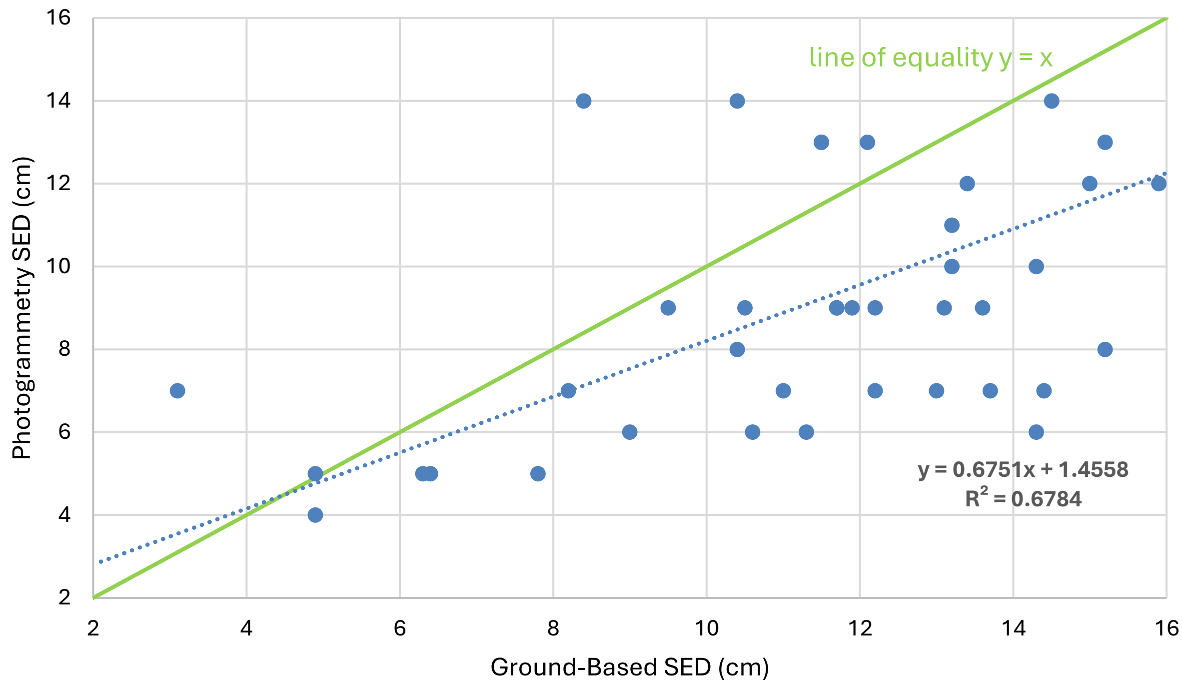


Figure 16: Relationship between ground-based and photogrammetry measurements of piece SED.

Figure 17 compares the ground-based and photogrammetry measurements of the piece LED. This scatter graph reveals a moderate positive correlation between the two methods, as evidenced by an r^2 value of 0.59. The regression line, described by y = 0.6551x + 4.9724, suggests that photogrammetry tends to underestimate LED measurements when compared to ground-based methods. Most data points fall below the line of equality, indicating a consistent underestimation, particularly as LED measurements increase.

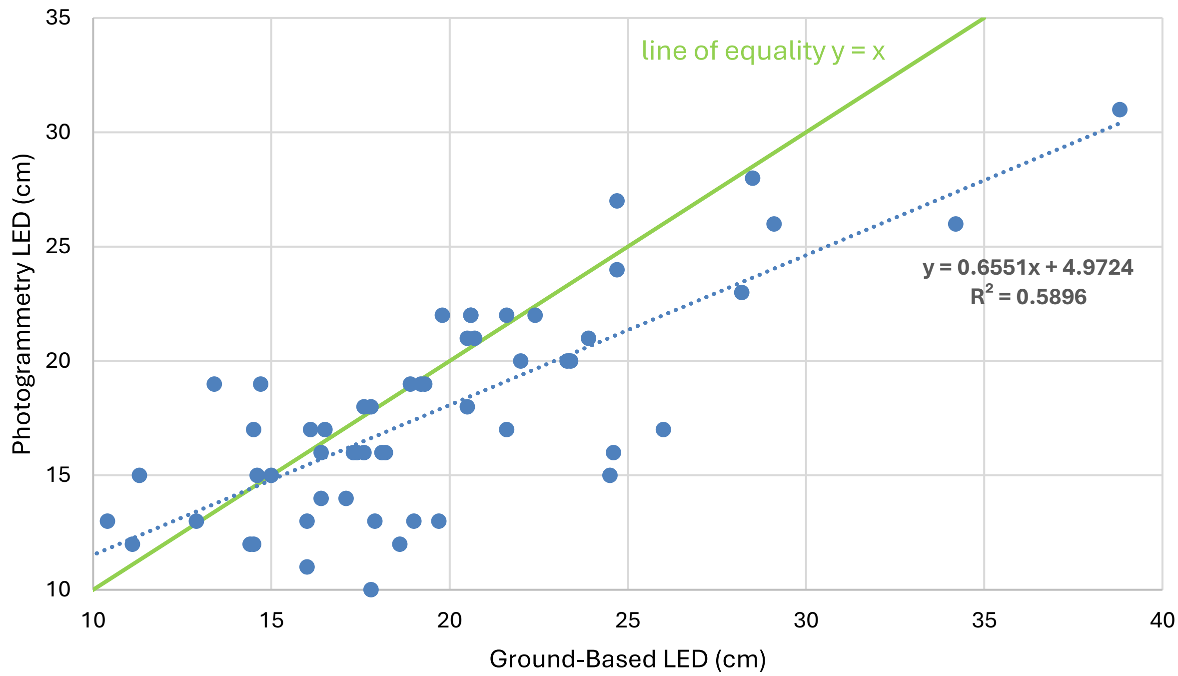


Figure 17: Relationship between ground-based and photogrammetry measurements of piece LED.

Figure 18 shows the relationship between ground-based and photogrammetry measurements of diameter at intercept. A moderate correlation can be seen, with an r^2 value of 0.60. The regression equation, y = 0.6535x + 4.1631, suggests that photogrammetry measurements are generally lower than ground-based measurements, especially as the diameter increases. This is shown by the slope of 0.65, which means that as the ground-based diameter increases, the photogrammetry diameter increases at a slower rate. Most data points fall below the line of equality (y = x), therefore, the underestimation of piece diameter at intercept partly explains the consistent underestimation of plot volume by the photogrammetry line intersect method.

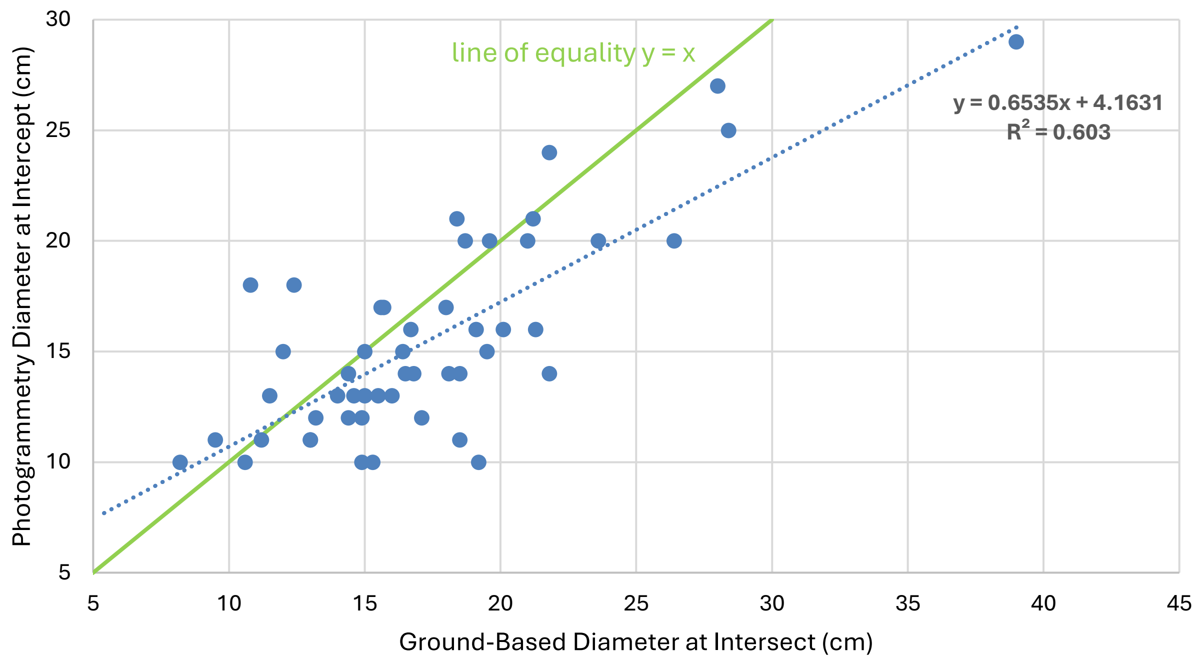


Figure 18: Relationship between ground-based and photogrammetry measurements of diameter at intercept for each piece.

In the ground-based procedure, certain pieces were measured but not detected in the photogrammetry procedure for various reasons as displayed in Figure 19. 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. The primary reason for this discrepancy was that many pieces (58%) were buried or partially obscured by foliage, other slash pieces, or soil. Consequently, these buried pieces appeared too short or did not intersect the transect line in the photogrammetry point cloud.

Another contributing factor was pieces having a diameter at intercept of less than 10cm (8%), which could be too small to measure accurately in photogrammetry. Pieces that were too short from an aerial view (10%) or not intersecting with transect (21%) were also not identified during the photogrammetry process, because they should not have been measured on the ground. In a few instances, there was uncertainty about the reason for the discrepancy. These factors firstly highlight the limitations of an aerial view in detecting smaller or obscured pieces, and secondly the potential limitations on the ground when attempting to visualise the transect line during the line intersect method.

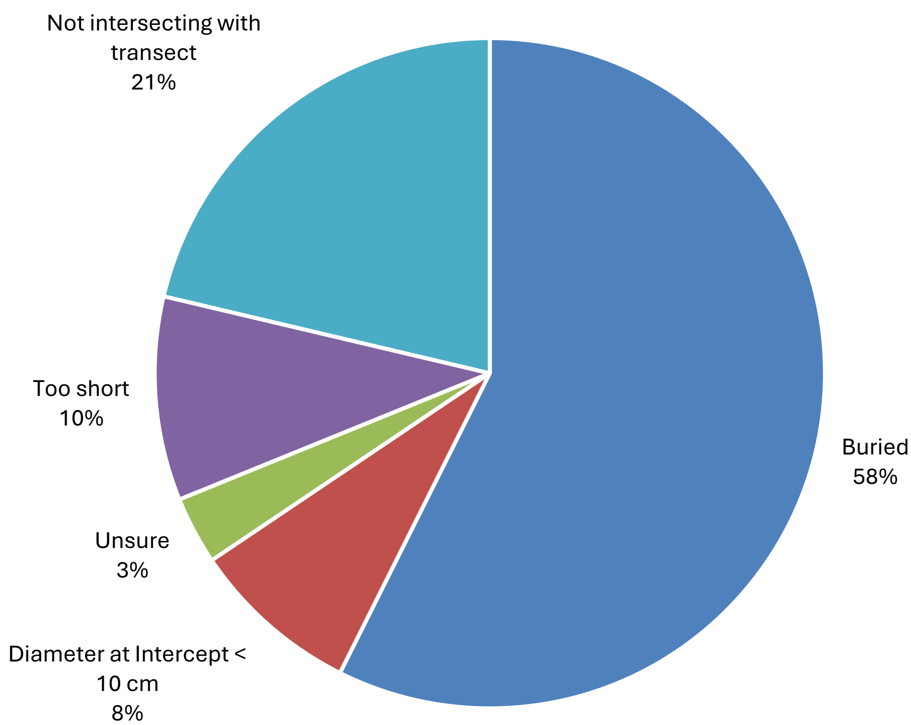


Figure 19: Reasons a piece was measured in the ground-based procedure, but not the photogrammetry procedure.

Figure 20 displays the volume per hectare for each plot based on pieces measured by both ground-based and photogrammetry methods. When the missed pieces are excluded, the correlation between the two methods strengthens, with an r^2 value of 0.85. Despite this improvement, most plots still fall below the line of equality, reflecting ongoing issues such as the underestimation of diameter in the photogrammetry point cloud and the reduction in length for partially buried pieces. This consistent trend of photogrammetry yielding lower measurements compared to the ground-based approach remains evident, even when assessing the same slash pieces across both methods.

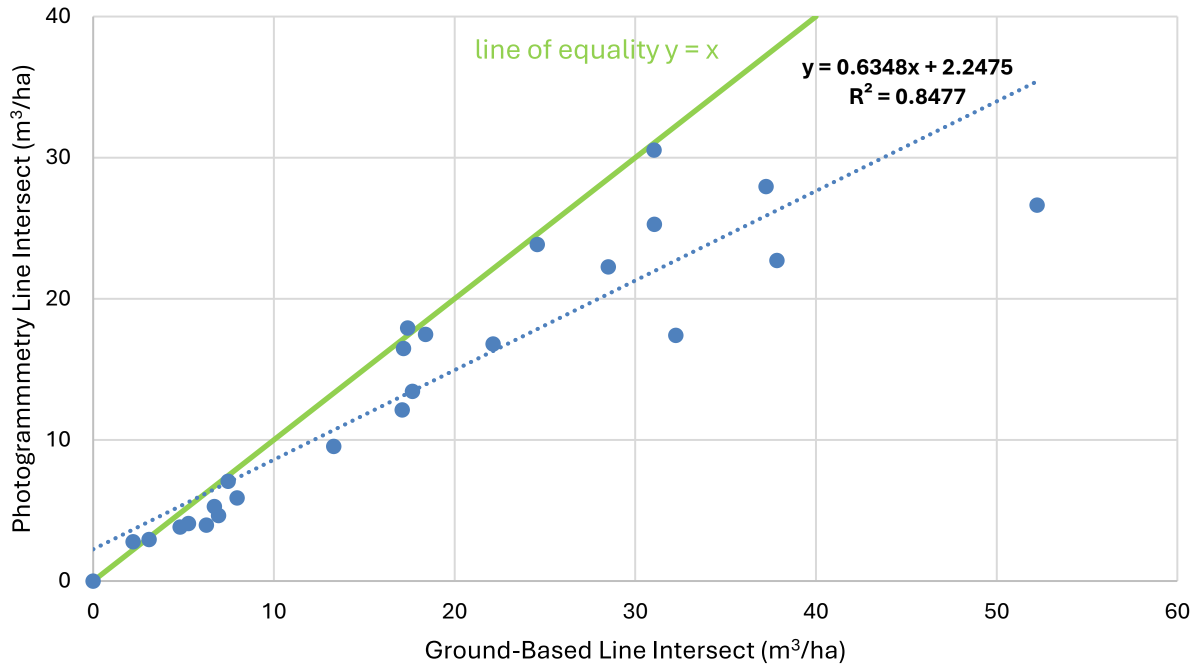


Figure 20: Volume per hectare at each plot for ground-based and photogrammetry based line intersect methods, only including pieces that were measured in both methods (excluding slash pieces missed in photogrammetry).

Machine learning results

The machine learning output creates a 'wall-to-wall' volume surface, as shown in Figure 21. The areas identified as very high slash volume also showed visually high amounts of slash in the orthophoto. This is especially relevant in the lower-most slash cluster identified because there are no plots in that location. Without the machine learning method, the high slash density area here could have been missed. Note that the machine learning was able to measure in the windthrow area, which did not have ground-based plots in it due to safety concerns measuring under unstable trees.

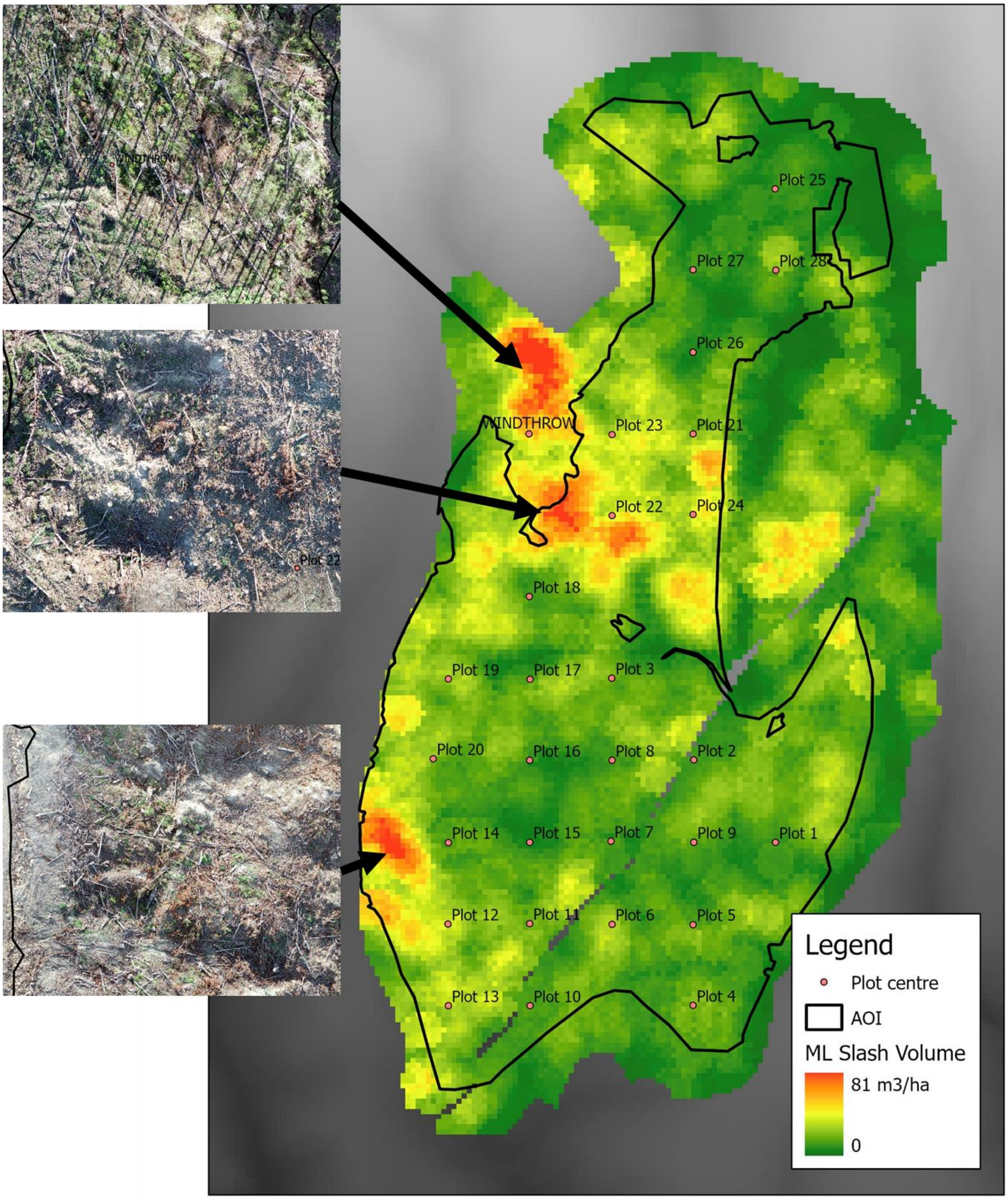


Figure 21: Average volume surface across the site from the machine learning slash detection and screenshots of the orthophoto for the highest density sites identified by the machine learning.

Figure 22 compares the total slash volume of pieces measured during the ground-based line intersect method with the total slash volume detected through machine learning, after combining split pieces across 25 plots, revealing considerable variations in measurements. The total volume at each plot represents the cumulative volume of all pieces measured at that location, which differs from the volume per hectare shown in Figure 13, as the plots were not of a fixed area. Generally, the ground-based method recorded higher slash volumes than the machine learning approach, especially in plots such as 17, 19, and 26. However, in some plots, such as 4, 10, and 28, machine learning detection aligned more closely with ground-based measurements.

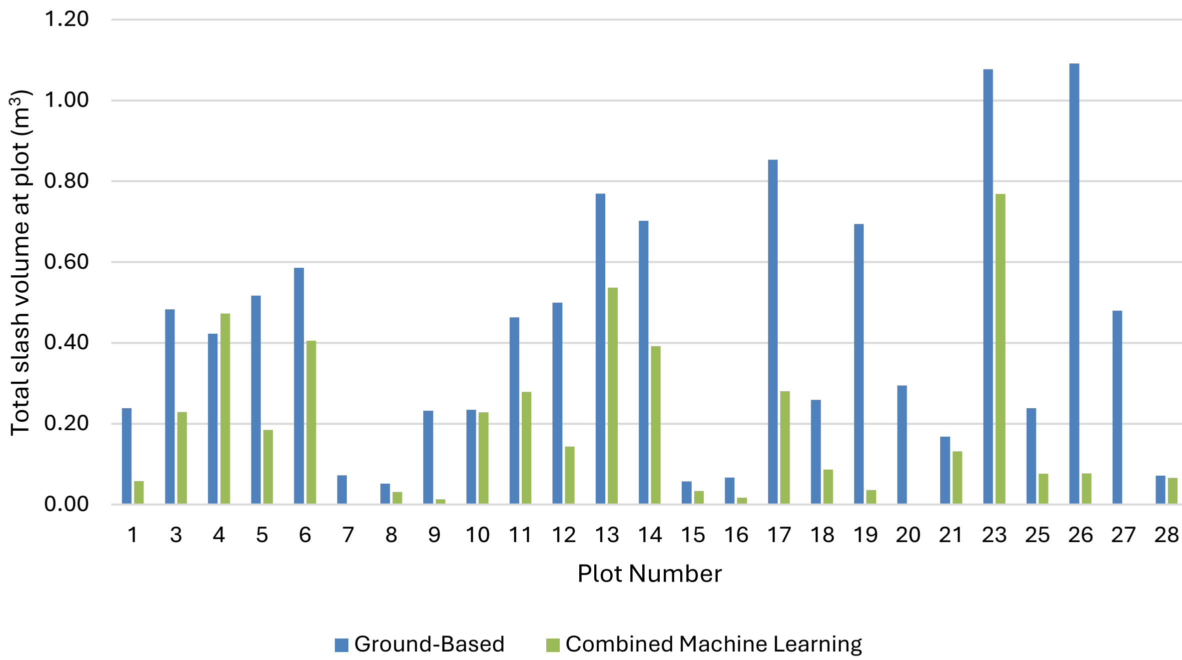


Figure 22: Total plot volume comparison between ground-based plots and machine learning detection at each plot.

In Figure 23, ground-based plot volumes are compared with machine learning detection plot volumes after combining split pieces. The ground-based values generally exceed the machine learning estimates. The trendline has an r^2 value of 0.39 which indicates a weak to moderate positive correlation between the two methods. This r^2 value suggests that while there is some relationship between ground-based measurements and machine learning estimated, it is not very strong. However, the positive correlation means that machine learning detects higher slash volumes for plots with a higher ground-based volume. The scatter plot shows that many machine learning estimates are lower than the corresponding ground-based values, with points generally lying below the line of equality. This pattern reflects a consistent underestimation by the machine learning method compared to the ground-based measurements.

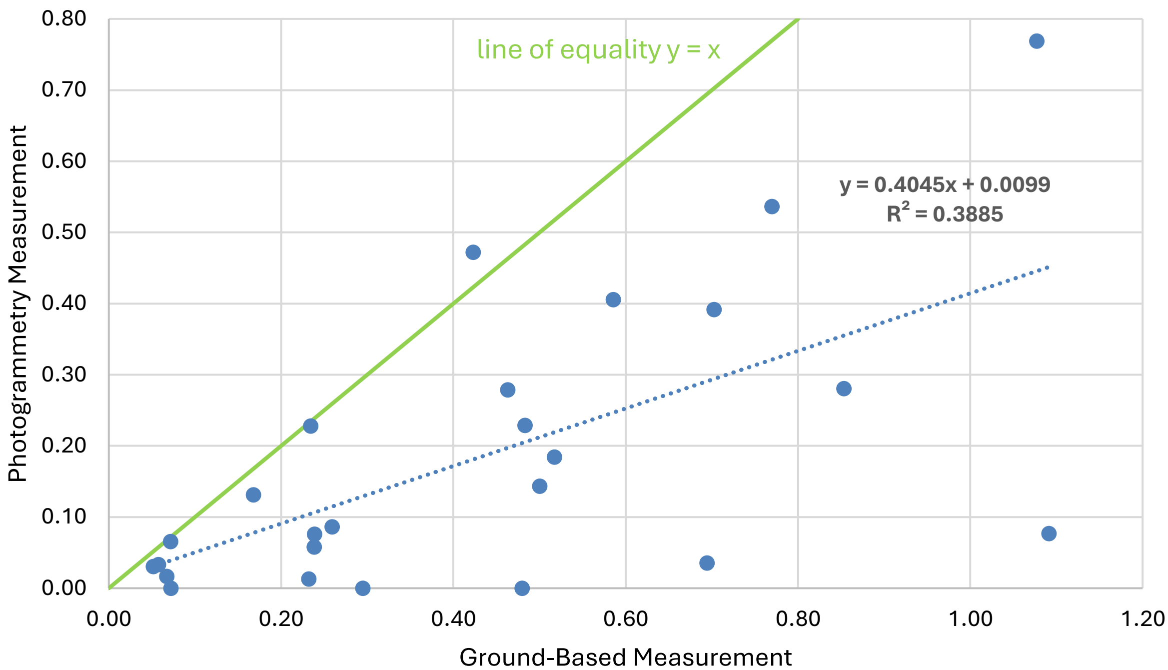


Figure 23: Graph of the volume per plot comparison between ground-based line intersect method and machine learning detection after combining split pieces.

Discussion

Ground-based line intersect method bias

After comparing the ground-based line intersect method to the photogrammetry measurements and orthophotos, it became apparent that 11% of all pieces measured had been mistakenly included in the ground-based line intersect method. These pieces were counted despite not actually intersecting the transect line, had it been followed in a direct path, as shown in Figure 24. Challenges were encountered when trying to maintain an accurate sight line along the transect line during the ground-based line intersect plots. This was due to the difficult terrain and obstacles, reducing visibility to the end of the transect line that had been marked with the transponder.

An alternative technique is to lay out the transect line with a tape measure. However, this method was not initially selected because the tape can easily become entangled with slash or branches protruding from the ground. Caratti (2006) verifies this experience as difficult, concluding that estimates could result in bias due to the inability of the tape to lie flat across the terrain. Additionally, the tape often fails to stay straight, leading to oversampling, particularly in areas where the transect line cannot be walked in a straight line due to obstacles like holes from root boles or steep, slippery terrain.

Figure 24: Examples of slash pieces that were mistakenly measured in the ground-based procedure but do not cross the transect line (turquoise line).

Importantly, the photogrammetry method did not detect any slash pieces that would have been measured if the correct transect line had been followed on the ground. If the photogrammetry method and ground-based method simply followed different transects, the photogrammetry method would have measured pieces on the straight transect that were missed on the ground when the transect deviated from a straight line. Instead, there is a clear bias to over-measure on the ground.

Other methods of defining the transect line, such as using a measuring tape or laser, may change the extent to which observer bias overestimates slash volume. Using a tape measure has the advantage of providing a clear physical representation of the transect line. However, during trials of the line intersect method for this study, the vertex and transponder was preferred over the measuring tape due to issues with snagging on slash pieces and other vegetation. The tape measure would be more likely to snag on slash pieces than empty ground, and therefore more likely to include extra slash pieces than extra empty ground. On the other hand, while a laser maintains a straight line, it could be difficult to see in the bright sunlight. Secondly, rolling terrain would create shadows where even a straight perfectly straight line would not be visible. Overall, modifying the method for defining the transect line may mitigate the overestimation issue, but it is unlikely to eliminate it entirely.

Another factor contributing to the bias in the ground-based method is the tilt of the slash pieces, which led to an overestimation in slash volume. Statistically, the line intersect method assumes the piece lies along the ground plane. In a complex cutover environment, many pieces are tilted vertically. This led to 5% of pieces that were measured in the field as a length of over 2 m were not included in the photogrammetry measurement since from an aerial view, the 2D piece length was less than 2 m. One method to address this is to apply a tilt correction factor developed by Wagner (1982) for tilted pieces. However, this requires measuring the tilt of each piece, which reduces the practicality of the ground-based method. The overestimation of length may be exaggerated where it was difficult to lay the tape measure exactly parallel to the piece if it was buried in other slash or partially underground. Overall, the ground-based line intersect method demonstrates bias in overestimating the volume of slash on steep, complex cutovers.

Photogrammetry line intersect accuracy

The overall underestimation of the photogrammetry method, when compared with the ground-based volume, is mostly attributed to the photogrammetry method not picking up pieces that were partially buried. Examples of these pieces are shown in Figure 25, where pieces are buried in the ground, under other slash pieces, or under foliage. During the ground-based procedure, one person kicked the slash piece at one end and the other person felt where the vibrations had reached to identify the full extent of a piece that was buried in the ground. However, there is an inherent issue for optical remote sensing because if an object is obscured from view, it cannot be measured.

The most widely used remote sensing technique that could penetrate through some obstructions is LiDAR (Manning, 2023). LiDAR cannot penetrate through soil or solid slash pieces, so will only increase the chance of identifying the buried slash pieces that are covered by foliage. Previous studies that selected LiDAR for woody debris measurement are measuring under the canopy (e.g., Joyce et al., 2019). Joyce et al. (2019)'s manual annotation of a LiDAR point cloud had a stronger relationship between volume, with an r^2 value of 0.92 compared to this study's photogrammetry r^2 value of 0.61, likely because the average piece size they targeted was larger, so was more likely to be identified. While LiDAR could potentially be used to measure slash pieces buried beneath foliage, it would incur significant additional costs beyond optical imagery and is unlikely to detect those pieces that are buried under soil or other slash pieces.

Unburied Length: 3.7 m
Total Length: 7.4 m

Unburied Length: 1.4 m
Total Length: 3.75 m

Unburied Length: 1.5 m
Total Length: 4.6 m

Figure 25: 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.

In general, the photogrammetry method tends to underestimate measurements for SED, LED, and diameter at intercept for the detected pieces. Đuka et al. (2023) similarly observed that diameter measurements taken at a 1.4 cm resolution often resulted in underestimations. This discrepancy is likely due to the challenge of accurately identifying the precise edge where a pixel overlaps both the piece edge and the background. Đuka et. al. (2023) overall found a stronger relationship between remote sensing measures of piece size than this study, at an average diameter of 80 cm. This is evidence for the theory that the closer the pixel resolution is to the size of the piece, the less likely it is to be measured accurately. Thus, the smaller the ground sampling distance, the greater the accuracy achievable with the photogrammetry method. In practical applications where only the photogrammetry method is employed, this accuracy can be enhanced by flying at a lower altitude specifically over the areas required for each transect line. Therefore, in most applications of the photogrammetry line intersect method, the issue of underestimation is expected to be less significant.

The photogrammetry method demonstrates less accuracy in measuring smaller diameters compared to larger ones. To address this limitation, a threshold was set, requiring a minimum diameter of 10 cm for detection. This allowed for more reliability in detection and prevented high levels of measurement error for pieces of smaller diameters. In contrast, the ground-based method was able to measure any diameter at intercept, with the smallest piece recorded having a diameter at intercept of 5.4 cm. However, these small diameters were excluded in the photogrammetry method, accounting for approximately 4% of all pieces in this study.

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 pieces were buried. The proportion of slash pieces missed will also increase with increasing slash density where it is more likely a slash piece will be obscured by another slash piece.

Machine learning validity

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 closely aligned with Udali et al. (2023) who found an r^2 between 0.17 and 0.31 after comparing their semantic segmentation model with ground truth volumes. Windrim et al. (2019) achieved a higher r^2 of 0.57 with their instance segmentation model, however also tended to significantly underestimate slash volume.

Importantly, both Udali et al. (2023) and Windrim et al. (2019) reported impressive performance metrics for their models, achieving an overall accuracy of 0.89 and a precision of up to 0.96, respectively. This highlights the importance of ground-truthing any machine learning model used for slash detection to validate its practical effectiveness in quantifying total slash volume. Overall, the correlation between the two methods is insufficient to rely on as the sole approach for managing slash. Despite this, the positive relationship between ground truth volume and machine learning volume indicated that the model was effective in identifying areas within a cutover that have relatively high or low slash volumes.

Machine learning is a complex statistical model, so its results depend heavily on how well the training dataset matches the specific condition of the study. The training data was from a wide variety of cutovers, but key differences exist between the situations represented in the training dataset used and the situation in this study:

1. Flight height: the flight height used was 40 m, but the training data had a flight height of 80 m. However, the ground sampling distance (pixel resolution) was the same as the training dataset, which is more critical for comparison.
2. Camera: the camera used was the Zenmuse L1, which is usually used as a LiDAR sensor, but also has a 20-megapixel RGB sensor. Training data was captured using a Zenmuse P1, which is designed for photogrammetry missions with a 45-megapixel sensor. However, the aerial photos were processed into an orthophoto by the same method, so any warping from the different cameras is unlikely to have had an effect on the final slash detection.
3. Time after harvest: in this study, 3 months passed between the end of harvest and drone capture to allow for time to complete the ground-based measurements and get a weather window. This is longer than the 2-6 weeks for the training data, but the additional time was during winter so minimal weed growth occurred.
4. Visible spray paint: the method for aligning the slash pieces between the ground and aerial images relied on spray paint being visible in the inputs to the machine learning. None of the training data included slash pieces with spray paint. However, this did not appear to limit the detection, as pieces with and without spray paint visible were detected similarly.

Overall, the training for the machine learning method adequately fits the test situation in this study.

A key limitation of the semantic segmentation approach used in the model is that overlapping pieces cannot be analysed individually because they are detected in the same polygon, as shown in Figure 26. The majority of pieces detected did not have an issue with this as the machine learning was annotated to focus on large pieces in most of the training data. However, this implies that a semantic segmentation approach where the volume is calculated from individual pieces will show decreasing accuracy with increasing slash density.

An alternative option would be to train a machine learning model for instance segmentation, which may better connect pieces even when their midsections are obscured. Windrim et al. (2019) achieved a higher r^2 of 0.57 when using an instance segmentation model, although this improvement may be partly attributed to differing site conditions, as their study did not include buried pieces. Instance segmentation is still worth pursuing in the New Zealand context since the regulations describe limits based on individual piece characteristics.

Figure 26: Examples of overlapping slash pieces where the two pieces were connected in the slash detection.

The most significant errors in the detection of individual pieces appeared to be due to the tiling of the orthophoto. As shown in Figure 26, slash pieces would often be identified with straight, parallel ends, cutting off a small section of the piece because the remainder of the piece fell into a different tile. While the combining method used was helpful in ensuring the comparison to the ground-based method was fair, it failed to combine sections of pieces that were too small to compute an accurate orientation. It also could not extend polygons that had been cut off before the end of the piece.

It is necessary to split up an orthophoto in all machine learning methods due to processing constraints, so other studies have proposed more advanced techniques to maintain accuracy than the 'combine split pieces' model. Windrim et al. (2019) addressed this using a 'moving window' of pixels so that each piece would have multiple chances to be detected over its full length. Windrim et al. (2019) then used non-maximum suppression so that no slash piece retained more than one detection. The treatment of large orthophotos under the processing constraints of machine learning architecture is a key area to focus on in order to improve machine learning slash detection.

Practicality considerations for methods

Practicality plays an important role when evaluating remote sensing methods for measuring residual slash. While drones offer an efficient way to cover large areas and gather detailed data, their effective use can be limited by environmental factors. Despite this, remote sensing techniques are the best way to gain information about large areas. The scale at which a method is to be deployed can also be considered in terms of the number of plots that need to be measured (Joyce et al., 2019).

The number of plots should be determined based on the desired level of precision for the estimate. In this study, the estimated number of plots was based on the variance found in Warren and Olsen's 1964 study. Achieving a 33% PLE with 25 ground-based plots was in line with the predicted PLE, but even a 25% error interval is substantial when attempting to demonstrate compliance. All plot-based methods that measure slash typically require a large number of plots to achieve meaningful precision, as slash measurements often exhibit high variation across different plots. In the context of a regulated slash volume, this could result in extra slash being removed from the cutover to ensure the average volume falls below the regulatory limit. However, over-removing slash may not significantly reduce the risk of slash mobilisation, making it an inefficient approach.

Weather is a critical factor that can impact the deployment of drones for remote sensing. Adverse weather conditions such as high winds, rain or fog can restrict flights. All of these were experienced over the time frame of this study and ultimately reduced the total plot count from the planned 40 to the 28 measured for the analysis. These conditions reduce the window of opportunity for data collection. In areas prone to frequent or sudden weather changes, this can delay measurements and affect the overall efficiency of the remote sensing process. Consequently, reliable slash volume assessments might require multiple attempts or extended timeframes, potentially limiting their practicality in meeting regulatory compliance deadlines and increasing costs.

This highlights the need for a flexible and adaptable approach, potentially integrating both remote and ground-based methods to achieve a comprehensive and defensible assessment of residual slash. In situations where timely decisions about slash volume are necessary, such as when a harvesting crew is relocating equipment, a visual approximation of slash volume will naturally be employed. The appendix to this report shows visual material that could be useful for this assessment. Purely visual methods are likely to be inaccurate, given the complexity of a cutover environment. These methods also lack repeatability and preservability, underscoring the importance of not solely relying on visual judgements for slash management.

Recommendations for method application

In assessing methods for measuring residual slash in New Zealand's erodible cutovers, it is crucial to match the measurement approach to the specific conditions of the site. Based on the project's objectives and the complex nature of residual slash management, the following recommendations for method application are proposed and detailed below:

1. Machine learning can be used to identify high slash density areas
2. Ground-based line intersect measurement should be used to quantify volume in high slash density areas
3. Photogrammetry can be applied broadly to characterise slash volume, especially in lower density areas where the pieces are less likely to be buried.

This combined strategy provides a balanced solution, leveraging the strengths of each method to achieve both practicality and defensibility.

Machine learning is a powerful tool for identifying areas with higher slash density across a cutover. The primary advantage of machine learning is that it is not confined to measuring plots and can instead identify the locations of high slash density anywhere on the cutover. Once these high-density areas are identified, targeted ground-based measurements can be employed to further investigate and quantity the slash volume. By using machine learning to narrow down the focus, ground-based efforts can be more efficient and less resource-intensive, avoiding the need for blanket coverage across the entire cutover.

In areas flagged by machine learning as having high slash density, ground-based measurement is recommended. The ground-based line intersect method allows for the direct examination of slash, so is necessary where buried or partly obscured pieces must be accounted for. The ground-based method is necessary to provide a higher degree of accuracy and precision compared with the photogrammetry line intersect method in areas of high slash accumulation when attempting to comply with regulatory requirements.

Photogrammetry is a valuable tool in scenarios where slash density is lower, or the method of harvesting makes burial of slash less likely. In such conditions, the visual nature of photogrammetry allows for efficient and comprehensive surveying, covering large areas in a fraction of the time required for ground-based methods. It is especially beneficial in areas where slash is less likely to accumulate in layers that obscure underlying pieces, reducing the risk of underestimating the total slash volume. However, photogrammetry's tendency to underestimate slash volume should be noted, particularly when comparing volume to regulatory limits. Therefore, when applying photogrammetry, it is recommended to use it in conjunction with ground-based methods or to focus its application in low-risk areas where underestimation is less likely to have regulatory implications.

Overall, selecting the appropriate method for measuring residual slash requires careful consideration of site-specific factors such as slash density, terrain, and the likelihood of slash being obscured. Employing machine learning to identify areas of higher slash density provides a focused approach to slash measurement, allowing ground-based methods to be applied more effectively. This integration ensures detailed investigation is applied where it is most needed. This strategy not only maximises resource use but also enhances the practicality and defensibility of slash volume assessments in New Zealand's erodible cutovers.

Future research considerations

Risk-based residual slash volume thresholds

A potential area for future research is conducting a risk-based comparison of slash location within the cutover to determine the likelihood of mobilisation. Slash on steep slopes mobilises due to landslides, so slash located near waterways or at the base of a slope face a greater risk of being swept into waterways by landslides compared to mid-slope slash (Te Uru Rākau – New Zealand Forest Service, 2024). Understanding the relationship between slash distribution, both surface and buried, and how this affects mobilisation risk would help guide the development of more targeted management strategies.

The current regulatory threshold of 15m^3 per hectare of residual slash is intended to reduce environmental risk, but there is limited empirical evidence to support its effectiveness. Therefore, further research could involve detailed studies to assess whether this volume threshold is sufficient for mitigating risks such as sedimentation and downstream impacts. Investigating whether this threshold should be adjusted based on site-specific factors such as slope, soil type, and slash proximity to waterways, could lead to more refined regulatory guidelines. This would offer a more comprehensive understanding of how volume thresholds impact environmental outcomes. Machine learning slash detection would be a valuable tool in this research as it can provide the spatial information of each slash piece on the cutover.

Cost estimation between methods

Comparing the costs associated with different slash measurement methods, such as ground-based line intersect, machine learning, and photogrammetry, can provide valuable insights into their practical application. This analysis should account for direct costs like equipment, labour and data processing, as well as the broader implications in terms of accuracy, efficiency, and overall cost savings.

Ground-based methods are typically more labour-intensive and time-consuming but provide higher accuracy in areas with dense slash or buried materials. In contrast, machine learning and photogrammetry offer the potential for more efficient data collection, reducing the need for extensive on-ground efforts. Although these remote sensing technologies may require significant initial investment, they can offer long-term cost savings, particularly by streamlining the measurement process.

One significant advantage of using remote sensing methods post-harvest is the ability to identify high-risk areas or problematic slash volume. This detection could assist crews if they are required to return later to clean up residual slash, which can be both costly and logistically challenging. By using photogrammetry or machine learning to identify areas requiring additional attention, forestry companies can avoid the expense of re-mobilising equipment and crews across an entire cutover and instead focus on high-risk areas. This proactive approach may result in significant cost savings, making remote sensing methods not only more efficient, but also more economically viable in the long run.

Balancing these cost considerations with the accuracy required for regulatory compliance will be key in determining the most suitable measurement method for New Zealand's erodible cutovers. Understanding trade-offs can guide forestry companies toward the most cost-effective solutions while maintaining operational and environmental standards.

Determining sound vs unsound wood

Differentiating between sound and unsound wood plays a major role in determining whether a 'piece' is counted towards the volume calculation under the NES-CF slash regulations. It was identified that the drone may be unable to pick up signs of decay and distinguish between sound and unsound pieces of wood. If drones cannot reliably distinguish sound wood from unsound wood, it becomes challenging to ensure compliance with these regulations with remote sensing methods. The response by forest owners may be to over-remove material, which is inefficient in achieving the desired level of slash mobilisation risk reduction.

Due to the nature of the recent harvest completed in Teviotdale, no pieces were found to be unsound wood in either the ground-based investigation or the photogrammetry-based investigation. Teviotdale was not a suitable site for determining this distinction, perhaps because the block did not have windthrow throughout the sample area and the measurement was conducted very shortly after harvest. No disagreement was found between the photogrammetry and ground-based since neither method found any rotted pieces. This preliminary finding shows no issue with remote sensing methods for piece soundness, but this study was not designed to validate these methods' abilities to determine the soundness of wood.

Fully addressing this issue would require further guidance from regulators and future research on developing reliable methods for this distinction. Establishing a standardised method for assessing rot levels would ensure more accurate volume measurements and consistent compliance with regulations. It would also help to identify which pieces of slash are more likely to break down quickly, therefore posing less of a risk in terms of long-term environmental impact.

Conclusion

This study set out to investigate various methods for measuring residual slash in New Zealand's erodible cutovers, with the primary objective of achieving a balance between practicality, accuracy and defensibility. The forestry sector faces increasing scrutiny from environmental regulators and local communities on the effective management of residual slash. Therefore, evidence-based management is essential for maintaining the social license to operate and comply with the NES-CF.

Our findings revealed that the ground-based line intersect method, while traditionally regarded as a reliable measurement tool, can lead to biases when applied to steep slopes and complex terrains. This method measured a mean slash volume of 31.0 m^3/ha, significantly higher than either remote sensing method. Conducting the ground-based line intersect measurements in such challenging environments can create bias towards an overestimation of slash volume due to the accidental inclusion of additional slash pieces. Analysis of orthophotos found that 11% of all pieces measured had been mistakenly included in the ground-based line intersect method. This challenges the conclusions made in previous studies regarding the method's repeatability and accuracy, suggesting that environmental context plays a critical role in the effectiveness of the method.

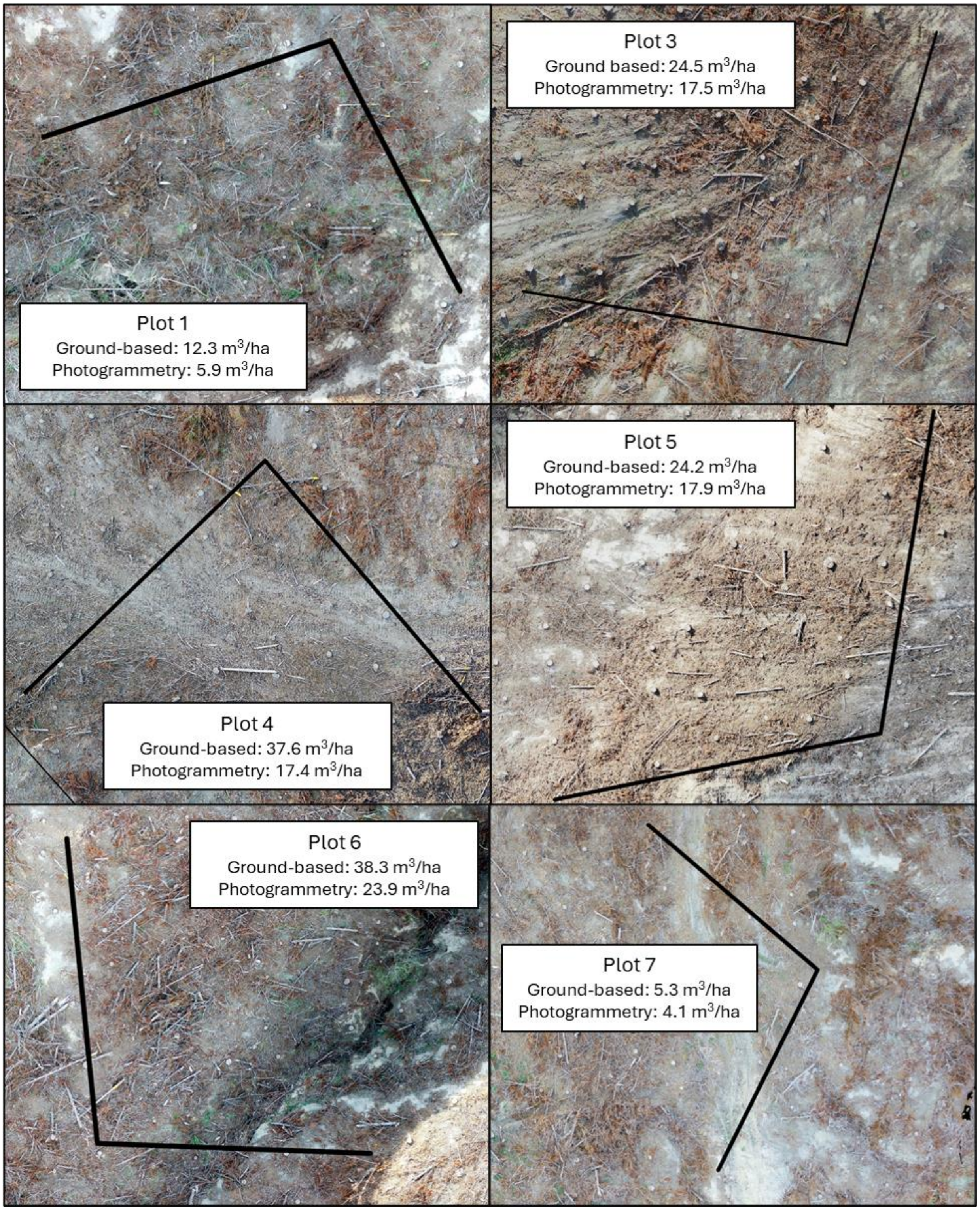
Machine learning methods demonstrated considerable efficiency in identifying areas of high slash density across cutovers. This method measured a substantially lower mean slash volume of 14.0m^3/ha, with a tendency to underestimate volumes, and a weak relationship to the ground-based volume (r^2 value of 0.39). A key reason for this low volume relationship was the splitting and tiling of the orthophoto to work around processing constraints, so improvements to this method should develop techniques to correct this in post-processing. However, the current model shows a positive relationship, and therefore the weak volume relationship does not detract from the potential for machine learning to play a crucial role in initial assessments. Foresters could utilise this initial assessment to focus their ground-based efforts on high-risk zones where accurate measurements are the most critical. By highlighting areas that require closer examination, machine learning enhances efficiency, which is vital in a sector experiencing increasing pressure to operate efficiently while adhering to environmental standards.

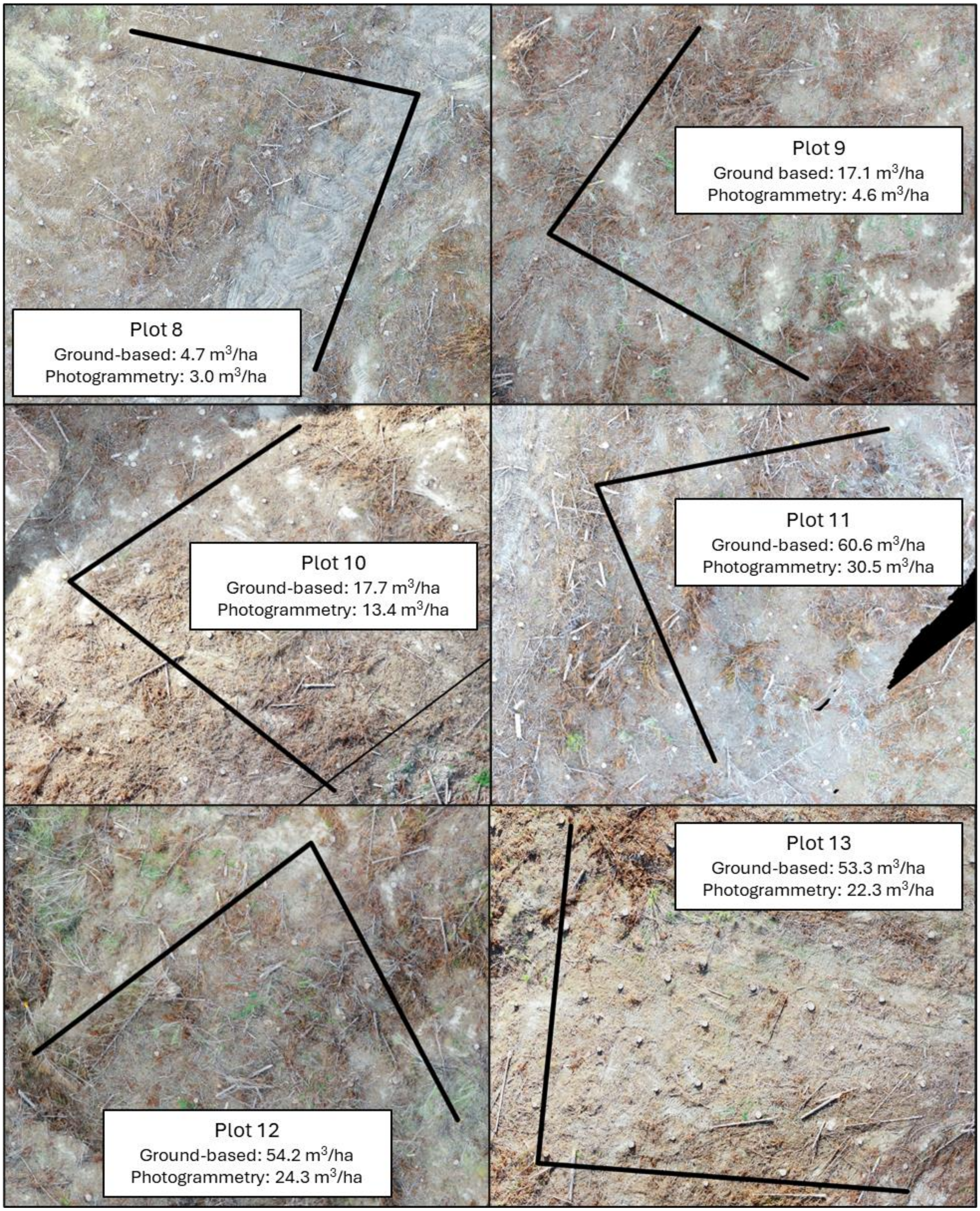
The photogrammetry line intersect method was consistent with machine learning, measuring a mean slash volume of 13.6 m^3/ha. Photogrammetry underestimated volume due to the inability to accurately measure pieces partially buried in the ground, under other slash pieces, or under foliage. Where plots had lower volume and fewer buried pieces, the photogrammetry line intersect method showed a closer relationship to the ground-based volume. Overall, the relationship between ground-based and photogrammetry volume per hectare at each plot was represented by an r^2 value of 0.61, demonstrating a moderate correlation that could be adequate for broad coverage of cutovers with minimal buried slash or low slash volume.

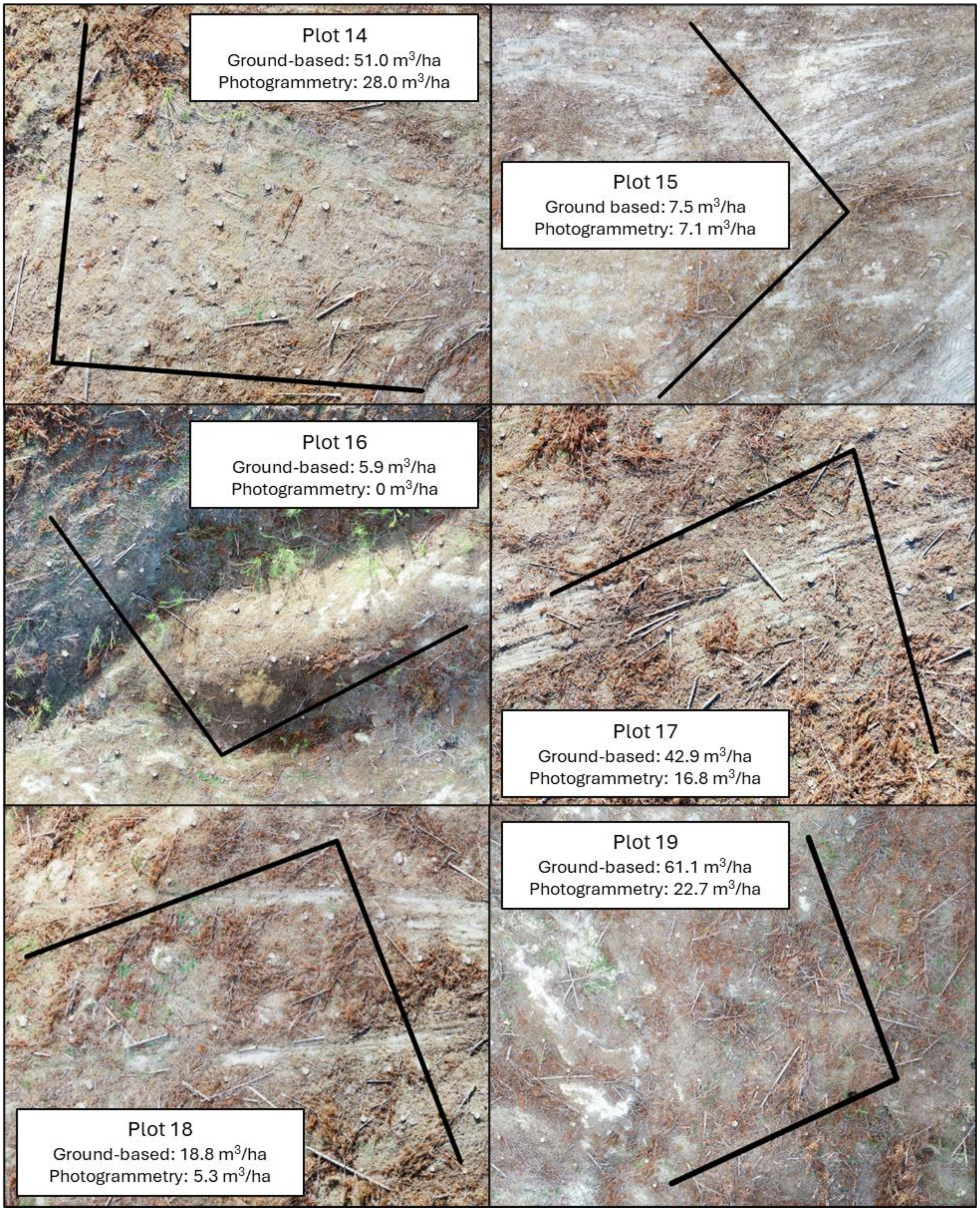
The findings of this study extend beyond technical methodologies, carrying significant implications for the forestry sector's social license to operate. As public expectations shift towards greater accountability and transparency, effective slash management not only mitigates potential environmental impacts, but also demonstrates a commitment to sustainable forestry practices. The complexities of slash management in New Zealand's unique landscapes necessitate collaboration to refine measurement techniques and address evolving challenges.

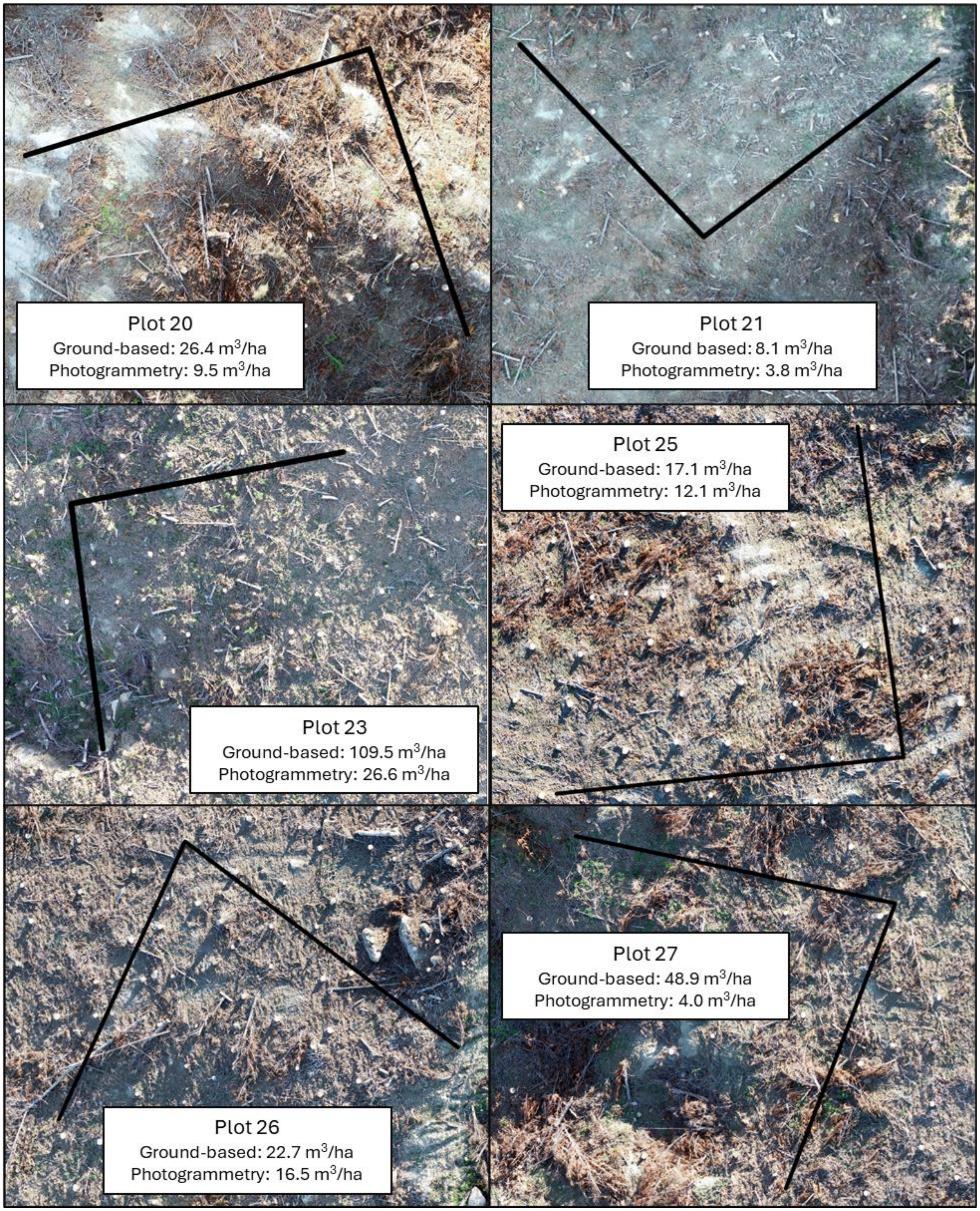
While no measurement method is without its limitations, the integration of ground-based techniques, machine learning, and photogrammetry presents a practical solution to the complexities of slash management. This study contributes to the ongoing discussion on sustainable forestry practices, emphasising the necessity of aligning measurement techniques and regulatory frameworks with evidence-based risk reduction and community expectations. This will be key in navigating the future of forestry on erodible terrain in New Zealand, as we strive for sustainable solutions that protect both the environment and the interests of local communities.

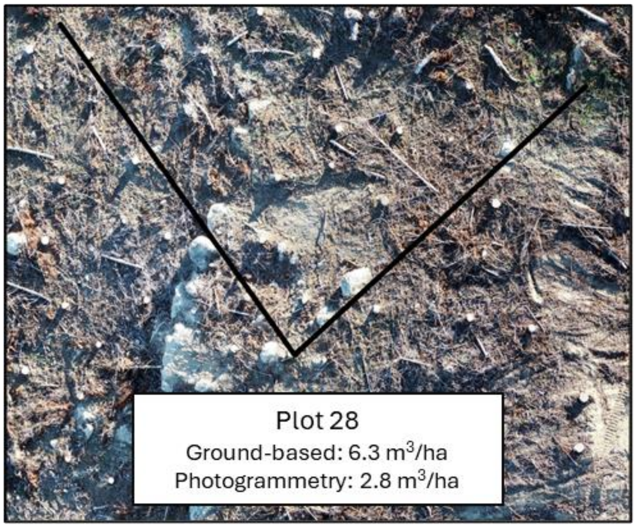
Appendix - Birds-eye view of each plot used in analysis




Plot 8
Ground-based: 4.7 m³/ha
Photogrammetry: 3.0 m³/ha
Plot 9
Ground based: 17.1 m³/ha
Photogrammetry: 4.6 m³/ha
Plot 10
Ground-based: 17.7 m³/ha
Photogrammetry: 13.4 m³/ha
Plot 11
Ground-based: 60.6 m³/ha
Photogrammetry: 30.5 m³/ha
Plot 12
Ground-based: 54.2 m³/ha
Photogrammetry: 24.3 m³/ha
Plot 13
Ground-based: 53.3 m³/ha
Photogrammetry: 22.3 m³/ha


Plot 14
Ground-based: 51.0 m3/ha
Photogrammetry: 28.0 m3/ha
Plot 15
Ground based: 7.5 m3/ha
Photogrammetry: 7.1 m3/ha
Plot 16
Ground-based: 5.9 m3/ha
Photogrammetry: 0 m3/ha
Plot 17
Ground-based: 42.9 m3/ha
Photogrammetry: 16.8 m3/ha
Plot 18
Ground-based: 18.8 m3/ha
Photogrammetry: 5.3 m3/ha
Plot 19
Ground-based: 61.1 m3/ha
Photogrammetry: 22.7 m3/ha


Plot 20
Ground-based: 26.4 m^3/ha
Photogrammetry: 9.5 m^3/ha
Plot 21
Ground based: 8.1 m^3/ha
Photogrammetry: 3.8 m^3/ha
Plot 23
Ground-based: 109.5 m^3/ha
Photogrammetry: 26.6 m^3/ha
Plot 25
Ground-based: 17.1 m^3/ha
Photogrammetry: 12.1 m^3/ha
Plot 26
Ground-based: 22.7 m^3/ha
Photogrammetry: 16.5 m^3/ha
Plot 27
Ground-based: 48.9 m^3/ha
Photogrammetry: 4.0 m^3/ha


Plot 28
Ground-based: 6.3 m3/ha
Photogrammetry: 2.8 m3/ha

References

Bailey, G. R. (1969). An evaluation of the line-intersect method of assessing logging residue. *Wageningen University and Research*. https://library.wur.nl/WebQuery/titel/382486

Bate, L. J., Torgersen, T. R., Wisdom, M. J., & Garton, E. O. (2009). Biased estimation of forest log characteristics using intersect diameters. *Forest Ecology and Management*, *258*(5), 635–640. https://doi.org/10.1016/j.foreco.2009.04.042

Beasom, S. L., & Haucke, H. H. (1975). A comparison of four distance sampling techniques in South Texas Live oak mottes. *Journal of Range Management*, *28*(2), 142. https://doi.org/10.2307/3897447

Beban, A., Korson, C., Reid, J., Procter, J., Halley, J., & Mackenzie. (2023). *Building a place-based social licence to operate*. Massey University. https://ourlandandwater.nz/wp-content/uploads/2023/10/Building-a-Place-based-Social-Licence-to-Operate-Report-Oct-2023.pdf

Bell, G., Kerr, A., McNickle, D., & Woollons, R. (1996). Accuracy of the line intersect method of post-logging sampling under orientation bias. *Forest Ecology and Management*, *84*(1–3), 23–28. https://doi.org/10.1016/0378-1127(96)03773-5

Bitterlich, W. (1984). The relascope idea. *Relative measurements in forestry*. (Issue 1). http://fipak.areeo.ac.ir/site/catalogue/18334194

Brown, J. K. (1974). *Handbook for inventorying downed woody material*. US Forest Service Research and Development. https://research.fs.usda.gov/treesearch/28647

Caratti, J. F. (2006). *Line Intercept (LI) Sampling Method*. US Forest Service. https://www.fs.usda.gov/rm/pubs_series/rmrs/gtr/rmrs_gtr164/rmrs_gtr164_11_line_inter.pdf

Cave, M., Davies, N., & Langford, J. (2017). *Cyclone Cook slash investigation*. Gisborne District Council. https://www.gdc.govt.nz/__data/assets/pdf_file/0013/10408/cyclone-cook-slash-investigation-2017-report.pdf

Davis, B. J. (2017). *Refinement of a drone-based method for estimating coarse woody debris and biomass residue following forest harvest* [Master's thesis, University of Georgia]. https://athenaeum.libs.uga.edu/handle/10724/37297

De Gouw, S., Morgenroth, J., & Xu, C. (2020). An updated survey on the use of geospatial technologies in New Zealand's plantation forestry sector. *New Zealand Journal of Forestry Science*, *50*. https://doi.org/10.33494/nzjfs502020x118x

Đuka, A., Papa, I., Lovrinčević, M., Bumber, Z., Poršinsky, T., & Tomljanović, K. (2023). Terrestrial vs. UAV-Based Remote Measurements in Log Volume Estimation. *Remote Sensing*, *15*(21), 5143. https://doi.org/10.3390/rs15215143

Edwards, B. (2023, February 26). Political Roundup: The horrific damage caused by forestry slash and vested interests. *NZ Herald*. https://www.nzherald.co.nz/nz/political-roundup-the-horrific-damage-caused-by-forestry-slash-and-vested-interests/URXFR7CC35GJTFP7ZPXF2UTHLA/

ESRI (n.d.) *Minimum Bounding Geometry (Data Management)—ARCGIS Pro | Documentation*. https://pro.arcgis.com/en/pro-app/latest/tool-reference/data-management/minimum-bounding-geometry.htm

Garmin. (n.d.). *GPS 17x HVS | Garmin*. Garmin. https://www.garmin.com/en-NZ/p/13191 https://www.garmin.com/en-NZ/p/13191

Gove, J. H., Ducey, M. J., Stahl, G., & Ringvall, A. (2001). Point relascope sampling: a new way to assess downed coarse woody debris. *Journal of Forestry*, *99*(4), 4–11.

Greater Wellington. (2023, June 23). *Slash*. https://www.gw.govt.nz/environment/land-use/forestry/slash/

Hansen, M. C., Potapov, P., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science,* 342, 850–853. Data available on-line from: http://earthenginepartners.appspot.com/science-2013-global-forest . Retrieved April, 24, 2024 from Global Forest Watch www.globalforestwatch.org

Harvey, C., & Visser, R. (2022). Characterisation of harvest residues on New Zealand's steepland plantation cutovers. *New Zealand Journal of Forestry Science*, *52*. https://doi.org/10.33494/nzjfs522022x174x

Herries, D. (2014, July 29). *Cutover residue assessment using line intercept sampling*. Interpine Innovation. https://interpine.nz/29-cutover-residue-assessment-using-line-intercept-sampling/

Interpine. (2021, May 11). *Drone based Harvesting Cutover Merchantable Volume Assessment*. Interpine Innovation. https://interpine.nz/drone-based-harvesting-cutover-merchantable-volume-assessment/

Interpine. (2022, July 24). *Stocking and cutover waste detection*. Interpine Innovation. https://interpine.nz/services/stocking-cutover-waste/

Jones, I., & Noone, H.-M. (2023, October 11). *Government tightens commercial forestry regulations one week out from election*. https://www.minterellison.co.nz/insights/government-tightens-commercial-forestry-regulation

Joyce, M. J., Erb, J. D., Sampson, B. A., & Moen, R. A. (2019). Detection of coarse woody debris using airborne light detection and ranging (LiDAR). *Forest Ecology and Management*, *433*, 678–689. https://doi.org/10.1016/j.foreco.2018.11.049

Karpachev, S. P., Zaprudnov, V. I., Bykovskiy, M. A., & Karpacheva, I. P. (2019). Simulation studies on line intersect sampling of residues left after Cut-to-Length logging. *Croatian Journal of Forest Engineering*, *41*(1), 95–107. https://doi.org/10.5552/crojfe.2020.531

Khan, M. N., Hijbeek, R., Berger, U., Koedam, N., Grueters, U., Islam, S. M., Hasan, M. A., & Dahdouh-Guebas, F. (2016). An Evaluation of the Plant Density Estimator the Point-Centred Quarter Method (PCQM) Using Monte Carlo Simulation. *PloS one*, 11(6), e0157985. https://doi.org/10.1371/journal.pone.0157985

Madden-Smith, Z. (n.d.). *Forestry slash has destroyed Tairāwhiti, who should pick up the bill?* Renews. https://www.renews.co.nz/forestry-slash-has-destroyed-tairawhiti-who-should-pick-up-the-bill/

Manning, A. (2023). *The Uptake and Barriers of Geospatial Technologies in New Zealand's Plantation Forestry Sector* [Honours Dissertation, University of Canterbury]. https://forestengineering.org/wp-content/uploads/2023/11/Anna-Manning-Technology-Uptake-NZ-Forestry-Final.pdf

Mathias, S. (2023, May 15). *Forestry slash devastated Tairāwhiti and Wairoa after Cyclone Gabrielle. The recommended changes are drastic*. The Spinoff. https://thespinoff.co.nz/society/16-05-2023/forestry-slash-devastated-tairawhiti-and-wairoa-after-cyclone-gabrielle-the-recommended-changes-are-drastic

Mathias, S. (2023, February 14). What is slash and why is it so dangerous in bad weather? *The Spinoff*. https://thespinoff.co.nz/business/15-02-2023/what-is-slash-and-why-is-it-so-dangerous-in-bad-weather

Ministerial Inquiry into Land Uses in Tairawhiti and Wairoa. (2023). *Outrage to optimism: Report of the ministerial inquiry into land uses associated with the mobilisation of woody debris (including forestry slash) and sediment in Tairawhiti/Gisborne District and Wairoa District*. Ministry for the Environment. https://environment.govt.nz/assets/Outrage-to-Optimism-CORRECTED-17.05.pdf

Ministry for Primary Industries. (2017). *Plantation Forestry Erosion Susceptibility Classification: Risk assessment for the National Environmental Standards for Plantation Forestry* (MPI Technical – Paper No: 2017/47). https://www.mpi.govt.nz/dmsdocument/19340-plantation-forestry-erosion-susceptibility-classification-risk-assessment-for-the-national-environmental-standards-for-plantation-forestry

Ministry for Primary Industries. (2022). *NES-PF Erosion Susceptibility Classification and Fish Spawning Indicator Tool WebMap* [Dataset; Web Map]. https://data-mpi.opendata.arcgis.com/maps/57836408302c49999c970f534ea16347/explore

Ministry for Primary Industries. (2024, May 17). *National Environmental Standards for Commercial Forestry | NZ Government*. https://www.mpi.govt.nz/forestry/national-environmental-standards-commercial-forestry/

Mitchell, K. (2023). *Quantitative Analysis by the Point-Centered Quarter Method* (arXiv:1010.3303 [q-bio.QM]). Hobart and William Smith Colleges. https://people.hws.edu/mitchell/PCQM.pdf

Morgenroth, J., & Visser, R. (2013). Uptake and barriers to the use of geospatial technologies in forest management. *New Zealand Journal of Forestry Science*, *43*(1), 16. https://doi.org/10.1186/1179-5395-43-16

O'loughlin, C., & Watson, A. (1979). Root-wood strength deterioration in radiata pine after clearfelling.. In *Scion Research*. Scion Research. https://www.scionresearch.com/__data/assets/pdf_file/0009/36918/NZJFS931979OLOUGHLIN284_293.pdf

Peng, W., & Sadaghiani, O. K. (2023). Enhancement of quality and quantity of woody biomass produced in forests using machine learning algorithms. *Biomass & Bioenergy*, *175*, 106884. https://doi.org/10.1016/j.biombioe.2023.106884

Pickford, S. G., & Hazard, J. W. (1978). Simulation Studies on Line Intersect Sampling of Forest Residue. *Forest Science*, *24*(4), 469–483.

Queiroz, G. L., McDermid, G. J., Castilla, G., Linke, J., & Rahman, M. M. (2019). Mapping Coarse Woody Debris with Random Forest Classification of Centimetric Aerial Imagery. *Forests*, *10*(6), 471. https://doi.org/10.3390/f10060471

Resource Management (National Environmental Standards for Commercial Forestry) Amendment Regulations 2023. https://www.legislation.govt.nz/regulation/public/2023/0277/latest/LMS912695.html

Rosecrance, J., Lagerstrom, E., & Murgia, L. (2017). Job Factors Associated with Occupational Injuries and Deaths in the United States Forestry Industry. *PubMed*, *58*, 115–120. https://doi.org/10.3303/cet1758020

Rosecrance, J., & Lagerstrom, E. (2018). Injury Claims from Steep Slope Logging in the United States. *Advances in intelligent systems and computing* (pp. 277–282). https://doi.org/10.1007/978-3-319-96083-8_37

Shokirov, S., Borevitz, J., Youngentob, K., Levick, S. R., Schaefer, M., Jucker, T., & Abdurahmanov, I. (2021). Multi-platform LiDAR approach for detecting coarse woody debris in a landscape with varied ground cover. *International Journal of Remote Sensing*, *42*(24), 9316–9342. https://doi.org/10.1080/01431161.2021.1995072

Smith, S. (2024). Application of an approach to Terrain Stability Assessment in the context of New Zealand Forestry Operations. In *UC Library*. https://ir.canterbury.ac.nz/items/dfbf7a54-06a4-4f1e-a672-dbf397a55bda

Tansey, J. T. E. (2014). *The Effects of Clumped Log Distribution on Line Intersect Sampling* [Honours Dissertation, University of Canterbury]. https://ir.canterbury.ac.nz/server/api/core/bitstreams/477a144f-1f62-4294-9b25-83a6d63d0286/content

Te Uru Rākau – New Zealand Forest Service. (2024). *Slash Risk Management Handbook* (ISBN No: 978-1-991285-97-3). Ministry for Primary Industries. https://www.mpi.govt.nz/dmsdocument/64617-Forestry-slash-risk-management-handbook

Thomaes, A., Van De Kerckhove, P., Van Calster, H., Keersmaeker, L. D., Espirit, M., Goessens, S., Leyman, A., Mijnsbrugge, K. V., Vanhellemont, M., & Vandekerkhove, K. (2023). Assessing lying dead wood by integrating full area sampling and line intersect sampling: combining the best of both worlds. *ResearchGate*. https://www.researchgate.net/publication/376666957_Assessing_Lying_Dead_Wood_by_I ntegrating_Full_Area_Sampling_and_Line_Intersect_Sampling_Combining_the_Best_of_Both_Worlds

Udali, A., Talbot, B., Ackerman, S., Crous, J., & Grigolato, S. (2023). Enhancing precision in quantification and spatial distribution of logging residues in plantation stands. *ResearchGate*. https://www.researchgate.net/publication/376165318_Enhancing_precision_in_quantification_and_spatial_distribution_of_logging_residues_in_plantation_stands

Visser, R. (2018). Best practices for reducing harvest residues and mitigating mobilisation of harvest residues in steepland plantation forests. In *Enviro Link*. https://www.envirolink.govt.nz/assets/Envirolink/Reports/1879-GSDC152-Best-practices-for-reducing-harvest-residues-and-mitigating-mobilisation-of-harvest-residues-in-steepland-plantation-forests2.pdf

Wagner, C. E. V. (1968). The Line Intersect Method in Forest Fuel Sampling. *Forest Science*, *14*(1), 20–26. https://doi.org/10.1093/forestscience/14.1.20

Wagner, C. E. V. (1982). *Practical aspects of the line intersect method* (Information Report PI-X-12). Petawawa Canadian National Forestry Institute. https://cfs.nrcan.gc.ca/pubwarehouse/pdfs/6862.pdf

Wallace, N. (2023, May 12). 'Forestry has lost its social licence in Tairāwhiti': panel. *Farmers Weekly*. https://www.farmersweekly.co.nz/news/forestry-has-lost-social-licence-in-tairawhiti-panel/

Warren, W. G., & Olsen, P. F. (1964). A Line Intersect Technique for Assessing Logging Waste. *Forest Science*, *10*(3), 267–276. https://doi.org/10.1093/forestscience/10.3.267

Weinbrenner, H., Bonadio, S., Bethmann, S., Kaulfuß, S., & Sauter, U. H. (2021). A matter of corporate culture – A multi-method analysis of accidents during forest work [Abstract]. *Allgemeine Forst- Und Jagdzeitung*, *191*(11–12), 262–272. https://doi.org/10.23765/afjz0002072

Windrim, L., Bryson, M., McLean, M., Randle, J., & Stone, C. (2019). Automated Mapping of Woody Debris over Harvested Forest Plantations Using UAVs, High-Resolution Imagery, and Machine Learning. *Remote Sensing*, *11*(6), 733. https://doi.org/10.3390/rs11060733