

Article

MLS-CAPS: Optimising Path Spacing for Mobile Laser Scanning of Vegetation Structure via Completeness Analysis

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Highlights

What are the main findings?

- MLS-CAPS converts a dense pilot scan into site- and metric-specific path spacing recommendations via empirical completeness decay functions.
- Completeness decayed at different rates across structural metrics, with the same path spacing providing acceptable accuracy for some metrics (e.g., DTM) while producing large errors in others (e.g., CHM).

What are the implications of the main findings?

- No single path spacing is universally optimal, so survey planning must account for both local vegetation structure and the structural metrics of interest.
- MLS-CAPS allows survey design to be based on site-specific evidence rather than trial-and-error.

Abstract

This study presents a data-driven approach, MLS-CAPS (mobile laser scanning completeness analysis for path spacing), for defining optimal path spacing (walking path) for backpack or handheld MLS surveys in ecological applications. By using an initial high-density pilot scan of the site, captured with the same MLS system intended for subsequent full surveys, MLS-CAPS quantifies how voxel occupancy completeness, digital terrain model accuracy, and canopy height model accuracy vary with lateral distance from individual walking trajectories. This provides an objective basis for translating local vegetation structure into path spacing recommendations for subsequent MLS surveys. Case study results showed that structural complexity strongly influences the rate of decay, with denser and more complex vegetation requiring closer path spacing to maintain data completeness. While this meets expectations, what has previously been lacking is a way to quantify it in a manner that directly supports data acquisition decision making. MLS-CAPS, provided as a Python tool, allows users to define thresholds aligned with their metrics of interest, recognising that no single spacing is universally sufficient across all structural attributes. The framework therefore enables MLS operators to plan surveys that balance efficiency with accuracy, while maintaining transparency in the trade-offs between path spacing and completeness. By formalising what has previously been a trial-and-error process, this method offers a practical tool to support ecological applications of MLS across diverse environments.



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1. Introduction

Vegetation structure, the three-dimensional distribution of plant material in the environment, represents a fundamental component of many ecosystem processes and functions. Habitat characteristics such as the availability of nesting sites, protective refugia, and movement corridors are directly influenced by the arrangement of plant components (stems, branches and foliage) in the environment [1]. Increased heterogeneity in vegetation structure, referred to as structural complexity, supports a wider range of habitat niches within an ecosystem and has been linked to increases in species diversity and ecosystem resilience [2–5]. Accurately measuring and mapping vegetation structure at both local and global scales therefore provides great benefit to ecological research, land management, and conservation efforts. However, traditional field-based methods for quantifying structure are often labour-intensive, time-consuming, and limited in both spatial extent and the range of attributes they can provide [6,7]. Active remote sensing techniques such as laser scanning offer a practical alternative and are seeing increased utilisation in ecological research as a result (e.g., [8–11]).

Mobile laser scanning (MLS) is a modern approach to deploying LiDAR sensors for studying the environment, providing high-density, plot-level point cloud data. MLS integrates LiDAR sensors with inertial measurement units (IMUs) and simultaneous localisation and mapping (SLAM) algorithms, to enable data capture while the scanner is in motion [12,13]. This mobility enables rapid data acquisition and makes MLS particularly effective for surveying densely vegetated or difficult-to-access environments. Recent use of MLS in ecological studies include linking vegetation structural characteristics to species presence [14–17] and monitoring forest rehabilitation work [18].

A key challenge impacting the utilisation of MLS is feature occlusion, i.e., the obstruction of laser returns by objects such as leaves and branches, resulting in shadowed areas with missing data [19]. Occlusion is particularly problematic in areas with dense or complex vegetation, where the increase in volume, biomass and diversity of vegetation arrangement increases the likelihood of laser pulses being obstructed [20,21]. This results in an incomplete reconstruction of the environment, which has been shown to affect the accuracy of both tree-level and plot-level structural attributes [22–25]. Understanding and managing occlusion is therefore important for obtaining reliable MLS-derived measures of vegetation structure.

Much of the research into how occlusion can be mitigated has been completed within the context of static terrestrial laser scanning (TLS). In this case, the most effective approach is to capture multiple discrete scans from different locations and align them into a single point cloud [26]. While effective for TLS, applying this logic to MLS is difficult due to the shift from static to mobile data capture. In TLS, occlusion remains fixed unless another scan location is introduced, while in MLS, new perspectives are acquired continuously as the sensor moves through the environment. This difference means that data completeness is dependent on both the geometry of the acquisition trajectory and the accuracy of the SLAM-based trajectory reconstruction, rather than the placement of static surveys. By adjusting the scanning trajectory, MLS operators can increase the range of perspectives achieved by the sensor, effectively “seeing around” obstacles and reducing data gaps [24,27]. One of the most important attributes that operators can control is the lateral distance between successive trajectory passes, hereafter referred to as path spacing. In densely vegetated landscapes, path spacing can be reduced to ensure that occlusion by vegetation close to the sensor does not result in data gaps between passes [28]. In contrast, wider spacing can be used where vegetation presence is sparse, to avoid unnecessarily long surveys and redundant data capture.

Despite the fundamental differences between MLS and TLS data capture, research investigating occlusion specifically in MLS point cloud data is still limited. As a result, MLS survey design remains a trial-and-error exercise rather than a data-driven, repeatable and informed process. As far as we are aware, there are no methods available to calculate the optimal spacing between trajectory passes that is tailored to local vegetation structure.

In this study, we address this knowledge gap by introducing the first data-driven method to derive optimal site-specific MLS path spacing directly from local vegetation structure. Our contribution is a workflow that uses a single, high-density pilot scan to quantify how completely vegetation structure is reconstructed as lateral distance from the scanning trajectory increases, and translates that relationship into an objective, site-specific spacing rule for subsequent surveys in the same or similar vegetation communities. Completeness is evaluated through a three-metric framework comprising voxel occupancy and mean differences in digital terrain model (DTM) and canopy height model (CHM) raster data. These metrics provide quantitative assessments to guide sampling strategies and achieve desired levels of completeness. This empirical approach contrasts with virtual simulation models, which predict occlusion within a synthetic forest scene that the user must build in advance [29,30]. Constructing that scene requires detailed structural information that is rarely available for an unsurveyed site, whereas our method derives the completeness and distance relationship directly from a pilot scan of the real vegetation. We demonstrate the method through case studies in three landscapes which vary in structural complexity: a closed forest, an open woodland, and a multi-stemmed sub-alpine woodland. To make the method accessible, we developed an open-source Python (v3.11.13) tool called MLS-CAPS (mobile laser scanning completeness analysis for path spacing), that applies completeness analysis to recommend path spacing for MLS surveys. By supporting reproducible and data-driven survey design, MLS-CAPS provides a resource for ecological and remote sensing research focused on the capture and analysis of vegetation structure.

2. Materials and Methods

2.1. Case Study Sites

Three eucalypt forests in south-eastern Australia were used as case studies to demonstrate and validate MLS-CAPS (Figure 1d). Sites were selected to provide a range of vegetation structural complexities to illustrate the performance of the method in varied landscapes, ranging from simple woody environments to complex dense forest environments.

Site 1 was a tall, closed forest located on Taungurung Country in Strathbogie, Victoria, approximately 130 km north-east of Melbourne (Figure 1a). This site had a densely vegetated understory primarily comprised of *Coprosma quadrifida* and *Pteridium esculentum* up to a height of approximately 4 m. The canopy was composed of a mixture of *Eucalyptus obliqua*, *Eucalyptus viminalis*, and *Eucalyptus radiata* with a height of 35–40 m.

Site 2 was an open woodland located on Woiworung Country in Warrandyte, Victoria, approximately 24 km north-east of Melbourne (Figure 1b). Understory vegetation at this site was sparse to non-existent, with isolated individuals of *Exocarpos cupressiformis* and *Kunzea ericoides* up to approximately 2 m. The canopy was composed of *Eucalyptus obliqua* ranging from 14 to 16 m in height.

Site 3 was a multi-stemmed (mallee) sub-alpine woodland located on Woiworung Country on the Mount Baw Baw plateau, Victoria, approximately 1.5 km east of the summit (Figure 1c). Understory vegetation, composed of *Leucopogon hookeri*, *Wittsteinia vacciniacea*, and *Polystichum proliferum*, formed a dense continuous layer between the ground and a

height of approximately 1.5 m. The upper canopy, approximately 18 m tall, was composed entirely of *Eucalyptus pauciflora*.

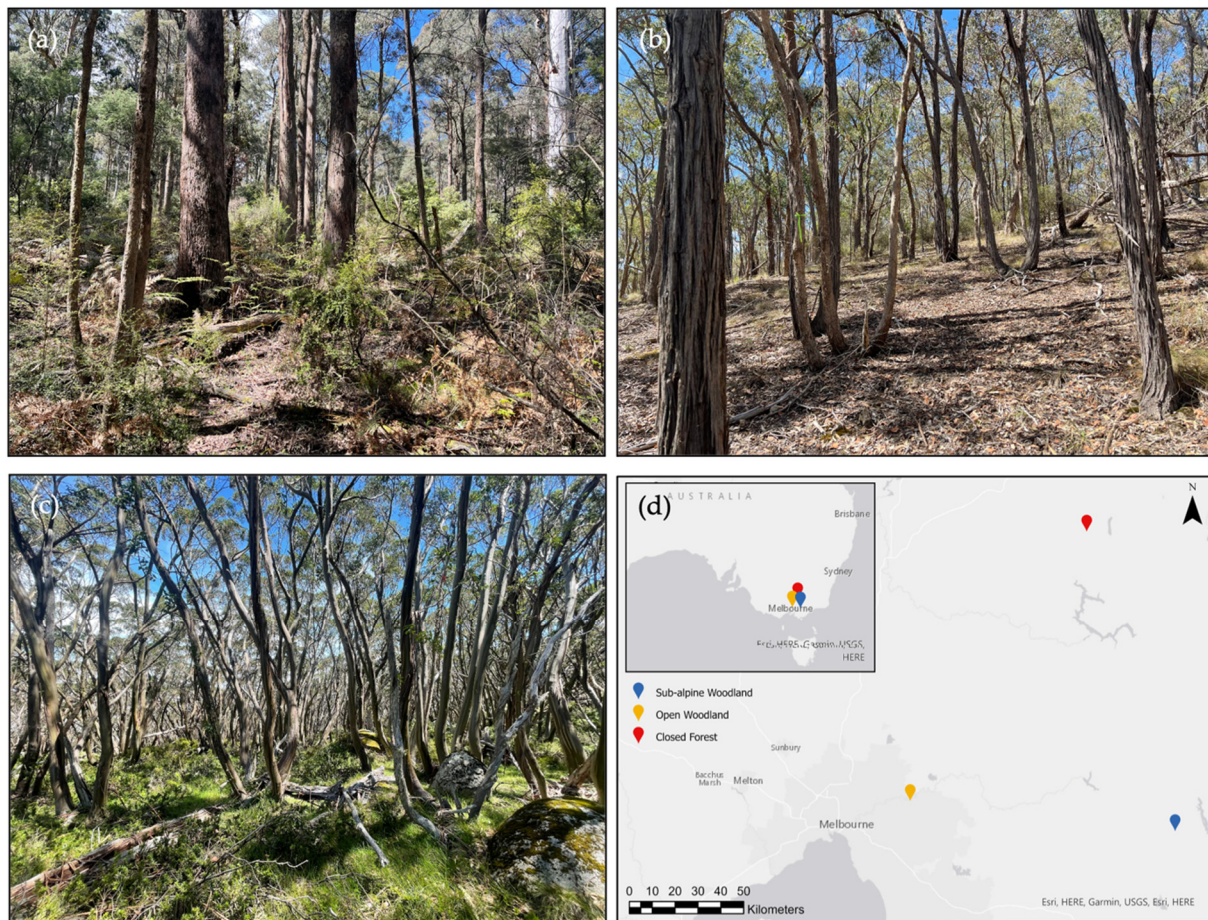


Figure 1. Photos captured from the closed forest (a), open woodland (b), and sub-alpine woodland (c) study sites illustrating their structural characteristics. (d) Map indicating the location of each study site.

2.2. Mobile Laser Scanning Data Acquisition and Pre-Processing

The MLS data utilised in this study were captured between March and May 2024. All point cloud data were acquired using the Hovermap MLS developed by Emesent (Emesent Pty Ltd., Milton, QLD, Australia). The Hovermap MLS uses a time-of-flight VLP-16 Lite LiDAR sensor with a vertical and horizontal beam divergence of 1.5 mrad and 3.0 mrad respectively; a maximum operating range of 100 m; and an absolute accuracy of ± 30 mm.

Point cloud data capture was conducted in $35\text{ m} \times 35\text{ m}$ (1225 m^2) study plots established at each case study site. For each plot, a total path length of 300 m was used, with the operator moving at a walking speed of approximately 1 m s^{-1} . Study plots were surveyed using the gridded acquisition path described in [28], as this configuration was found to provide an even spatial distribution of sampling across the plot (Figure 2a), therefore minimising the risk of undersampling which could bias the completeness analysis. The design also provides many opportunities for SLAM loop closure to occur, both through direct path crossovers where the trajectory intersects itself and through overlapping coverage areas where previously surveyed regions are re-scanned. For SLAM-based MLS systems like the Hovermap, loop closure can occur whenever the sensor re-observes previously captured features [31] rather than just the survey endpoint [32]. All surveys were completed by the

same operator, with the MLS in backpack configuration. When deployed in this manner, the sensor is oriented vertically and positioned approximately 2 m above the ground.

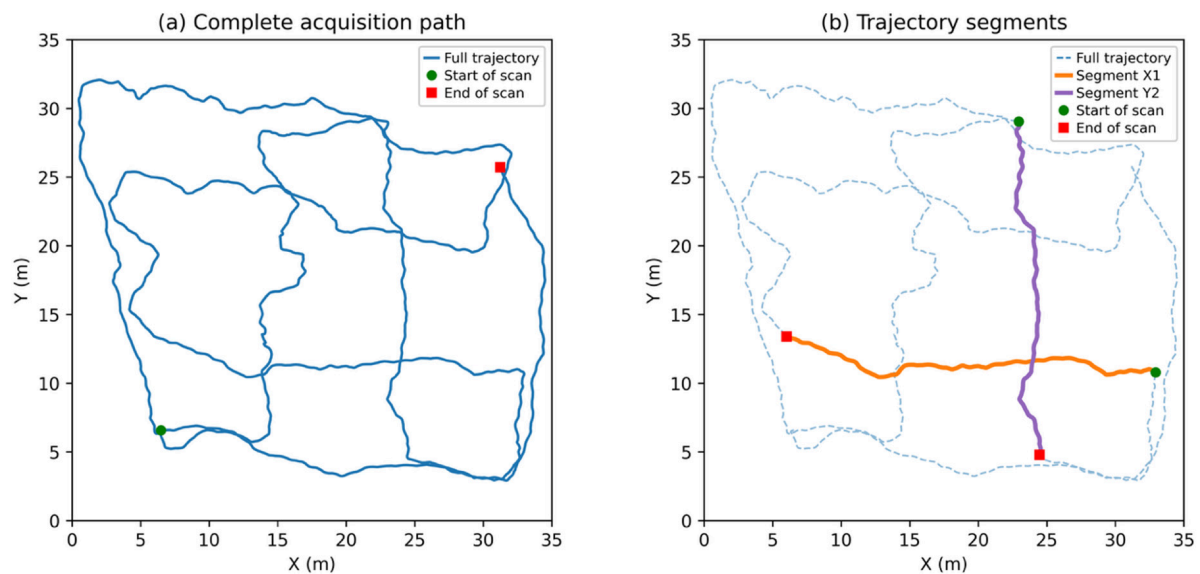


Figure 2. Example acquisition path and trajectory segment. (a) Gridded acquisition path used for MLS data capture within each 35 m × 35 m study plot. (b) Two trajectory segments, X1 running along the x axis and Y2 running along the y axis, representing the subset of points captured along individual straight-line subsets of the overall acquisition path.

Point cloud data were processed from raw scanning data into .laz files using Emesent’s proprietary ‘Aura’ processing software (Emesent Pty Ltd., Milton, QLD, Australia) using default settings (version 1.4). Aura exports a companion trajectory file in .xyz format containing the SLAM-based position and orientation of the sensor during data capture. GPS time stamps are also included as scalar fields for each return in the .laz file and each position in the .xyz file. Point clouds were manually clipped to the plot extent via the segment tool in CloudCompare v2.12.3 using the position of reflective targets deployed at the plot corners prior to data capture.

2.3. Defining Completeness

To determine the distances required between individual passes of an MLS survey, the decay in information captured by the sensor perpendicular to the acquisition path can be quantified. This can be achieved by segmenting each point cloud dataset into individual subsets and then comparing these subsets to the original point cloud data. From here on, these subsets are referred to as “trajectory segments”, as they correspond to the points captured while the MLS operator walked along each internal straight-line transect of the gridded acquisition paths (Figure 2b).

We use the term “completeness” to describe the proportion of each study plot that is reconstructed by each trajectory segment relative to the complete point cloud. Low completeness therefore reflects the undersampling of vegetation in the plot. Our intention was not to achieve a perfect reconstruction, but to establish when a trajectory segment has captured enough information for key structural metrics to remain consistent with the reference data.

Section 2.4.4 describes how completeness and decay functions are computed.

2.4. MLS-CAPS Workflow

MLS-CAPS transforms a single, densely sampled pilot scan into a distance-decay curve that indicates how rapidly structural information is lost as distance from the scanning

trajectory increases. The key steps for this process are summarised in Figure 3. First, the user manually delineates each transect using a graphical user interface (GUI) digitiser, allowing corresponding points from the reference point cloud to be exported. Second, each trajectory segment and the reference point cloud are processed through a Point Data Abstraction Library (PDAL) pipeline, which classifies ground returns, normalises point heights to ground level, and exports DTM and CHM rasters. Normalised points are subsequently voxelised to generate a vertical voxel occupancy profile. Third, completeness is quantified by comparing the structural information derived from each segment to the reference data. Finally, a Gaussian function is fitted to the resulting differences in structural attributes as a function of distance from the scanning trajectory, providing a decay function that can be used to guide maximum path spacing for future surveys.

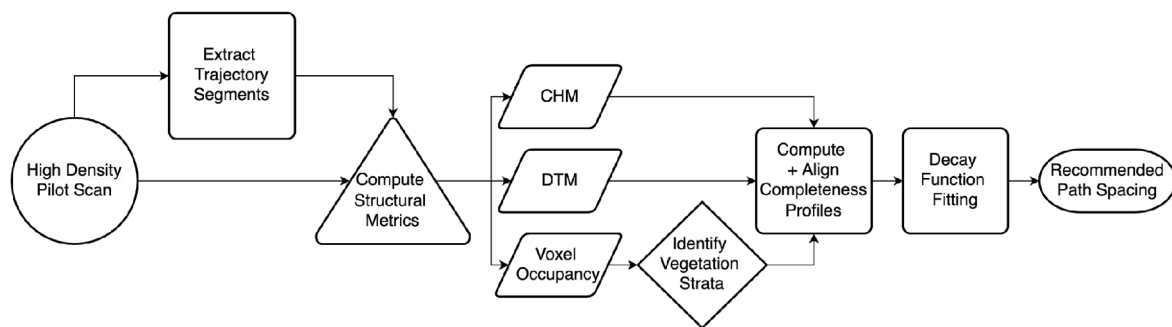


Figure 3. Workflow diagram illustrating the steps used to derive trajectory-specific completeness and translate decay functions into recommended path spacing. A dense pilot scan is first segmented into individual trajectory passes, from which structural metrics (voxel occupancy, DTM, and CHM) are computed. Vegetation strata are identified to enable height-specific completeness assessment. Completeness profiles from each trajectory segment are then computed, aligned, and averaged to produce site-level decay functions. Decay functions are subsequently used to determine the maximum path spacing required to maintain user-defined completeness or error thresholds.

2.4.1. Extraction of Trajectory Segments

When running MLS-CAPS, the user is prompted with an interactive GUI allowing them to visualise the complete trajectory for their pilot scan in planar view. The user then selects the extents of their proposed trajectory segments. Timestamp values from the start and end of each segment are extracted and used to filter the reference point cloud, isolating only those points captured along each section of the trajectory. Trajectory segments are exported as individual point clouds for further processing. Each segment is named according to its order of selection and its orientation within the plot, i.e., X1 for the first segment running east to west within the coordinate system of the pilot scan, and Y2 for the second segment running north to south (Figure 2b). While the operator's scanning trajectory is unlikely to be perfectly straight in practice, each selected segment is treated as a straight-line transect for subsequent analysis so that structural differences can be summarised as a function of lateral distance from the trajectory. If the point cloud data is not already oriented such that the transects run parallel to the X and Y axes of the coordinate system, the user should rotate their dataset before running the workflow. In its current implementation, MLS-CAPS requires these transects to run approximately parallel or orthogonal to the plot axes so that lateral distance can be measured consistently across all segments. It cannot derive lateral decay from diagonal or arbitrarily sinuous trajectories.

2.4.2. Derivation of Structural Metrics

To assess the decay in information captured by the MLS, three key vegetation structural metrics are analysed: voxel occupancy, DTM and CHM. All three metrics are commonly

used for the characterisation of structural information via laser scanning [33] and represent established descriptors relevant to a broad range of downstream metrics and applications. In addition, their combination enables an overview of the completeness achieved across the entire vertical profile, rather than a specific region alone.

The values of each structural metric are first computed for the complete pilot survey to form the reference data for the analysis. Then, the process is repeated using each of the individual trajectory segments. Differences in the values of each metric between the reference and each trajectory segment are computed perpendicular to the direction of the trajectory from which the segment data was derived.

Ground Classification and Height Normalisation

The elevation of each point in SLAM-based MLS point clouds are recorded relative to the local coordinate system of the survey, not their height above the ground. Point heights must therefore be normalised to ground level to analyse the height and distribution of vegetation within each study plot. To estimate ground height, points likely to represent the ground's surface are classified using the cloth simulation filter (CSF) in PDAL. The CSF simulates a virtual cloth mesh laid over an inverted point cloud, classifying points as ground via their proximity to the mesh [34]. A cloth resolution of 0.5 m, a rigidity of 1, and the default slope adjustment were used. The rigidity parameter controls how flexible the simulated cloth is, with higher values allowing it to stretch across undulations in the ground's surface and lower values allowing it to drape further into depressions.

DTM and CHM Rasters

DTM and CHM rasters were generated in PDAL at a 0.5 m resolution. For the DTM, only points classified as ground in the CSF stage (Ground Classification and Height Normalisation Section) are used. DTM cell values are interpolated with inverse-distance weighting [35] using the default 6 m search radius. Cell values are subtracted from the heights of all non-ground-classified points to normalise their elevation to ground level. CHM rasters are then computed using the 98th percentile of non-ground-classified point heights in each 0.5 m cell to reduce the effects of noise on the results. For each trajectory segment, the CHM is derived using that segment's own DTM. Any ground-height error from a single pass is therefore carried into the CHM decay functions, so that the recommended path spacing reflects what is required to keep canopy height error below the user-defined threshold.

Voxel Occupancy Profiles

Reference and trajectory segment point cloud datasets are translated to equally sized voxel grids with a resolution of 0.1 m. This resolution has been identified as suitable for the characterisation of forest canopy [36] and understory vegetation structure [37] and represented a good balance between leaf size in both regions of our study plots, as recommended by [36]. In addition, this resolution matches the resolving scale of the VLP-16 sensor onboard the Hovermap, whose laser footprint remains close to the 0.1 m voxel size at the 35 m maximum range of our case study plots [38,39]. Each voxel is classified as either occupied if it contains at least one point, or unoccupied if it does not. Processing is completed using a combination of Laspy (2.5.4) for data input and Numpy (1.26.4) for array operations and voxel binning. It should be noted that voxel resolution is a user-configurable variable in the toolbox to allow users to define a value suitable for their site and/or sensor characteristics.

2.4.3. Deriving Strata Layers

Occlusion is a significant contributor to the decay in information captured with laser scanning. In natural landscapes, this is primarily driven by the density and characteristics

of the vegetation itself and can therefore vary greatly with height [28]. Collapsing the entire vertical profile into a single decay curve would not allow height-specific trends to be observed. Decay curves were therefore reported across two dominant strata layers (canopy and understory), in addition to the gap between these layers. To determine the width of the strata at each site, a modified version of the layer-finding approach in [40] was utilised. In our case, a height-frequency distribution of the fraction of occupied voxels per layer was used as an analogue to the distribution of biomass. Inflection points where the second derivative changed sign were used to identify layer boundaries, with a positive to negative change indicating a layer top and the reverse indicating the layer bottom. An example of the height-frequency distributions and the resulting layer boundaries for all study sites is shown in Appendix A, Figure A1.

2.4.4. Computing Completeness and Decay Functions

For each trajectory segment, completeness values are converted into a profile of completeness by lateral distance from the scanner. Due to differences in the data formats of the candidate metrics, completeness is quantified using one of two methods. For the DTM and CHM data, signed difference rasters are computed for each of the trajectory segments by subtracting the reference raster from the trajectory segment raster. Elevation values are then averaged within 0.5 m slices parallel to the walking path (1).

$$\Delta_k = \frac{1}{n_k} \sum_{(i,j) \in k} (z_{i,j}^{seg} - z_{i,j}^{ref}) \quad (1)$$

where Δ_k is the mean signed difference for slice k , n_k is the number of raster cells in that slice, $z_{i,j}^{seg}$ is the elevation value of cell (i, j) in slice k from the trajectory segment raster, and $z_{i,j}^{ref}$ is the corresponding elevation value from the reference raster.

For the voxel occupancy data, decay curves were only computed within the height layer extents identified in Section 2.4.3. Each grid is collapsed into 0.1 m wide slices parallel to the walking path. The proportion of reference voxels not captured by the trajectory segment, computed as the reference count minus the segment count, normalised to the reference data, is then computed for each slice (2). The normalised difference is then utilised to ensure that apparent agreement is not inflated in sparsely vegetated regions.

$$normalised\ difference = \frac{N_{ref} - N_{seg}}{N_{ref}} \quad (2)$$

where N_{ref} is the number of occupied voxels in the slice of the reference point cloud and N_{seg} is the corresponding count from the trajectory segment.

The origin of each profile ($x = 0$) is set to the median coordinate of its corresponding trajectory segment's path, measured along the axis perpendicular to its direction of travel within the plot. This step is required to align the profiles of each trajectory, despite their different locations and orientations within the plot, assuming that the proposed grid-style trajectory is used (i.e., Figure 2a). The aligned profiles from all of the trajectory segments are then averaged to provide a site-level decay curve for each of the target metrics. Gaussian functions are fitted to the average curve to provide a continuous model from which the distance (x) where completeness drops below a user-defined threshold (y) can be identified.

2.4.5. Translating Decay Functions to Path Spacing

To translate the decay functions into a recommended path spacing, the user first needs to define a target error or completeness threshold. The decay curves can then be used to determine the distance from a trajectory at which that threshold will be met. The

recommended path spacing is therefore twice this distance, ensuring that the threshold value is only met at the midpoint between two adjacent parallel trajectories (Figure 4). For example, if a DTM error of 0.25 m is deemed acceptable, and the decay function indicates that this will occur at 5 m from the scanning trajectory, then later trajectories should be positioned within 10 m of the first. This spacing ensures that the DTM error remains at or below the specified threshold. In effect, this distance defines a coverage criterion. Provided every trajectory lies within 10 m of another, the threshold is maintained throughout, irrespective of the overall path configuration. Because decay is analysed on both sides of the trajectory (left and right of the path), the distance used for path spacing is reported as the mean of the absolute distances from either side.

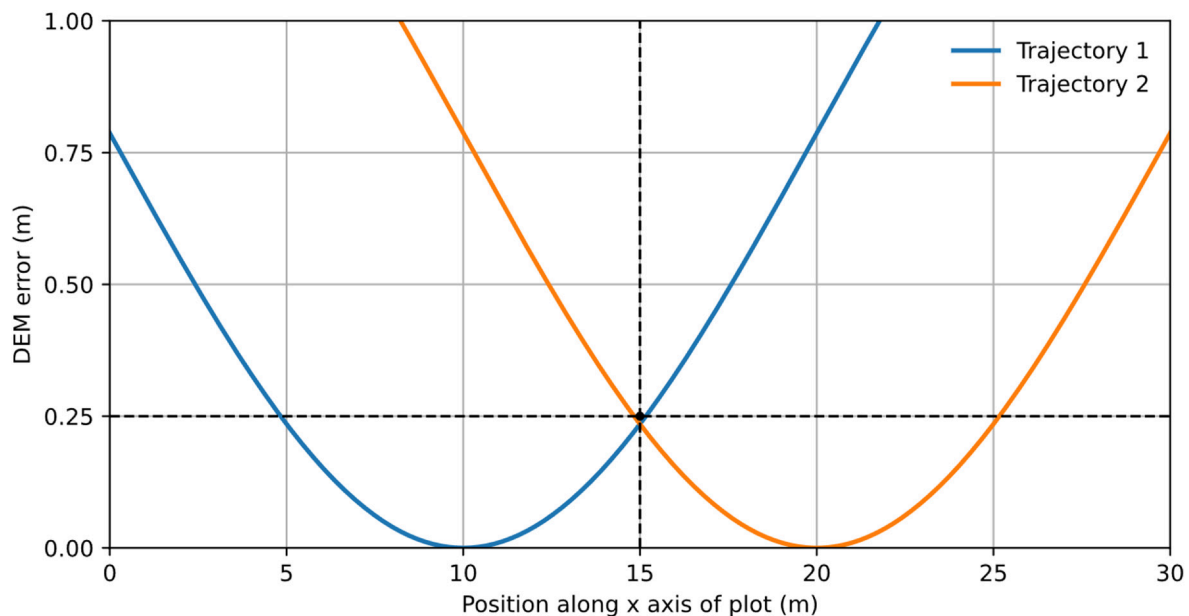


Figure 4. Illustration of how decay functions translate the recommended path spacing. The Gaussian curves represent DTM error as a function of distance from two adjacent MLS trajectory segments. Each curve reaches the target threshold (0.25 m; horizontal dashed line) at 5 m from its respective trajectory (vertical dashed line). Placing the trajectories 10 m apart ensures that the midpoint between them coincides with the threshold so that DTM error remains at or below 0.25 m across the entire interval.

3. Results

3.1. Decay in Voxel Occupancy Completeness

Figure 5 illustrates the decay in voxel occupancy count completeness between each point cloud segment and the corresponding reference point cloud as a function of distance from the scanning trajectory. The site-level average completeness curves and their associated Gaussian decay functions are shown in Figure 6. Completeness values are presented for three vertical height layers, reflecting the vegetation strata within each landscape. Table 1 contains the Gaussian fit parameters and associated goodness-of-fit statistics for the voxel occupancy decay functions, in addition to the maximum distances from a trajectory's position at which the specified completeness levels were maintained. Across all sites, voxel occupancy completeness showed a negative trend with increasing distance from the trajectory. The most significant reductions in completeness consistently occurred in the understory. By 10 m from the trajectory, completeness in the understory had dropped to approximately 20% in the closed forest and 10% in the sub-alpine woodland, while the open woodland maintained higher completeness at approximately 40%. Beyond 10 m from the trajectory, all sites showed a decreasing rate of decay in completeness. Importantly,

completeness along the trajectory position itself was rarely higher than 80%, with the highest completeness tending to occur in the lower strata layers. Gaussian decay functions for each site and stratum showed a high goodness of fit in all cases, indicating a consistent rate of decay between the individual trajectory segments, regardless of their orientation in the plot (Table 1).

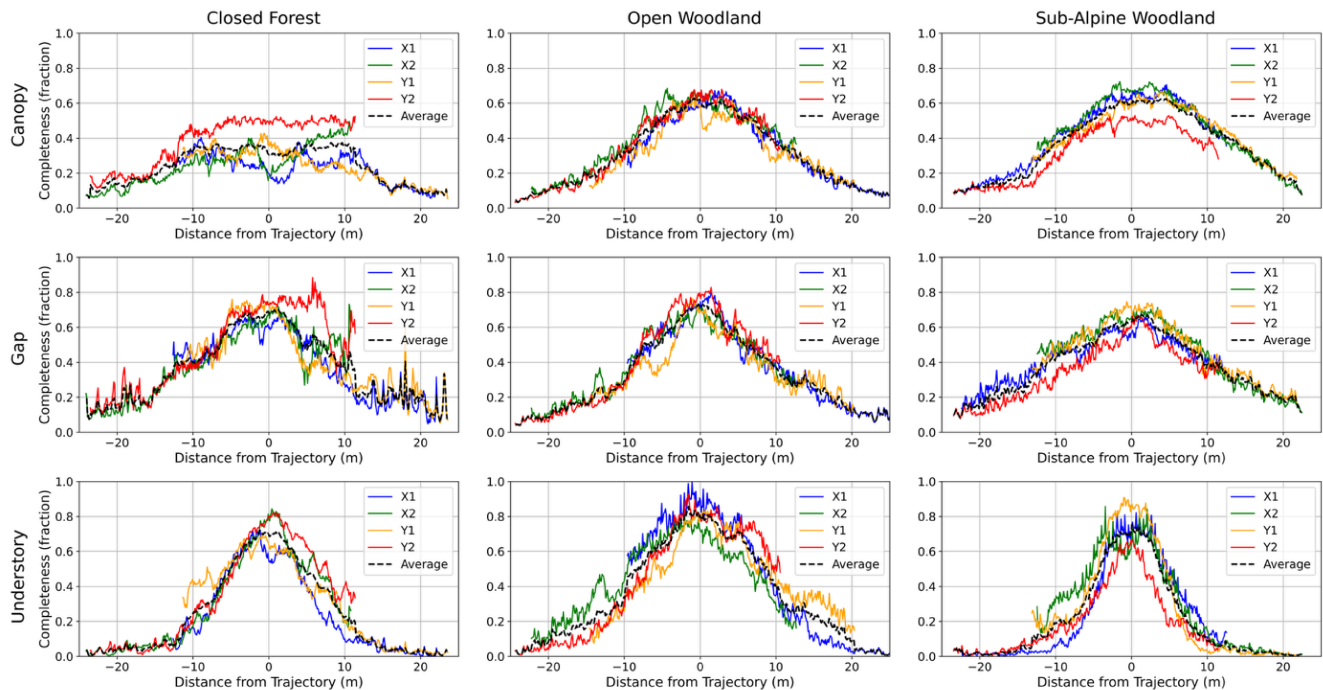


Figure 5. Normalised differences between the occupied voxel count of each trajectory segment and respective reference point clouds. X1 and X2 represent trajectory segments oriented along the x axis, whereas Y1 and Y2 are oriented along the y axis. Negative and positive distance values represent positions to the left and right of the walking trajectory, respectively.

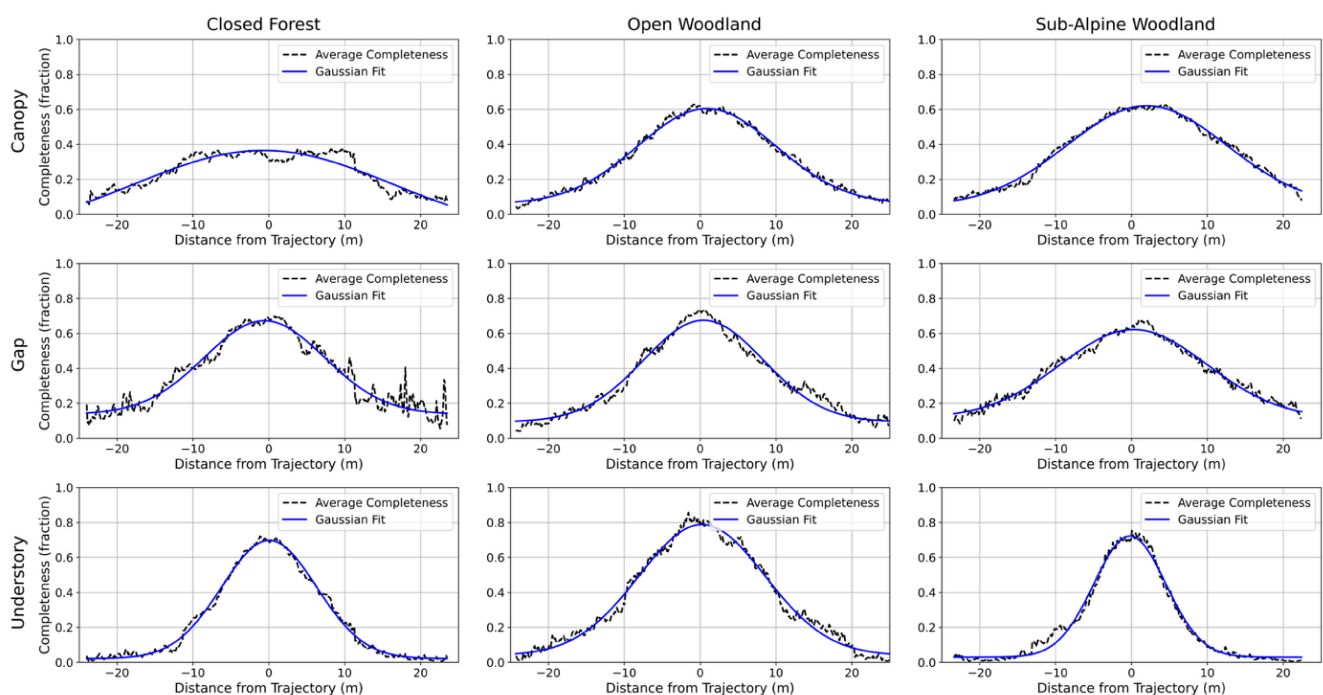


Figure 6. Average normalised difference in occupied voxel counts for all trajectory segments, and Gaussian function fit to distribution.

Table 1. Gaussian fit parameters and goodness-of-fit values (R^2 and RMSE) for voxel-occupancy-normalised differences between trajectory segments and the reference point cloud. For each site and vegetation stratum, the distance (m) at which completeness reaches thresholds between 0% and 100% are reported at 10% intervals. In the decay functions, x is the lateral distance from the scanning trajectory (m) and y is the normalised difference in the voxel occupancy count between a trajectory segment and the reference point cloud.

					Distance (m) Required to Meet Occupancy Completeness Thresholds											
Site	Strata Layer	Decay Function	R ²	RMSE	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%		
Closed Forest	Canopy	$y = 0.4932 \times \exp\left(-\frac{(x+0.7119)^2}{586.94}\right) - 0.1280$	0.890	0.034	21.28	15.47	9.12	-	-	-	-	-	-	-		
	Gap	$y = 0.5350 \times \exp\left(-\frac{(x+0.5845)^2}{125.83}\right) + 0.0460$	0.947	0.044	-	16.45	12.25	9.47	7.00	4.29	-	-	-	-		
	Understory	$y = 0.6758 \times \exp\left(-\frac{(x-0.0404)^2}{78.015}\right) + 0.0217$	0.889	0.034	12.97	10.20	8.32	6.73	5.19	3.49	-	-	-	-		
Open Woodland	Canopy	$y = 0.5457 \times \exp\left(-\frac{(x-0.8791)^2}{165.96}\right) + 0.0589$	0.992	0.017	20.72	14.98	11.64	8.83	5.94	1.19	-	-	-	-		
	Gap	$y = 0.5817 \times \exp\left(-\frac{(x-2.0228)^2}{125.63}\right) + 0.0936$	0.973	0.034	23.78	14.61	11.41	8.97	6.71	4.17	-	-	-	-		
	Understory	$y = 0.7491 \times \exp\left(-\frac{(x-0.2480)^2}{138.36}\right) + 0.0394$	0.984	0.033	18.65	14.60	12.09	10.06	8.20	6.33	4.17	-	-	-		
Sub-Alpine Woodland	Canopy	$y = 0.5747 \times \exp\left(-\frac{(x-2.0228)^2}{221.95}\right) + 0.0460$	0.989	0.019	22.91	17.10	13.46	10.37	7.23	2.85	-	-	-	-		
	Gap	$y = 0.5069 \times \exp\left(-\frac{(x-0.2881)^2}{185.96}\right) + 0.1153$	0.978	0.025	-	18.24	13.70	10.36	7.16	2.89	-	-	-	-		
	Understory	$y = 0.6924 \times \exp\left(-\frac{(x-0.2184)^2}{44.79}\right) + 0.0298$	0.988	0.026	10.13	7.93	6.49	5.30	4.16	2.95	1.21	-	-	-		

3.2. Differences in DTM

Figure 7 contains the mean difference values between the DTMs computed via each trajectory segment and those computed from the reference point cloud data. All sites showed an increase in DTM difference as distance from the trajectory increased. However, this increase in difference was substantially larger for the closed forest and sub-alpine woodland sites. Despite this, mean differences along the trajectory remained very low, close to 0 m, in all three sites.

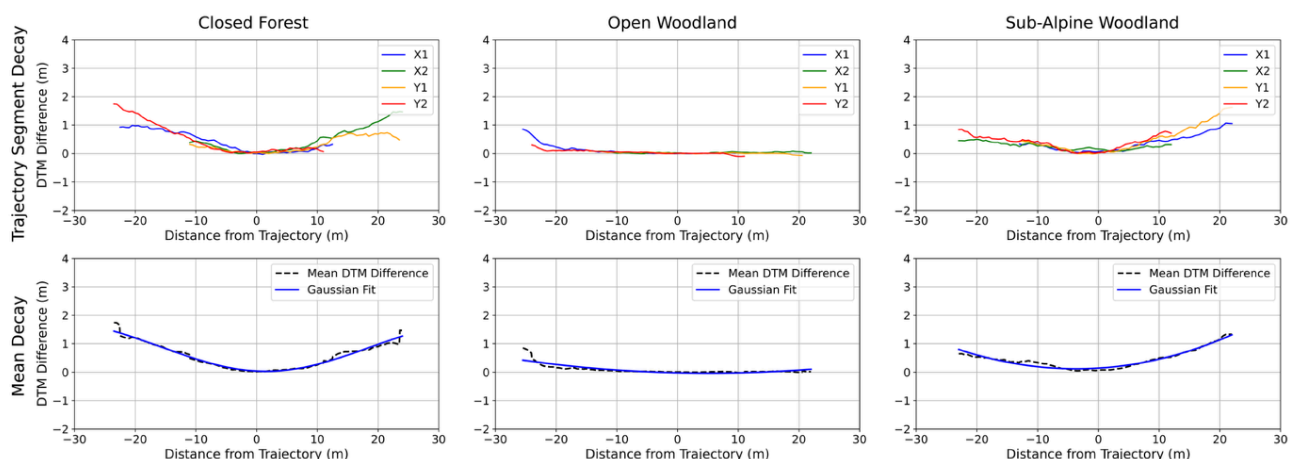


Figure 7. Top row: Differences in DTM raster values between each trajectory segment and reference DTM rasters. Lower row: Average DTM raster difference of all segments and Gaussian functions fit to distribution.

Inverse Gaussian decay functions fitted to the DTM difference data for each site provided a high goodness of fit in all cases, with R^2 values exceeding 0.68 and low RMSE values (Table 2). In the closed forest, differences reached 0.5 m at approximately 12.06 m

from the trajectory and increased to 1 m at 18.80 m. In the open woodland, the increase in differences were more gradual, with 0.5 m of difference only occurring in locations 33.20 m from the trajectory. Surprisingly, the sub-alpine woodland site showed DTM differences more similar to the closed forest than to the open woodland. Despite the lower complexity of its understory vegetation, differences in the sub-alpine woodland reached 0.5 m at 14.52 m from the trajectory and 1 m at 22.05 m. Importantly, no path spacing in this site was sufficient to maintain DTM differences below 0.1 m (Table 2), indicating that, even directly along the trajectory, minor ground surface estimation errors were present.

Table 2. Inverse Gaussian fit parameters and goodness-of-fit values (R^2 and RMSE) for DTM differences between trajectory segments and the reference point cloud. For each threshold, the reported distance represents the mean of the two distances either side of the trajectory at which the decay function meets the specified DTM difference. In the decay functions, x is the lateral distance from the scanning trajectory (m) and y is the DTM difference (m) between a trajectory segment and the reference.

Site	Decay Function	R^2	RMSE	Distance (m) for Δ DTM Thresholds									
				0.1 m	0.2 m	0.3 m	0.4 m	0.5 m	0.6 m	0.7 m	0.8 m	0.9 m	1.0 m
Closed Forest	$y = -2.1554 \times \exp\left(-\frac{(x-1.5432)^2}{590.92}\right) + 2.1850$	0.967	0.079	4.43	6.98	8.90	10.56	12.06	13.48	14.84	16.17	17.48	18.80
Open Woodland	$y = -3957.4874 \times \exp\left(-\frac{(x-5.0988)^2}{8,128,420.87}\right) + 3957.4510$	0.679	0.085	16.74	22.04	26.29	29.94	33.20	36.16	38.89	41.45	43.86	46.14
Sub-Alpine Woodland	$y = -5426.0405 \times \exp\left(-\frac{(x+3.6472)^2}{2,989,359.70}\right) + 5426.1579$	0.954	0.069	-	6.75	10.03	12.48	14.52	16.31	17.92	19.39	20.77	22.05

3.3. Differences in CHM

The horizontal distribution of mean differences between the CHM data generated from each trajectory segment and those of the reference point clouds is presented in Figure 8. At all sites, CHM values showed a negative difference compared to the reference data, including at 0 m from the trajectory, indicating a general underestimation of canopy heights across all trajectory segments.

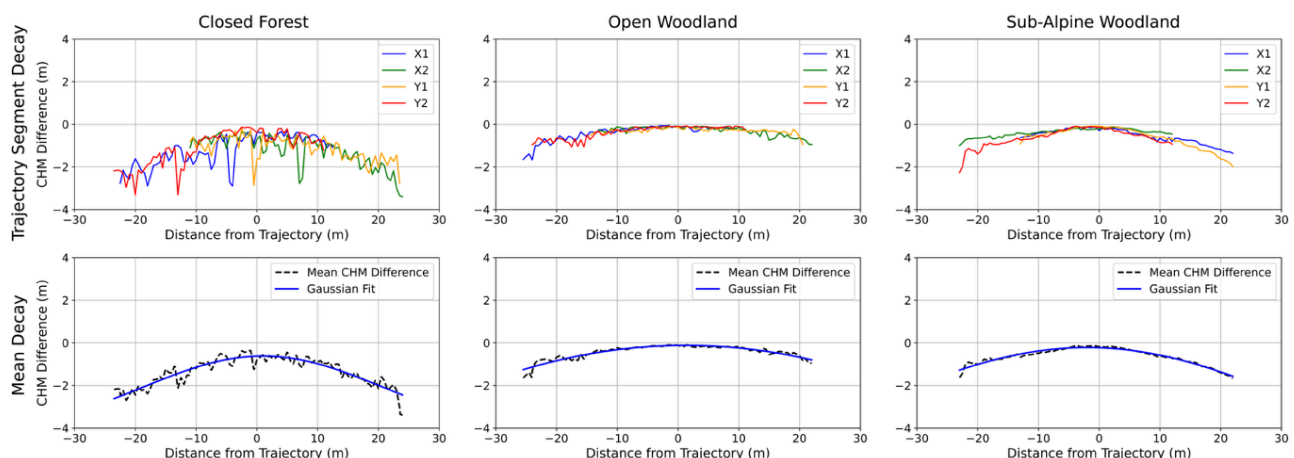


Figure 8. Top row: Differences in CHM raster values between each trajectory segment and reference CHM rasters. Lower row: Average CHM raster difference of all segments and Gaussian functions fit to distribution.

Gaussian decay functions fitted to the CHM difference data provided a high goodness of fit in all cases, with R^2 values exceeding 0.87 (Table 3). However, some CHM error thresholds could not be achieved by bringing adjacent survey paths closer together, specifically

−0.6 m in the closed forest, −0.1 m in the open woodland, and −0.2 m in the sub-alpine woodland. This is because, in each case, underestimation at the trajectory position itself already exceeded the nominated value. In the closed forest, CHM differences reached −1 m at approximately 9.23 m from the trajectory. In the open woodland, differences were more gradual, with −1 m reached at approximately 23.54 m from the trajectory. In the sub-alpine woodland, CHM differences reached −1 m at an intermediate distance of approximately 17.89 m from the trajectory.

Table 3. Gaussian fit parameters and goodness-of-fit values (R^2 and RMSE) for CHM differences between trajectory segments and the reference point cloud. For each threshold, the reported distance represents the mean of the two distances either side of the trajectory at which the decay function meets the specified CHM difference. In the decay functions, x is the lateral distance from the scanning trajectory (m) and y is the CHM difference (m) between a trajectory segment and the reference.

Site	Decay Function	R^2	RMSE	Distance (m) for Δ CHM Thresholds									
				−0.1	−0.2 m	−0.3 m	−0.4 m	−0.5 m	−0.6 m	−0.7 m	−0.8 m	−0.9 m	−1.0 m
Closed Forest	$y = 3.8329 \times \exp\left(-\frac{(x-1.0107)^2}{815.45}\right) - 4.4530$	0.872	0.230	-	-	-	-	-	-	4.15	6.26	7.86	9.23
Open Woodland	$y = 8621.8498 \times \exp\left(-\frac{(x-1.2841)^2}{5,411,788.77}\right) - 8621.9672$	0.903	0.098	-	7.20	10.71	13.32	15.50	17.41	19.12	20.70	22.16	23.54
Sub-Alpine Woodland	$y = 8.1290 \times \exp\left(-\frac{(x+1.9658)^2}{3162.41}\right) - 8.3468$	0.961	0.075	-	-	5.67	8.47	10.57	12.34	13.91	15.33	16.65	17.89

4. Discussion

Occlusion has long been recognised as a fundamental limitation of laser scanning, where the obstruction of laser returns by vegetation and other features causes incomplete reconstructions of the environment [22]. In densely vegetated or structurally complex landscapes, more intensive sampling is needed to overcome these data gaps and maintain completeness [28]. While this problem has been partly addressed in TLS through the co-registration of multiple static scans, utilisation of mobile laser scanning presents a different challenge. In this case, occlusion mitigation depends primarily on the design of the acquisition path, with path spacing and configuration determining the level of completeness that can be achieved [28,41–44].

Here, we address this gap in knowledge with MLS-CAPS, a data-driven framework for defining optimal MLS path spacing. MLS-CAPS is intended to inform the design of a full-scale MLS survey based on a small, purposefully dense pilot scan conducted in a representative area of the target landscape. By mapping the decay in the ability to derive voxel occupancy, DTM and CHM data relative to the pilot survey, we provide an objective method to determine optimal MLS path spacing for vegetation structural assessment. The proposed toolbox formalises sampling decisions that were previously intuitive or ad hoc, providing MLS users with a structured approach to achieve a level of completeness suitable for their analysis.

The use of a data-driven framework is valuable for MLS survey design because the extent and spatial pattern of occlusion can be difficult to reliably anticipate prior to data capture. Structural complexity and vegetation density influence the rate at which structural information is lost with distance from the sensor [22,28], and these effects can differ substantially between landscapes [45,46], making it important to quantify completeness directly rather than assume similar behaviour across environments. By quantifying completeness empirically from a dense pilot scan, MLS-CAPS provides site-specific decay functions that capture the local interaction between vegetation structure and sensor perspective. This enables survey design to be tailored to the specific structural characteristics and

accuracy requirements of the study, rather than relying on assumptions on generalised sampling recommendations.

4.1. Method Demonstration and Case Study Results

Applying the method to our case study sites produced decay functions that showed clear declines in completeness as distance from the scanning trajectory increased. This relationship is consistent with the findings of previous TLS and MLS research documenting the impacts of occlusion on the ability to characterise vegetation structure [22,28]. We found the rate of this decay to vary between the different sites due to the difference in structural complexity between them. For example, the closed forest and sub-alpine woodland showed steep declines in DTM estimates and voxel occupancy completeness in understory strata. This was primarily due to occlusion from dense understory vegetation obscuring the ground's surface and vegetation behind. In contrast, the open woodland site, with little understory vegetation presence, showed a much more gradual decline, as the improved visibility of the ground's surface allowed accurate ground height estimates to be resolved at distances exceeding 20 m from the trajectory.

Canopy height values also showed increasing underestimation with increased distance from the scanning trajectory for two reasons. Firstly, measuring canopy height requires laser returns to penetrate through the bulk of the canopy to reach its upper surface. Under-canopy laser scanning therefore tends to underestimate canopy height, as foliage and branches block the line of sight to the uppermost canopy elements. As distance from the trajectory increases, returns encounter the canopy at more oblique angles, further increasing the probability that they will be intercepted before reaching the upper canopy. This effect is most pronounced in dense forests and is a well-documented limitation of under-canopy laser scanning surveys [46–49]. Secondly, because canopy heights in our workflow were intentionally normalised to the DTMs derived from each trajectory segment, any upward bias in ground surface estimates was directly propagated into the CHM, further reducing height estimates. As a result, the CHM decay functions represent the combined influence of canopy occlusion and DTM error propagation, and the distance thresholds they provide can be interpreted directly as the path spacing required to maintain canopy height estimates within a given tolerance.

The case studies also showed that the distance at which a given accuracy could be achieved varied substantially between metrics within the same site. For example, in the closed forest site, a path spacing of approximately 24 m was sufficient to keep DTM errors within 0.5 m, but that same distance would result in CHM errors of -1.15 m. In the open woodland site, DTM accuracy could be maintained under 0.5 m as far as 33 m from the scanning trajectory; however, this path distance also introduces a CHM error of -1.7 m. The same path spacing can therefore result in very different outcomes depending on the structural metric of interest.

The voxel occupancy results extend this further. In all cases, completeness rarely exceeded $\sim 80\%$, and at a 24 m path spacing in the closed forest, completeness was only $\sim 25\%$ in the canopy layer and $\sim 10\%$ in the understory. It is important to acknowledge, however, that the reliability of the occupancy decay functions, and of the spacing recommendations derived from them, depends on the characteristics of the sensor used. Because the laser footprint widens with distance, voxel size and path spacing must be chosen together. The voxel must be large enough to contain the footprint at the furthest point the vegetation sits from the scanner, or occupancy cannot be recorded accurately [37]. Where a recommended spacing would place vegetation beyond the range that the sensor can support at that voxel size, the user should increase the voxel size or use a tighter spacing.

In some cases, the decay functions returned no valid path spacing for a given error threshold, meaning the specified accuracy cannot be achieved through parallel passes alone. This was most evident for the CHM in the closed forest, where error values less negative than -0.7 m were unattainable (Table 3), and for the DTM in the sub-alpine woodland at the 0.1 m error threshold (Table 2). This is because the decay functions are derived from single passes only, rather than the combined effect of overlapping passes. Closer spacing would likely continue to improve completeness, as overlapping passes increase sampling density and improve the probability of returns reaching otherwise occluded structure, such as the upper canopy. Passes in other orientations, such as perpendicular segments, would have a similar effect. Both are consistent with the well-established relationship between viewing angle diversity and occlusion reduction in laser scanning [22,24,26,27]; however, neither is captured by the single-pass analysis. Further research into how path orientation specifically influences the accuracy of structural metrics derived from MLS would help quantify the relative benefit of perpendicular passes and inform more comprehensive survey design recommendations.

Together, these findings highlight the utility of the method for MLS operators. It can provide a practical means of determining path spacing which can consider both the structural complexity of vegetation in the study area, as well as the metrics which are of interest to the user. Importantly, the method enables users to define the level of error they consider acceptable for their use case, such as the maximum DTM difference or minimum voxel occupancy completeness, and then translate that tolerance directly into a suitable path spacing. MLS-CAPS therefore enables MLS operators to be confident that their sampling configuration will provide a sufficiently representative characterisation of vegetation structure whilst avoiding unnecessary oversampling, which can increase survey effort and place greater reliance on SLAM-processing performance over longer acquisitions.

4.2. Use of MLS Trajectories in Workflow

In principle, completeness decay can be analysed using either real MLS trajectories or simulated paths generated within pre-built virtual laser-scanning environments [30,50,51] or custom simulation frameworks [29,52]. Simulated approaches offer flexibility in sensor configuration [30] and could be used to generate large numbers of synthetic trajectories, enabling an increased sample size available for estimating decay functions. However, they still require the creation of a detailed virtual reconstruction from an initial pilot scan [29] and are computationally intensive, particularly when many trajectories are simulated.

In this study, we used real MLS trajectories, as they offer a more computationally efficient, and therefore, more practical, basis for repeatedly estimating path spacing. They also retain the inherent imperfections of an actual MLS survey, such as the micro and macro movements, rotations, twists, and shifts that occur when the scanner is operated in handheld or backpack configurations. In practical terms, these movements continually alter both the sensor's position and viewing geometry during data capture. With regard to occlusion, this means vegetative elements are seen from a range of perspectives rather than a single fixed line of sight. This allows returns to pass through gaps and around obstructions that a fixed viewpoint may leave obscured, mitigating occlusion in dense vegetation [19,28,46]. At the same time, these movements must be estimated and compensated for by the LiDAR-inertial SLAM algorithm [31]. Because this pose estimation is imperfect, this motion can also introduce positional uncertainty and local registration artefacts into the resulting point cloud [53]. Simulated approaches typically follow prescribed acquisition paths [30], often with simplified assumptions about walking speed and scanner orientation [29], and therefore may not reproduce these operator-induced variations unless they are explicitly modelled. This effect can be seen in [29] who found real MLS datasets

to exhibit lower tree-detection success and systematically higher DBH errors than their simulated pairs.

While real trajectories limit the number of internal segments available for analysis, the consistently high goodness-of-fit values achieved in our case studies suggest that they nevertheless provide a representative basis for deriving decay functions. Future work could explore simulated trajectories to test the robustness of the method under alternative sampling configurations, but for the purposes of method development, real-world trajectories offered a practical and realistic foundation for evaluating completeness decay.

4.3. Implementation Guidance

A practical strength of MLS-CAPS is that the structured acquisition design required to derive a decay function via the pilot scan is separate from that needed to apply it. The pilot survey should follow a gridded trajectory with passes running in roughly parallel and perpendicular directions, as used in our case studies (Figure 2). This configuration allows individual trajectory segments to be extracted, aligned to a common origin, and averaged into a site-level decay function (Section 2.4.4). It also delivers an even sampling density and a broader range of sensor perspectives across the plot, which reduce undersampling bias and so provide a more reliable reference for deriving the decay functions [28]. The pilot does not, however, need to follow this grid precisely. Minor deviations from straight, parallel passes are expected in the field, and likely unavoidable in most environments, but have only a limited effect on the resulting functions (see Section 4.4).

When the decay functions are applied, this structured geometry is no longer required. The output of MLS-CAPS is a coverage criterion: a maximum permissible distance between neighbouring passes, beyond which the chosen completeness or error threshold would no longer be satisfied midway between them (Section 2.4.5). Any trajectory geometry is therefore suitable, provided that neighbouring passes are never spaced more widely than this maximum distance and that SLAM requirements are met. In practice, an operator can follow common acquisition path designs such as parallel transects [54], spirals [55], or paths that weave around obstacles [41], provided the spacing constraint is met. We do recommend the use of structured acquisition path designs, as they are easier to plan and apply against a target spacing. However, this is for the sake of convenience rather than a strict requirement. In situations where a landscape forces an irregular path to be applied, operators should compensate by reducing path spacing below the recommended value to ensure that coverage is preserved.

4.4. Limitations

A critical limitation of the MLS-CAPS method is that the validity of the decay functions depends on both the completeness of the reference reconstruction and the extent to which the vegetation structure within the pilot survey plot is representative of the broader area targeted by the subsequent full survey. If structure within the pilot survey deviates substantially from that of the broader survey area where the resulting path spacing will be applied, the resulting decay functions may not adequately capture the occlusion dynamics, leading to sub-optimal path-spacing recommendations. Likewise, if the pilot scan itself is undersampled, i.e., if the trajectories are already too widely spaced, the decay curves will underestimate the true extent of occlusion and provide a misleading optimal path-spacing estimate. In practice, this limitation is best managed by ensuring that the pilot survey is intentionally oversampled, to provide a sufficiently dense baseline against which trajectory segments can be compared. The specific spacing required to achieve this will of course vary with the vegetation structural complexity of the environment and the structural metrics

of interest. As a practical starting point for the pilot survey, we suggest no more than a 10 m path spacing applied through a grid-style acquisition design, whose perpendicular passes help produce the dense reference reconstruction required for the decay analysis. At this path spacing, each pilot survey in our case studies required approximately 8 min to complete. This configuration proved sufficient in our previous work [28], even for the closed forest, the most structurally complex of our case study sites.

A further limitation of the workflow relates to the alignment of trajectory segments within the pilot survey. To compute the final decay function, individual decay curves are translated so that the median coordinate of each trajectory segment aligns with the plot origin. This process can introduce a degree of positional uncertainty where the MLS trajectory is not perfectly straight, as different parts of the path may not coincide exactly with the function's origin. While this effect cannot be entirely avoided where obstacles are present, it did not prevent reliable use of the method in our case studies, whose pilot trajectories were themselves not perfectly straight. The decay functions we obtained were still well described by the fitted models (high R^2 , low RMSE; Tables 1–3). Small departures from a strictly parallel grid are therefore acceptable in practice, though paths should be kept as straight as conditions allow. Importantly, however, this same principle also applies to the choice of acquisition path design. Curved or irregular paths complicate the computation of signed differences for DTM and CHM rasters. This is because decay functions are evaluated in straight slices relative to the trajectory, and curved paths cannot follow these slices precisely. As a result, only part of the path aligns closely with the function's origin, while other sections are offset, reducing accuracy in the near-path region. Although this does not absolutely preclude the use of curved designs, straight-line trajectories simplify both data capture and processing and generally yield more reliable decay profiles. As set out earlier in Section 4.3, it is important to note that this constraint applies only to the pilot survey used to derive the decay functions, not to the operational survey to which the spacing is applied.

5. Conclusions

This study presents MLS-CAPS, a data-driven method for determining optimal MLS path spacing in MLS surveys, and a demonstration of its application using case studies in landscapes which varied in structural complexity. Results show that completeness of MLS surveys declines with distance from the scanning trajectory and that the rate of this decay varies with vegetation structural complexity. By converting these decay relationships into recommended path spacing based on small pilot surveys, MLS-CAPS provides a simple, repeatable way to design full MLS surveys that are tailored to local conditions. While the method requires a sufficiently complete pilot scan to establish the decay functions, it provides a clear basis for making transparent, defensible sampling decisions. Ultimately, the framework moves MLS survey design beyond ad hoc trial-and-error sampling, offering a practical tool for ecological studies that depend on accurate representations of vegetation structure.

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Appendix A

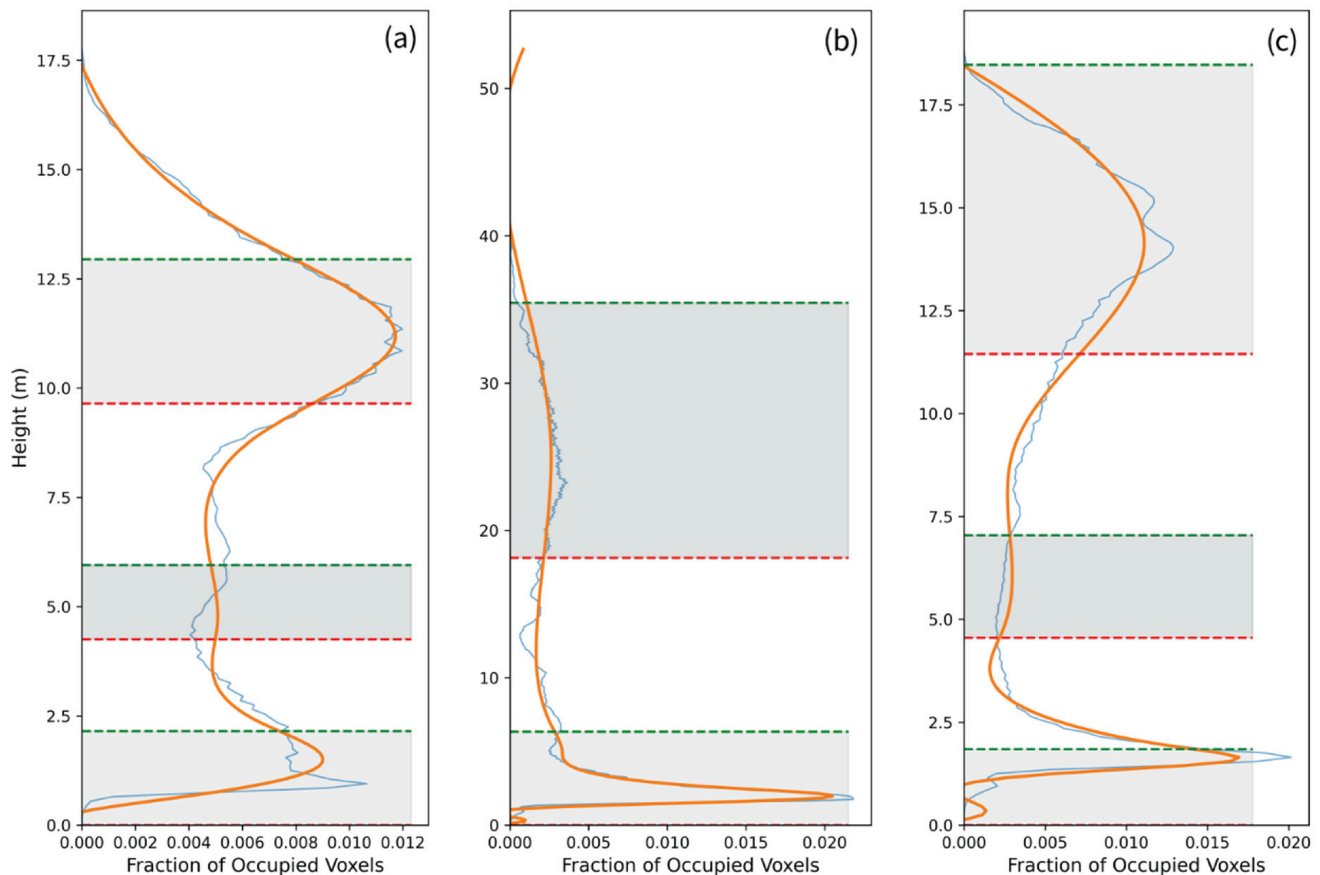


Figure A1. Height–frequency distributions of occupied voxels for the three study sites: (a) open woodland, (b) closed forest, and (c) sub-alpine woodland. The raw profiles (blue) and smoothed curves (orange) are shown for each site. Red and green dashed lines denote the detected understory and canopy layer boundaries, respectively. Shaded regions indicate the vertical extents used for reporting voxel occupancy completeness.

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