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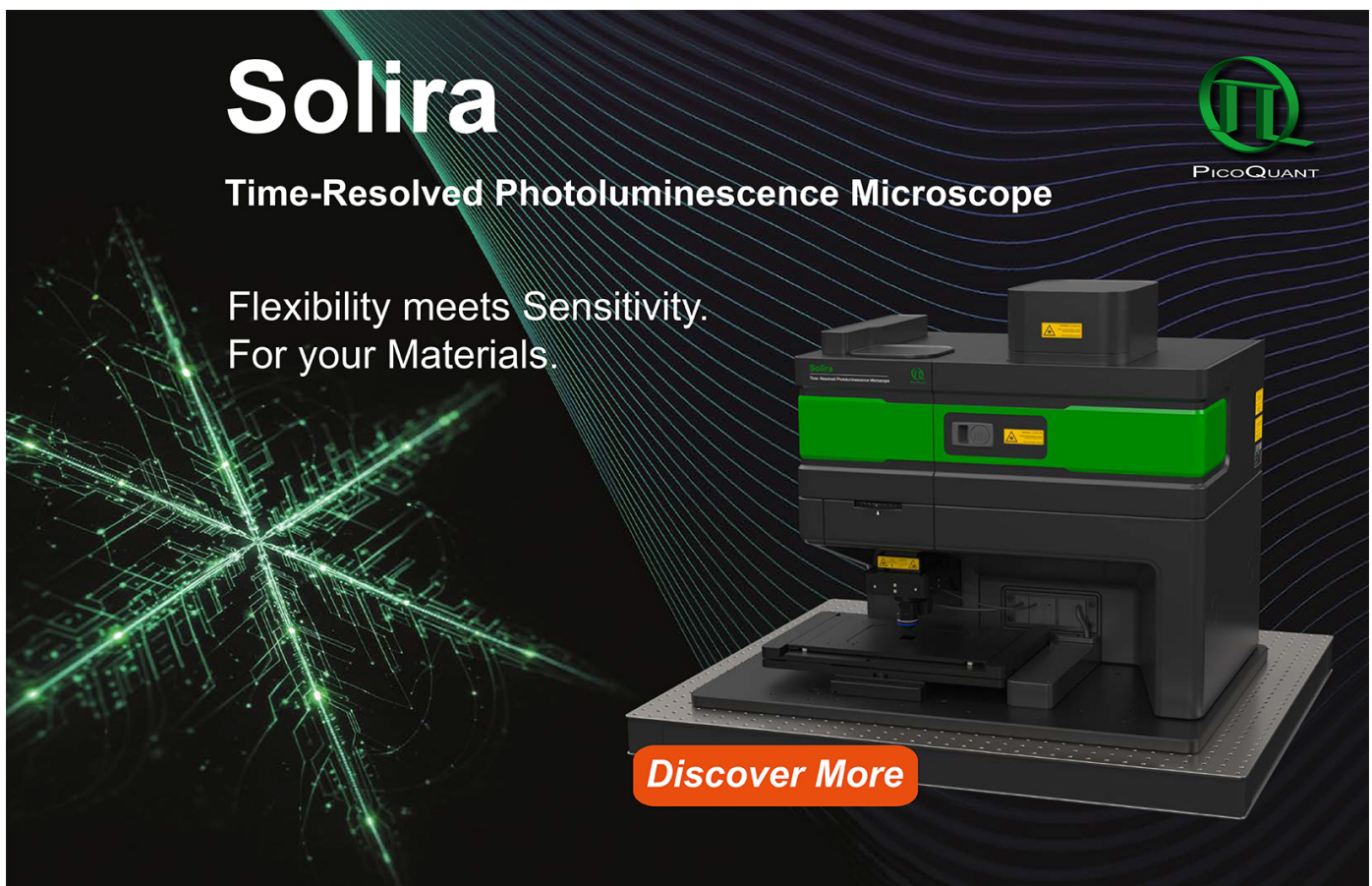
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Laser scanning of high frequency tree movement

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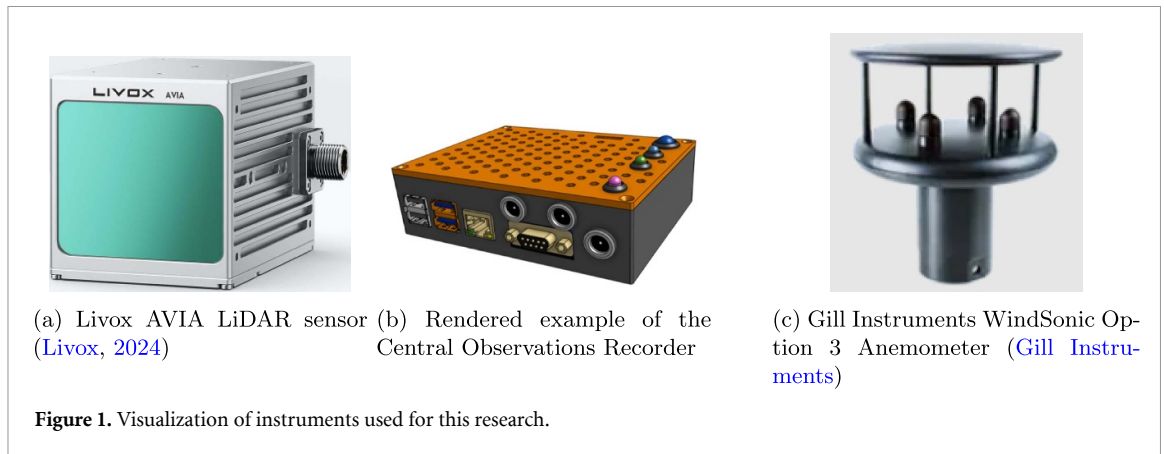
Abstract

Botanical trees demonstrate complicated motion patterns under wind forcing. Studying these motion patterns is relevant as tree parts may become hazardous during storms, and the movement of these trees affects the surrounding wind field, providing, for example, wind shadows. Eventually, wind enforced tree motion may even be incorporated in wind simulation models used to design liveable neighbourhoods. These motion patterns are, however, difficult to assess as *in situ* sensors lack coverage while video imagery lacks full 3D capacity. Recently, fast 3D laser scanners became available. For one such scanner, the Livox Avia, a workflow is presented that allows scanning tree movement at frequencies of up to 2 Hz. The scanner, possibly triggered to scan by a wind-meter, is building up a space-time array, consisting of range measurements at a give time, in a given direction. In a consecutive step, this space-time array is decomposed into single point clouds of a certain duration. The decomposition can be done over different time intervals; point clouds of shorter duration show lower coverage of measurements, but are also less affected by moving tree parts during scanning. After decomposition, motion vector fields between consecutive point clouds representing different time frames are estimated using the existing PlantMove algorithm. Applications of the workflow on different moving tree scenarios demonstrate how this novel measurement strategy is able to reveal complex and detailed spatial and temporal patterns of tree movement, with observed displacements on the order of decimeters, under wind stress. Extending the setup to e.g. three scanners will enable to capture wind induced complex tree movement at branch level, which is essential input for running reliable wind flow simulations at neighbourhood level.

1. Introduction

The remote sensing of dynamic natural environments is a rapidly evolving field, where advancements in sensor technology enable more detailed, cost-effective and efficient data collection of natural and anthropogenic changes (Cheng *et al* 2024). LiDAR (Light Detection and Ranging) sensors have been widely used for various environmental monitoring applications, offering high-resolution 3D point clouds that capture the structure and movement of natural elements (Eitel *et al* 2016, Perks *et al* 2024). Traditionally, LiDAR systems have been used to measure quasi-static or slow varying environments, such as landscape mapping (Shi and Kissling 2025). In recent years, there has been a growing interest in using their capabilities for monitoring dynamic phenomena in, for example, self-driving cars or robotics (Leong and Ahmad 2024).

LiDAR sensors designed for robotics and autonomous systems are relatively small and capable of producing very high point rates per second (Li *et al* 2022). Unlike large terrestrial laser scanners (TLSs), they are cost effective and often capable of scanning continuously rather than frame-by-frame (Zhang *et al* 2014). Their non-repetitive scan patterns, become an advantage when time-resolved sampling is the goal. Such small sensors are typically used in kinetic scanning where the scanner is an integrated part within the moving acquisition platform. Kinetic applications notably include obstacle detection



from a moving rover (Leong and Ahmad 2024), robotic SLAM applications (Sier *et al* 2023) and UAV-LiDAR (Bartmiński *et al* 2023). In this article we are specifically interested in one such application where time-resolved sampling (Geiß endörfer and Holst 2025) is required, namely: capturing and analysing the instantaneous 3D movement of trees in response to wind forcing (Schindler *et al* 2012). Monitoring this dynamic process requires a sensor that can scan at high temporal resolution and maintains accuracy and precision in windy outdoor environments (Zanotto *et al* 2024).

In this work, we explore such an unconventional application of a low-cost LiDAR sensor: using it not as a static scanner, but as a time-resolved 3D motion recorder (Geiß endörfer and Holst 2024). Specifically we consider the Livox AVIA sensor (Vybostok *et al* 2025, see figure 1(a)). The Livox AVIA has a promising design and specifications; a non-repetitive scanning pattern, moderate detection range (up to 300 m) and range precision of 2 cm (Livox 2024), however the real-world practical application and validation of these sensors remains to be further explored (Felix *et al* 2026). This research therefore addresses the challenge of determining whether compact LiDAR sensors can function as reliable tools for monitoring the dynamic movement of trees under wind forcing.

The main contributions of this paper are as follows. First, by segmenting the AVIA's continuous, non-repetitive scan into short temporal frames, we demonstrate that it can effectively function as a three-dimensional 'video' system operating between 1–2 Hz. Second, this approach is applied to measure wind-driven tree motion. We show how this affordable LiDAR sensor combined with a portable computer hub (the Central Observations Recorder or COR, figure 1(b)) can be configured to capture subtle structural dynamics of trees.

2. Related work

2.1. TLS

TLSs have become a standard tool for high-resolution 3D mapping of static and quasi-static environments. Traditional phase-based and time-of-flight TLS instruments are capable of delivering sub-centimetre positional accuracy over ranges of hundreds of metres, making them well suited to tasks such as structural inspection, terrain modelling, and forest inventories (Eitel *et al* 2016). However, their design is optimized for single-epoch or repeat-epoch surveys rather than for continuous, time-resolved monitoring. A complete scan of a moderately complex scene typically requires several minutes, and the instruments themselves are large, heavy, and costly, limiting their deployment in field campaigns that require rapid scanning and setup.

In recent years, a new class of compact LiDAR sensors has emerged from the robotics and autonomous-driving industries (Li *et al* 2022). These sensors sacrifice absolute range precision in for higher point rates, lower cost, and ability to operate continuously. Rotating multi-beam sensors such as the Velodyne HDL-64E have been applied for mobile mapping (Zhang *et al* 2014), while more recent solid-state devices exploit repeated petal-shape (Lissajous) scan patterns to achieve dense spatial coverage over time. This non-repetitive behaviour can be an advantage for time-resolved sampling: successive short temporal frames each capture a slightly different spatial subset of the field of view (FOV), and together they can reconstruct a complete representation of a dynamic scene at frequencies far exceeding those available to traditional TLS over their full FOV (Geiß endörfer and Holst 2024).

The practical consequence is that the gap between slow, accurate TLS and fast but two-dimensional video-based methods can now potentially be bridged by compact LiDAR sensors operated in an unconventional stationary monitoring mode. The present study exploits exactly this gap, applying the Livox AVIA as a stationary 3D motion recorder for vegetation dynamics.

2.2. Livox AVIA

The Livox AVIA is a compact solid-state LiDAR developed by Livox Technology primarily targeting mobile, drone, and autonomous systems applications. Its key feature is a non-repetitive, petal-shaped scan pattern. Unlike conventional rotating scanners, which revisit the same angular directions on every revolution, the AVIA's scan trajectory is non-periodic. Each pass of the beam traces a different path across the FOV, so that spatial coverage accumulates continuously over time rather than in discrete, identical frames (Livox 2024, Geiß endörfer and Holst 2025). According to manufacturer specifications table 1, the sensor reaches complete FOV coverage after approximately 800 ms, operates at point rates of up to 720 000 points per second in triple-return mode, and achieves a distance random error of less than 2 cm (σ) at 20 m range.

The scan quality and detection range specifications have also been tested and validated prior to this research. They were found to be well within the specifications for the scan quality, and somewhat over-estimated for the detection range. In practice, the detection ranges was found to be at least 100 m in bright outside environments.

These specifications make the AVIA attractive for monitoring dynamic vegetation processes, but published independent validations of its real-world performance are limited. Vybostok *et al* (2025) characterized the sensor as part of a low-cost terrestrial scanner prototype for forest monitoring and noted favourable point density characteristics at close range. Felix *et al* (2026) conducted a comparative study of dome-shaped, solid-state, and spinning LiDAR and highlighted sensor-to-sensor variability in coverage and range accuracy that deviates from factory specifications. The present study specifically addresses how these and manufacturer specified characteristics compare and lead to sensor configuration for monitoring of dynamic scenes by providing an characterization of FOV coverage development and spatial point density distribution to determine applicable sensor configuration for tree movement scanning.

2.3. Tree monitoring

Both video (Barbacci *et al* 2014), stereo vision (Busch *et al* 2021) and repeated laser scanning (Wang *et al* 2022, Lindenbergh *et al* 2025) offer possibilities to monitor the effect of wind on individual tree branches. Tree parametrization from point clouds evolved quickly in recent years. Methods were developed to segment individual trees, obtain diameter at breast height (Laino *et al* 2024), and complete tree skeletons, e.g. Du *et al* (2019), from notably laser scanning point clouds. Leaf area index (Wang and Fang 2020), established itself as the main parameter to quantify canopy density. Some studies explicitly involved the effect of wind on tree stem and foliage parameter estimation (Zhao and Barbic 2013, Vaaja *et al* 2016). Aerodynamic roughness (Kent *et al* 2017) is a parameter that directly relates wind to tree drag. Although all these parameters summarizing crown characteristics (Weiser *et al* 2022) are related to wind induced tree movement, they are typically acquired in a static setting.

Laser scanning was used in several studies in recent years to actually monitor tree movement. In Puttonen *et al* (2016), repeated TLS was used to assess overnight branch and foliage motion of birch trees. In Zlinszky *et al* (2017) overnight motion of trees of different species are compared. Notably, a permanent laser scanning station has been constructed in Hyytiälä, Finland, which allows to monitor tree change in 24/7 mode (Campos *et al* 2021). To estimate change between different scans of the same tree or plant, the PlantMove software (Wang *et al* 2022) was developed. PlantMove estimates motion vectors between tree point clouds from different acquisitions. What these approaches have in common, is that they focus on repeated instantaneous acquisitions. Scanning is not continuous, but aims at acquiring several 3D 'snapshots', that are used to assess tree growth or circadian movement (Puttonen *et al* 2016).

Only recently, small and fast laser scanners came available that allow to monitor tree movement in a continuous way. Chau *et al* (2022) describes how a small multi-beam Ouster OS1-64 flash LiDAR sensor is used to scan a tree at 10 Hz. During scanning, the eight considered trees underwent pull-and-release tests, which allowed to extract Fourier spectra of tree vibration. Tree movement was estimated by fitting polynomials to trunks and branches. This approach allowed to study the tree response during two different typhoons. While this approach notably focussed on tree and branch movement as a whole, using the polynomial fit, during extreme conditions, our approach considers heterogenous response of canopy parts during more daily wind conditions.

Table 1. Livox AVIA sensor specifications (Livox 2024).

Category	Specification	Value
Point rate & returns	Single return (First or Strongest)	240,000 points/s
	Dual return	480,000 points/s
	Triple return	720,000 points/s
Field of view (FOV)	Non-repetitive FOV	70.4° (H) × 77.2° (V)
	Non-repetitive mode coverage time	≈ 800 ms
Scan quality	Distance random error (1 σ at 20 m)	<2 cm
	Angular random error (1 σ)	<0.05°
	Beam divergence	0.03° (H), 0.28° (V)
Detection range	100 klx @ 10% reflectivity	190 m
	100 klx @ 20% reflectivity	230 m
	100 klx @ 80% reflectivity	320 m

3. Methodology

To assess the application of the Livox AVIA for wind induced tree motion monitoring, we apply a two step methodology. First, in section 3.1, we assess the scan pattern and related coverage of the Livox AVIA, to derive applicable integration times for the sensor. Second, in section 3.2 we obtain point clouds using these obtained integration time and assess the movement of trees using the PlantMove algorithm. The movement is compared to wind measurements to assess the validity.

3.1. Assessment and configuration of scanning characteristics

The proposed measurement approach converts the AVIA's continuous non-repetitive scan into short temporal frames to obtain time-resolved point cloud sequences. The limits of this frame-by-frame extraction depends on how quickly spatial coverage and point density develop within the FOV. As manufacturer coverage specifications (table 1, Livox 2024) are based on idealized scenarios, an independent test and validation of temporal coverage behaviour and spatial point distribution is first performed.

The assessment is structured into three components: overall FOV coverage percentage, spatial point density distribution within the FOV (evaluated using point density heatmaps), and regionalized FOV coverage analysis. Controlled flat-surface scans at a distance of 2.2 m are used to quantify (i) FOV coverage percentage and scan pattern development over time, and (ii) resulting spatial density non-uniformity across the FOV.

These analyses are intended to derive operational limits and parameter choices to be used for time-segmented dynamic measurements, such as frame duration and preferred FOV region usage. All tests are performed in triple-return mode to maximize point yield for vegetated targets.

3.1.1. FOV coverage percentage

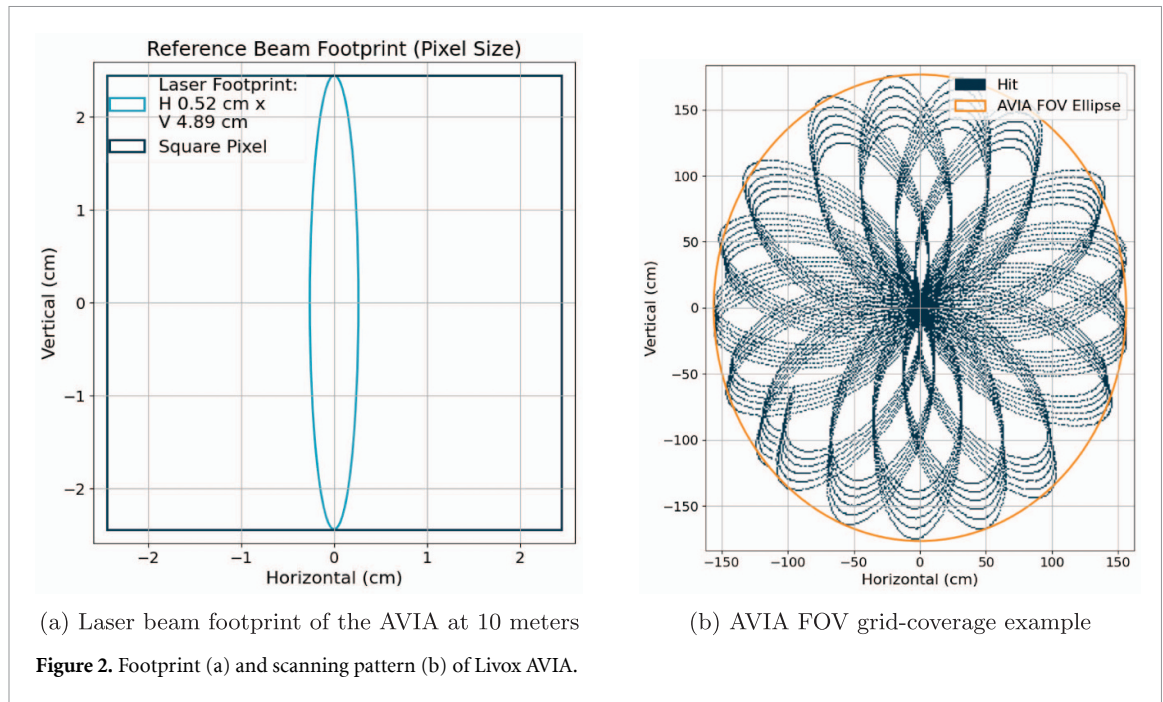
To compute the coverage percentage in the FOV, the FOV is discretized into a grid with square 'pixels' whose side lengths equal the laser beams elliptical footprint, specifically, the largest diameter (based on the semi-major axis) at a given distance. By using the given laser divergence angles it is possible to calculate that, for example, at 10 m the AVIA's beam footprint has a semi-major axis of 2.44 cm and a semi-minor axis of 0.26 cm (figure 2(a)). Using square cells for this grid-occupancy estimation method does overestimate the effective beam width and coverage estimates, but provides a consistent upper-bound metric.

Each return is assigned to a grid cell, and coverage percentage is computed as the fraction of occupied cells as a function of elapsed scan time. A fitted FOV ellipse based on the specified FOV angles is used as the reference boundary. Measured points slightly exceeded this idealized boundary at the edges (figure 2(b)); however, the nominal ellipse is kept for consistent normalization, leading to a small positive bias in reported coverage percentages.

Coverage is computed using both the square and footprint-matched rectangular cells to assess sensitivity to discretization assumptions.

3.1.2. FOV point density heatmap

To analyse the spatial distribution of 'hit' points within the FOV over time, and to assess the uniformity of the point density, heatmaps are created. The FOV coverage ellipse is discretized using the same pixel



grid as in the coverage analysis, and for each pixel the number of returns accumulated during the scan is recorded to be able to see which areas of the FOV obtain the most hits.

The heatmaps are produced for several timestamps between 100 and 5000 ms. These heatmaps are used for further assessment of the spatial variations in point distribution across the FOV and will aid in finding the possible limit in achievable frame rates.

3.1.3. Regional FOV coverage percentages

Because central FOV regions are covered more frequently by the scan pattern, regional coverage develops faster than full-FOV coverage. This property can be exploited to increase effective temporal resolution when the target occupies only a limited angular extent.

Coverage is therefore further analysed per circular sub-regions, defined as fractions of the nominal FOV semi-minor axis (figure 3). For each region size, coverage-versus-time curves are computed using the previous grid-occupancy method. These curves are combined into a parameter selection diagram that relates region size, required coverage threshold, and achievable sampling frequency.

3.2. Tree movement estimation

The unconventional application of the Livox AVIA focuses on assessing how trees move and deform under varying wind conditions. Individual trees are scanned under natural wind conditions using a stationary tripod setup, with the sensor oriented such that the tree crown primarily occupied the central FOV region identified in section 3.1.3. Total scan durations range from 30–60 s, providing sufficient data for temporal analysis.

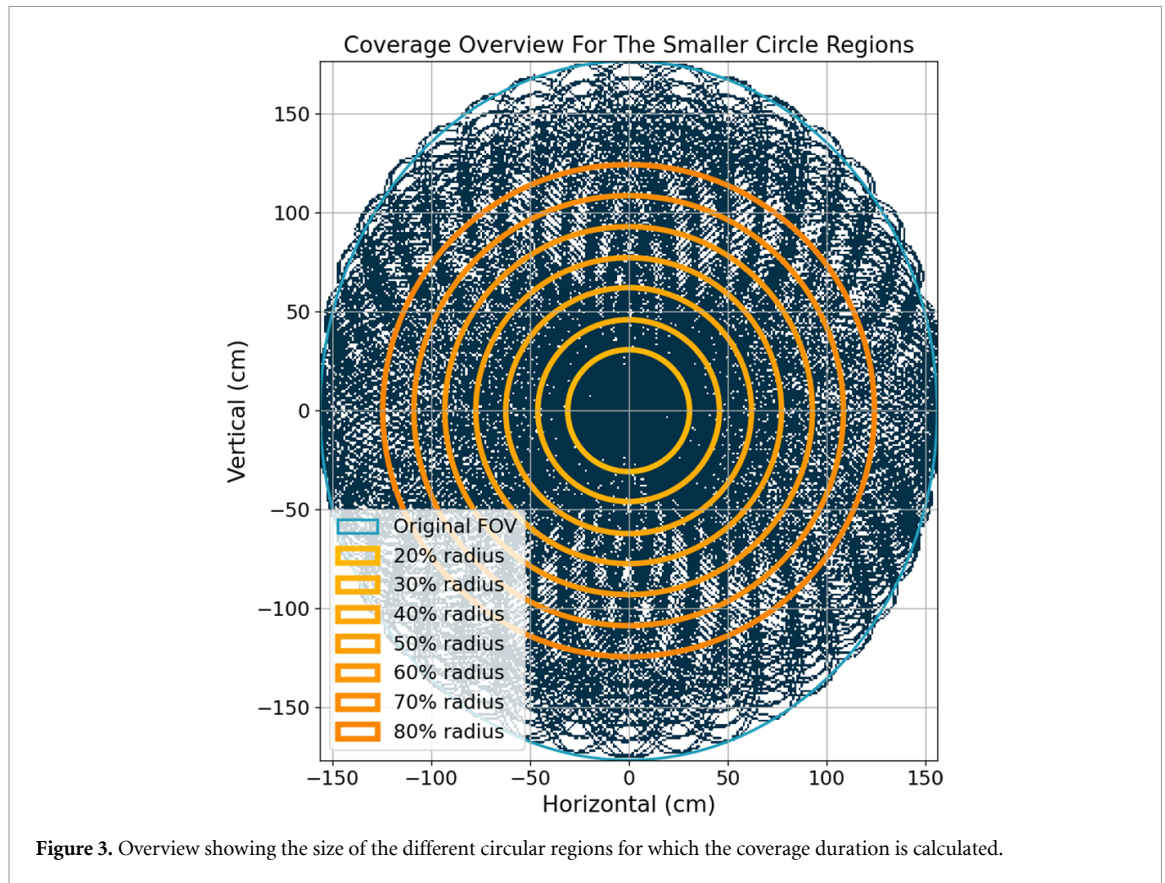
Simultaneous wind measurements are obtained by an ultrasonic anemometer (figure 1(c)) placed near the AVIA, providing an independent reference for wind speed and direction. The wind data supports later correlation analysis with the structural displacements measured by the scanner.

3.2.1. Temporal frame segmentation

Instead of producing a single static point cloud per scan, the continuous AVIA output is divided into consecutive frames, producing a time-resolved sequence of point clouds.

Shorter frames increase temporal resolution and allow detection of rapid branch oscillations, but result in sparser spatial coverage. Longer frames improve structural completeness as they obtain double the amount of points, making it possible to resolve the overall tree shape and volume more reliably. Both regimes are evaluated to demonstrate practical trade-offs and guide temporal parameter selection for dynamic targets of different sizes.

Frames are cropped to isolate the target tree, after which minor geometric alignment is applied where necessary. When the AVIA is tilted during the scan, the resulting point cloud inherits this tilt, causing the extracted tree to deviate from a vertical reference. To ensure consistency across frames, the



data is adjusted so that the trunk is approximately aligned with the vertical axis, allowing for reliable comparison of displacement estimates over time.

3.2.2. Motion estimation from point cloud sequences

Tree branch displacements between consecutive frames are estimated using PlantMove (Wang *et al* 2022), a non-rigid registration method for voxelized point clouds. It operates in a coarse-to-fine framework where correspondences are inferred implicitly through neighbourhood matching, while a regularized deformation model enforces spatially coherent motion. This approach estimates three-dimensional motion vectors for each point, capturing both the overall rigid tree sway and more localized branch deformations.

Within PlantMove, key parameters were set to control the analysis: $\text{de-noise} = 4$, $\text{dsp} = 3$, and $k = 5$ ($k = 10$, a larger voxel size, for bigger trees to speed up the processing). These settings were determined through iterative testing to balance sensitivity to small movements with noise reduction and acceptable processing times.

Two registration strategies are employed:

Consecutive registration, comparing each frame to its immediate predecessor, which captures short-term dynamics and high-frequency motion.

Comparative registration, comparing all frames to a reference frame, which emphasizes cumulative displacement over the scan period.

Resulting displacement vectors are visualized using magnitude-coloured scatter plots and vector (quiver) plots, providing immediate insight into which parts of the tree move most and in which directions. Vertical slice averaging and per-frame histograms summarize height-dependent and frame-wise motion for quantitative interpretation.

3.2.3. Wind-motion correlation

To relate tree motion to environmental forcing and confirm validity of captured movement, mean frame-wise displacement magnitudes are compared with anemometer wind records captured at the same time. Because structural response might lag behind wind gusts, and the anemometer is not placed directly near the tree, a cross-correlation analysis is applied to determine the temporal offset between

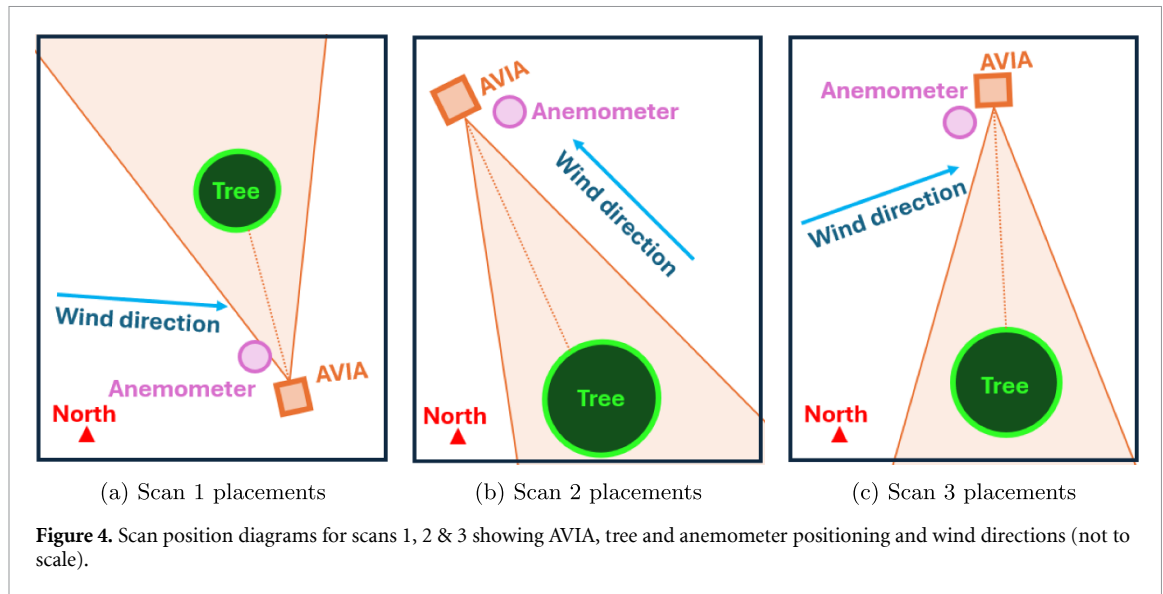


Table 2. Scan statistics as a function of scan duration measured at a distance of 10 m.

Scan duration (ms)	Number of points	Coverage percentage	Points per m^2
50	11 926	13.43	1376
100	23 835	25.09	2753
200	47 664	43.43	5505
300	71 565	56.40	8266
400	95 377	66.01	11 016
500	119 189	73.40	13 766
800	190 647	87.19	22 007
1000	238 553	92.08	27 551
2000	476 973	98.84	55 084
5000	1193 235	99.93	137 773

wind and motion. Signals are then aligned, and both Pearson and Spearman correlation coefficients are computed, to quantify the relationship between wind speed and tree deformation.

The positioning of the tree, AVIA and anemometer varied between scans. To help interpretation of the wind vs movement results, figure 4 illustrates the configuration and main wind directions during scans 1–3.

This combined workflow; continuous scanning, temporal segmentation, movement quantification through PlantMove and wind correlation, demonstrates the AVIA's capability as a 3D motion sensor. It makes it possible to create '3D videos' of tree movement that would be unfeasible to capture with slow and large traditional TLS, or video cameras.

4. Results

4.1. Scanning characteristics and configuration

4.1.1. Scan pattern and temporal resolution

The applied workflow requires splitting the continuous scans into temporal frames. To obtain these frames at a minimal integration time but sufficient coverage, the FOV coverage percentage development over time needs to be known. Coverage analysis shows that the AVIA's non-repetitive scan pattern fills the FOV more slowly and less uniformly than suggested by the nominal 800 ms full-coverage specification.

Table 2 summarizes the scan statistics across different temporal windows using the flat-surface scans discussed in section 3.1. The table includes the total number of points, coverage percentage, and derived point density per unit area as a function of scan duration. At a distance of 2.2 m the point density in the FOV area is estimated to be approximately $8.65 m^2$.

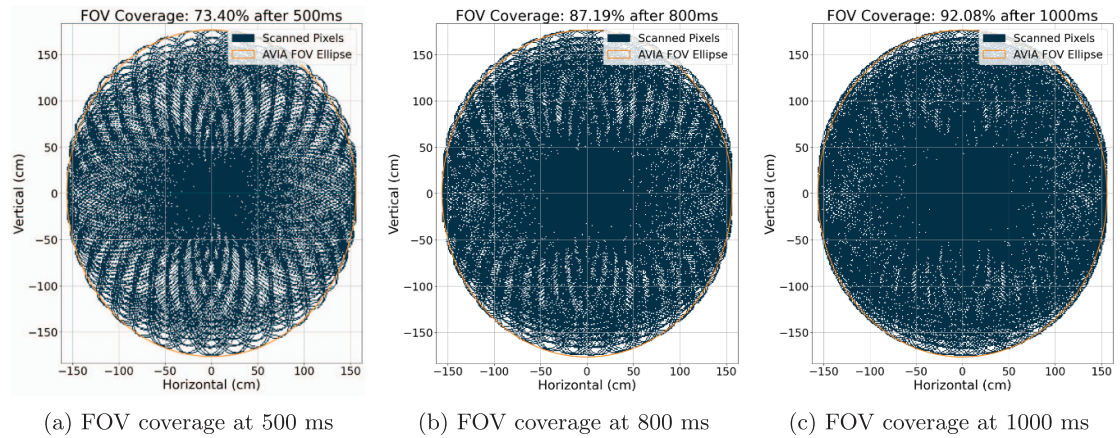


Figure 5. Coverage pattern of the FOV at different integration times.

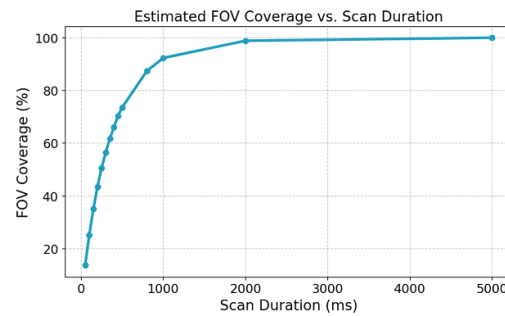


Figure 6. Estimated FOV coverage percentage for scan durations from 0–5000 ms.

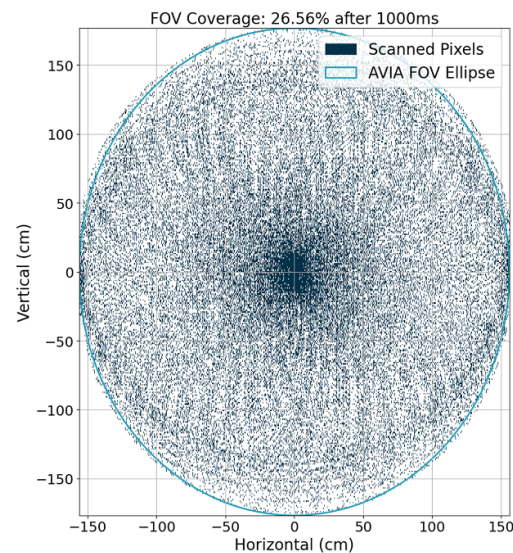
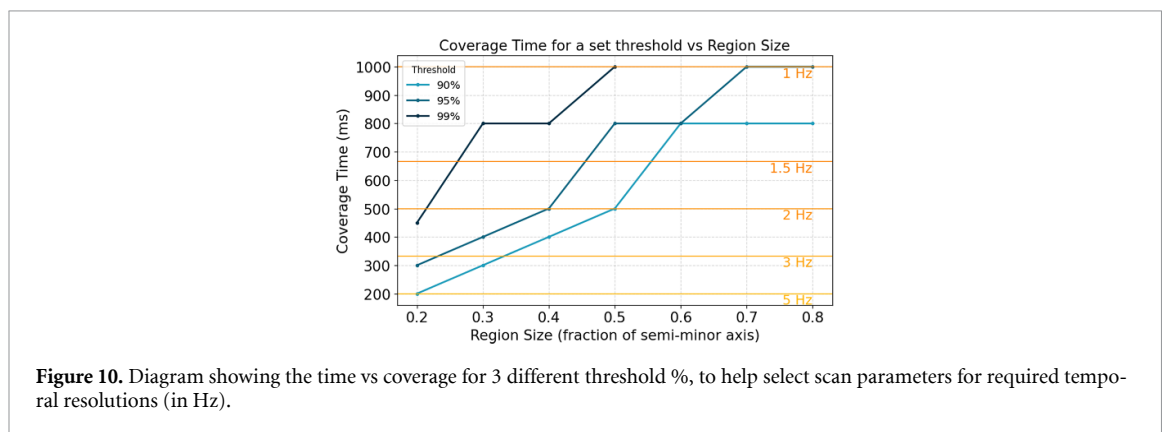
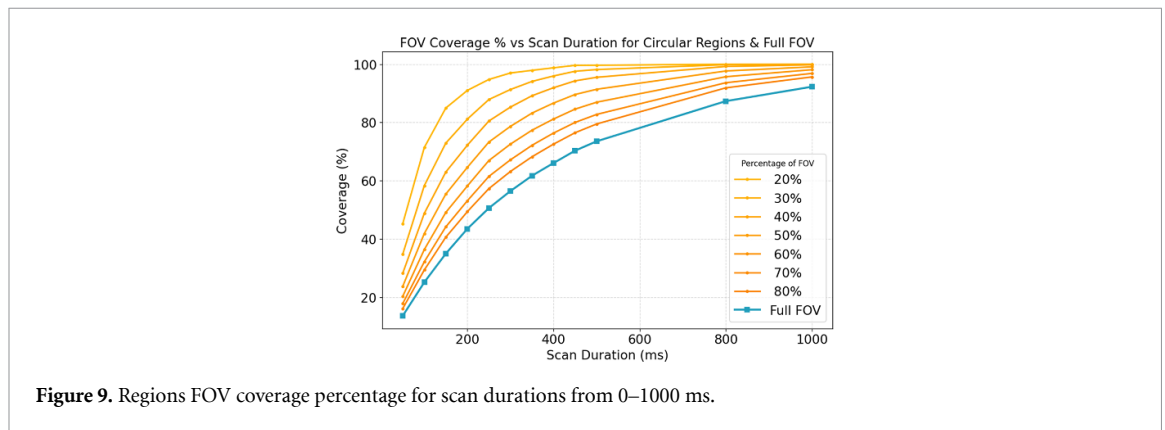
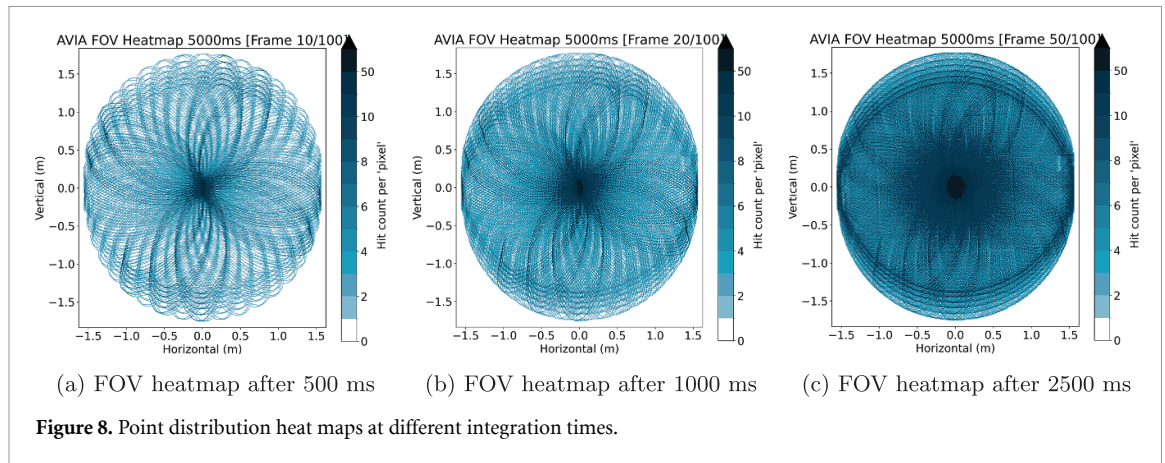


Figure 7. FOV coverage after 1000 ms when using rectangular pixels.

After 800 ms of scan time, the coverage is estimated to be (only) 87.19% which is not close to the 100% that is stated in the AVIA's manual. For a scan time of 1000 ms the coverage is estimated to be 92.08% where a majority of the 'gaps' can be seen in the outer edges of the ellipse (figure 5).

Extending the scan duration beyond 2 s is required to approach near-complete coverage (figure 6). Using footprint-matched rectangular cells instead of square cells produces substantially lower coverage estimates (figure 7), confirming that reported coverage percentages depend strongly on how coverage is defined.



The created point density heatmaps (see section 3.1.2), can be seen in figure 8. They reveal a clear non-uniform coverage inherent to the non-repetitive petal-shaped scan pattern. The central FOV accumulates hits much faster than the outer regions.

This non-uniformity can be used to achieve higher temporal resolutions in smaller regions within the FOV. Regional coverage analysis shows that central subregions reach high coverage substantially faster than the full FOV (figure 9). The inner 20% of the FOV reaches a coverage of over 90% in roughly 200 ms, enabling effective sampling rates up to about 5 Hz for small targets.

The parameter selection diagram (figure 10), summarizes the trade-off between region size, coverage threshold, and achievable frame rate. The results support the idea that even shorter temporal framing for dynamic targets is possible, given that they occupy only a small part in the centre of the FOV, such as could happen when monitoring a smaller individual tree. For trees that fit within the inner 50% of the FOV, processing can therefore be performed at a temporal resolution of 2 Hz to achieve similar coverage as the full FOV at 1 Hz.

Table 3. Overview of tree scans, including wind data availability, tree type, height, and subsampling parameters.

Name	Wind data	Tree type	Height (m)	Subsampling (ms)	Scan-time (s)
Scan 1	Yes	Narrow-leaved Ash	~10	500, 1000	60
Scan 2	Yes	Canadian poplar	~27	1000	30
Scan 3	Yes	Birch	~20	500, 1000	60



(a) Tree 1: Narrow-leaved Ash



(b) Tree 2: Canadian poplar



(c) Tree 3: Birch

Figure 11. Imagery of the three trees scanned in this research.

4.2. Wind induced tree movement

Following the identification of effective integration times to achieve 100% FOV coverage (between 500 and 1000 ms depending on the size of the object), we investigate the AVIA's ability to capture wind-driven tree motion from a sequence of consecutive 3D point clouds. This is done by scanning three different sized trees (see table 3, figure 11). Using PlantMove we compute frame-to-frame displacement magnitude and vector fields for the trees, which describe both global sway and local branch deformation for a tree per frame.

Displacement magnitude (scatter) and vector (quiver) plots (figures 12 and 13), provide complementary views of the motions. The scatter plots highlight which canopy regions experience the largest movement, while the quiver plots reveal directional patterns and more local deformation modes, like opposing branch motions within the crown. When viewed as sequences, these frames form a high-frequency 3D motion record of the tree. Animated sequences of the scatter plots can be found in the supplementary material, in combination with RGB imagery taken at the same time.

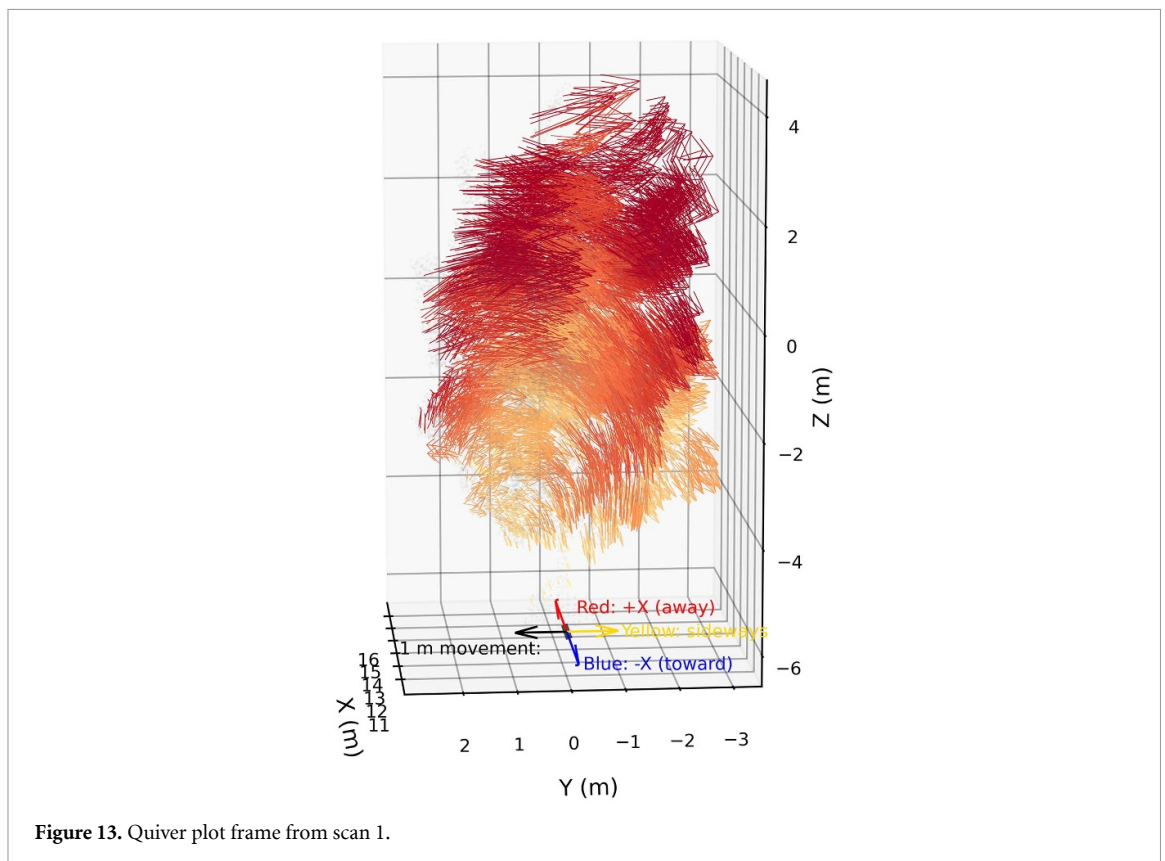
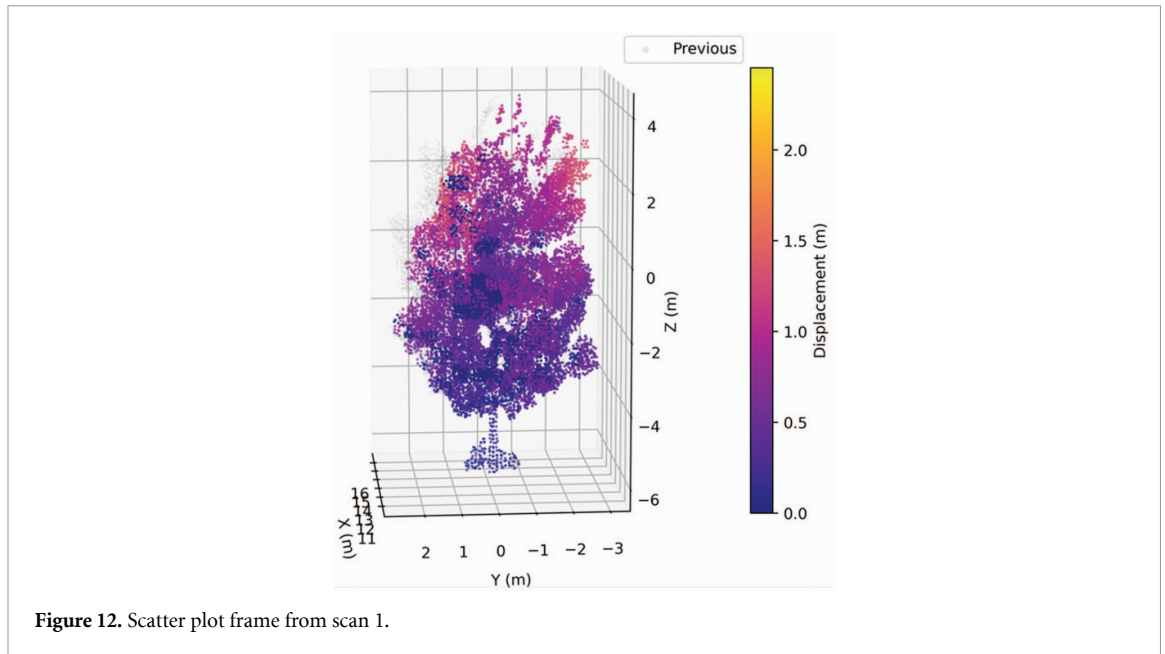
Two registration strategies were evaluated, as introduced in section 3.2.2. Consecutive frame registration makes it possible to capture short-term incremental motion and produces stable temporal behaviour. Comparative registration emphasizes cumulative displacement, and shows to be sensitive to reference-frame choice. An example of this can be seen in figure 14: the comparatively processed frames show the top right part of the tree moving away from the scanner while the consecutively processed frames do not reveal noticeable movement.

For the measuring of moving trees, consecutive registration proved more robust for motion tracking, while comparative registration is better suited for total-offset estimation when a low-motion baseline frame is available.

4.3. Temporal resolution: 500 Ms vs 1000 Ms subsampling

Based on the coverage analysis results from section 4.1.1, frame durations of 500 ms (2 Hz) and 1000 ms (1 Hz) were compared in field scans. The shorter frame length increases temporal responsiveness but reduces spatial completeness and point density.

For smaller or nearby trees that occupy mainly the central FOV, temporal resolutions of 500 ms seem to preserve structural coherence and captures faster oscillations effectively (figure 15). For larger trees covering more of the FOV, 500 ms frames show increased canopy fragmentation and reduced registration stability due to sparse sampling (figure 16). When subsampling at 1000 ms, the results produce more consistent geometry and more stable displacement estimates, with fewer registration artefacts (figure 16). The optimal frame duration therefore depends on angular target size.



4.3.1. Quantifying tree movement

The frame-wise displacement magnitudes enable statistical summaries of structural motion. Per-frame displacement histograms like shown in figure 17 reveal a strong peak near zero. These points correspond to points on the trunk and major branches that do not move between frames (figure 12). Whereas the tail of the distribution represents the movement of points on the flexible canopy elements.

While histograms of individual frames are useful for summarizing global behaviour, they do not capture how movement varies vertically throughout the tree. To address this, the tree can be divided into horizontal slices to compute the (mean) displacement magnitude per height segment as can be seen in figures 18 and 19.

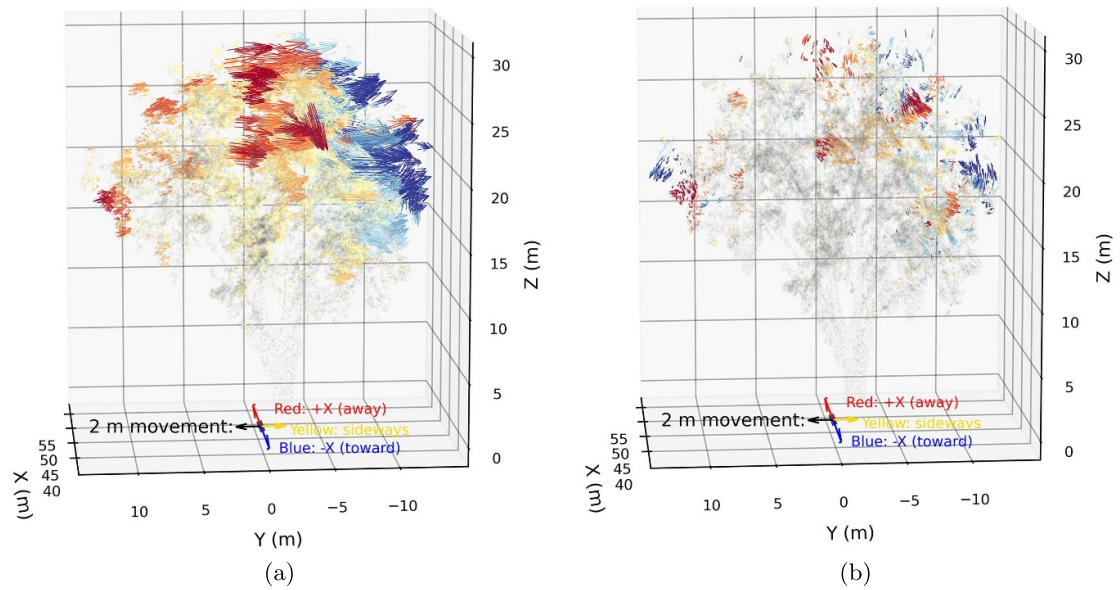


Figure 14. Magnitude of comparative (a) vs consecutive (b) tree movement quantification.

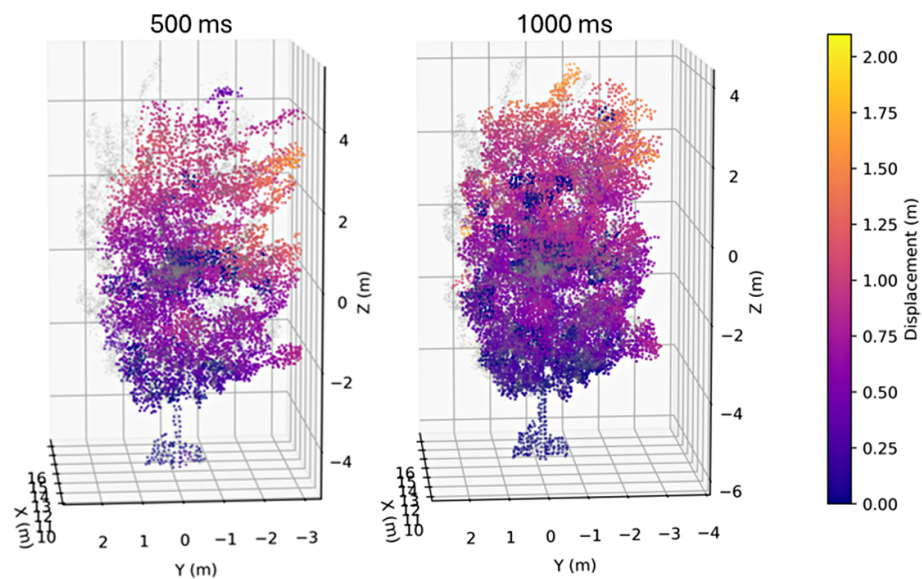


Figure 15. Scatter plots from scan 1 of a single frame subsampled at 500 and 1000 ms.

Extending this approach to the full duration of a scan results in time-averaged slice movement profiles, shown for tree 1 in figure 20. The averages provide an estimate of which height intervals experience the most motion over the entire scan sampling period.

This coincides with the expected wind and structural behaviour, as wind speeds generally increase with height (even in urban areas: Plate and Kiefer 2001), and the upper branches are thinner and more flexible, so are expected to have larger movements. In contrast, the lower branches are usually thicker and more rigid, and the trunk remains the most structurally constrained as it is fixed in the ground.

4.3.2. Wind-tree motion relationship

For scans with simultaneous anemometer measurements, the derived mean displacement per frame was compared with wind speed. Since the wind data was collected using an anemometer at a distance of ≈ 11 m (table 4) from the tree, the measured movement and wind speed signals were not automatically aligned in time. A visual inspection revealed that peaks in movement consistently occurred after peaks

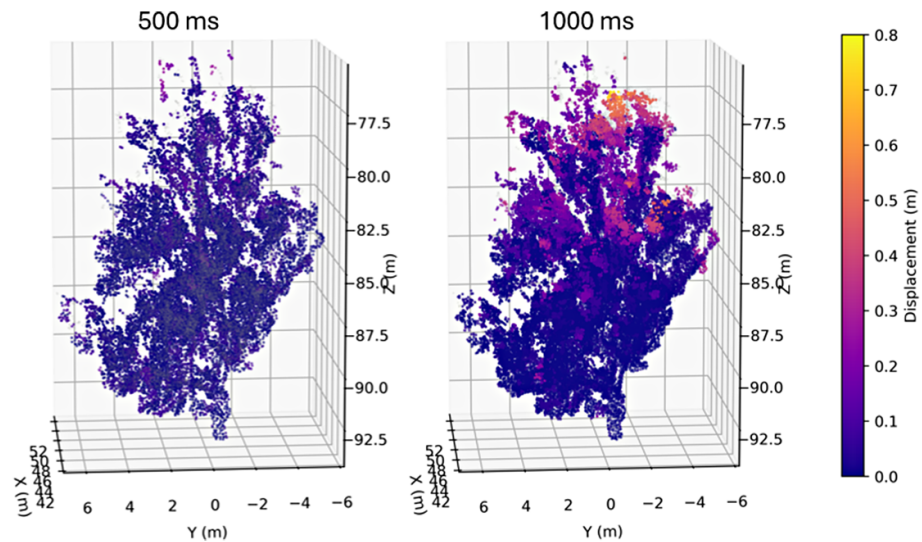


Figure 16. Scatter plots from scan 3 of a single frame subsampled at 500 and 1000 ms.

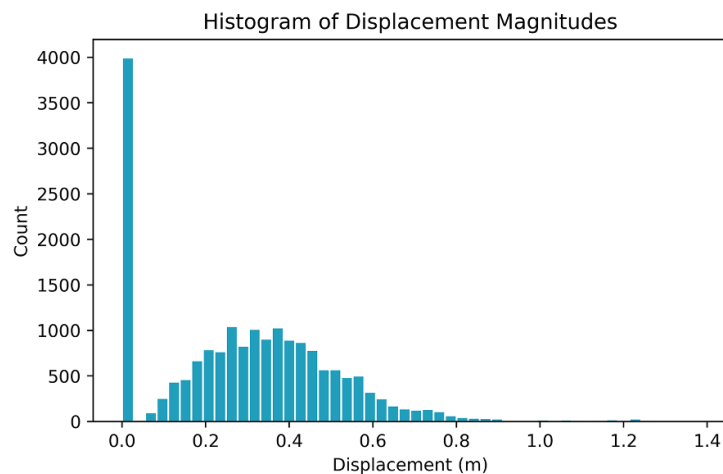


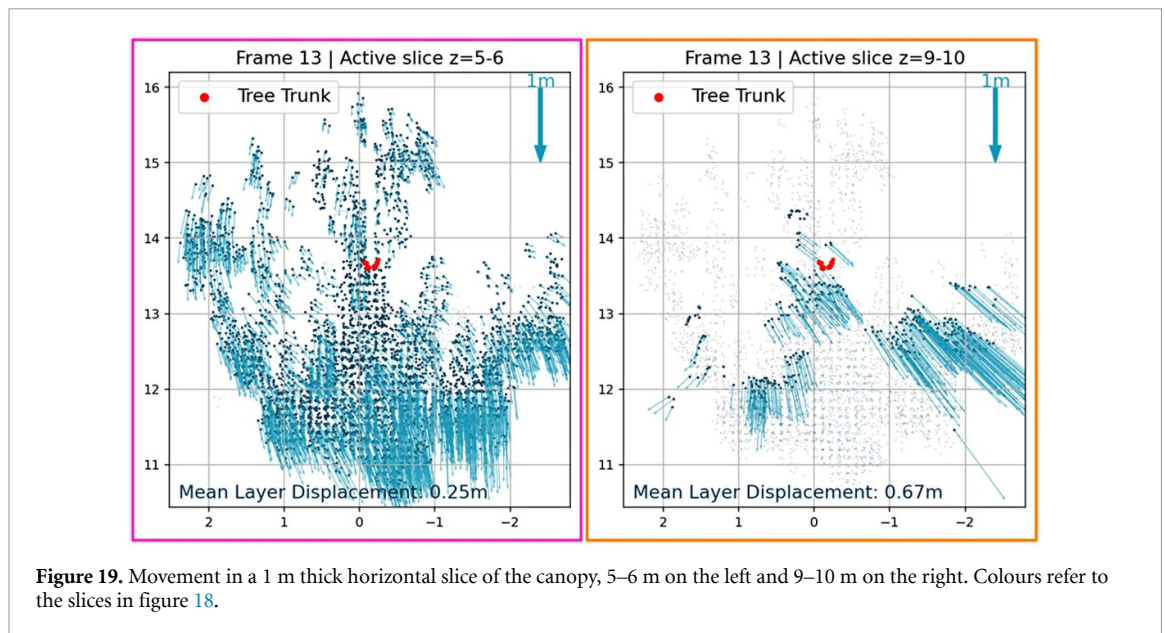
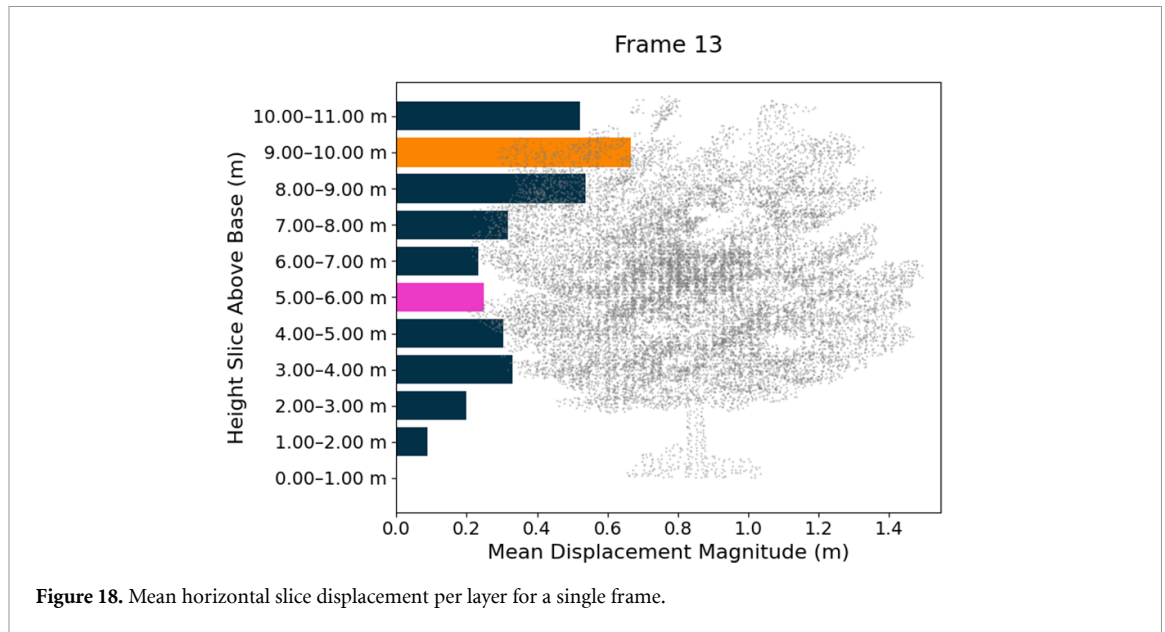
Figure 17. Example histogram of a frame from scan 1, showing the quantified movement magnitudes of the points in a single frame.

in wind speed. To quantify this offset, a cross-correlation analysis was performed. This method systematically shifts the movement data relative to the wind data and calculates the correlation at each possible time lag, identifying the shift that produces the strongest correlation.

Cross-correlation analysis shows that tree motion lags wind forcing by several seconds, this is likely caused by both the wind needing to travel the distance between the anemometer and the tree (10–20 m) and the structural (tree) response time. After lag correction (5.08 s in scan 1), wind speed and mean displacement show a moderate positive correlation (Pearson $r = 0.64$, Spearman $\rho = 0.59$, figures 21 and 22), consistent with higher wind speeds producing larger measured displacements in this scan.

The results from the other two scans with wind data are shown in table 5. A positive lag indicates the movement is estimated to occur later than the measured wind, a negative lag means the movement was measured before the predicted corresponding wind reached the anemometer.

There is no correlation found between the wind and movement in scan 2, this can possibly be attributed to the very low wind conditions resulting in more small and random movements or the distance between the tree and the anemometer. The results from scan 3 show a lower moderate correlation, it must be noted that for the full scan duration (60 s) only 500 ms subsampled data was processed. As the tree was later found to be slightly too large for this temporal resolution, the lack of point-density could have had an influence on the quality of the PlantMove movement estimation.



4.3.3. Wind direction vs movement direction

Directional analysis shows that mean horizontal displacement vectors generally align opposite to wind direction when transformed to a common reference frame, consistent with expected mechanical response. This directional agreement is clearest during higher wind conditions and becomes more dispersed at lower wind speeds (figure 23).

When the scan data is processed consecutively (figure 24), the movement between frames is more irregular as this method captures the smaller back and forward movements of the tree instead of the movement compared to a reference scan. Looking at a movement direction plot made with these results shows smaller and less unidirectional tree displacements.

Together, these results demonstrate that short-frame segmentation of the compact non-repetitive Livox AVIA lidar enables time-resolved, physically interpretable measurements of vegetation dynamics, supporting its use as a high-frequency 3D motion sensing system.

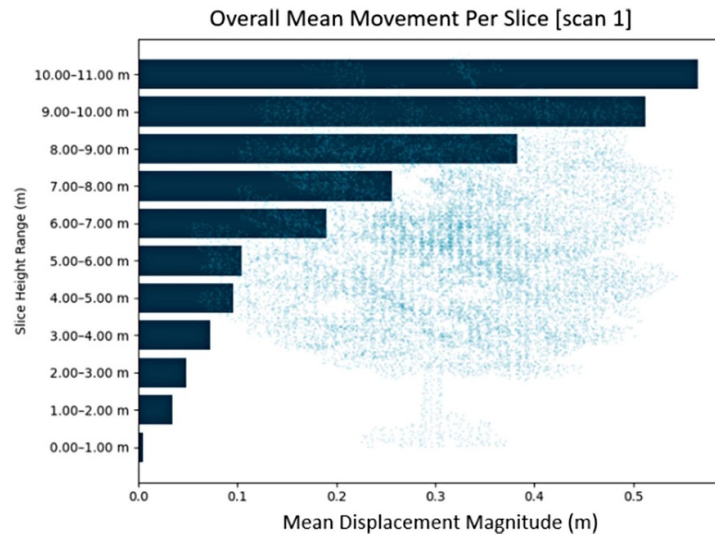


Figure 20. Mean movement per 1 m horizontal slice of all scan 1 frames.

Table 4. Average wind characteristics recorded during the scans.

Name	Median speed (m/s)	Peak speed (m/s)	Average direction (°)	Wind direction (Cardinal)	Anemometer-tree distance (m)
Scan 1	5.17	10.57	287	W	~11
Scan 2	2.05	3.67	121	SE	~20
Scan 3	2.34	5.97	249	WSW	~17

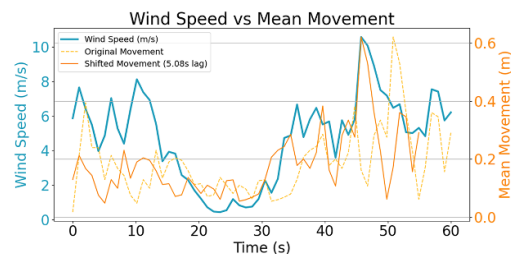


Figure 21. Comparison of wind speed and mean movement during scan 1. The movement data has been aligned using a cross-correlation lag of 5.08 s, accounting for the time delay between wind forcing and structural response.

5. Discussion

5.1. Scanning configuration and coverage behaviour

The coverage characterization results reveal a discrepancy between the manufacturer specified 800 ms full-coverage time and the observed behaviour. At 800 ms, measured FOV coverage reached only approximately 87%, with nearly complete coverage requiring scan durations of over 2 s (figure 6).

A source of variability in reported coverage figures is the choice of pixel geometry used to discretize the FOV for coverage analysis. Using square cells sized to the beam's semi-major axis, as adopted here and by the manufacturer, produces a systematic upward bias relative to footprint-matched rectangular cells (figure 2(a)). This is not a flaw in either approach but rather showcases the variation stemming from how coverage is defined for an asymmetric beam. Future applications could benefit from defining coverage by the point density needed to reconstruct the scanned structure adequately for motion to be detected. For trees with thicker branches a lower point density could be required for adequate reconstruction than for trees with thinner branches, increasing the effective scanning frequency. This would, however, require rigorous testing of the PlantMove parameterization and resulting effectiveness with respect to validation data. The latter of which is hard to obtain but could be assisted by dynamic virtual laser scanning (VLS-4D, Weiser and Höfle 2025).

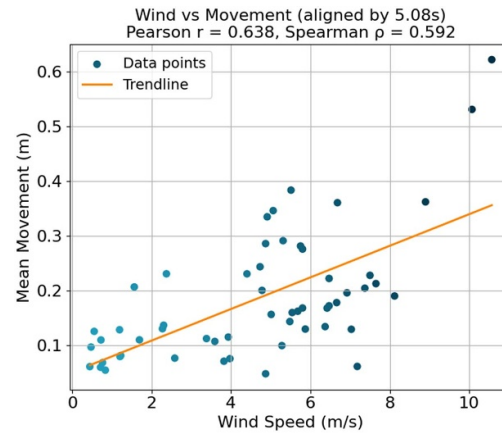


Figure 22. Scatter plot of wind speed and lag-corrected mean movement with fitted regression line for scan 1.

Table 5. Wind correlation and lags for the three scans.

Name	Pearson correlation	Spearman correlation	Best lag (s)
Scan 1	0.638	0.592	5.08
Scan 2	± 0.1	± 0.1	N/A
Scan 3	0.323	0.290	−5.1

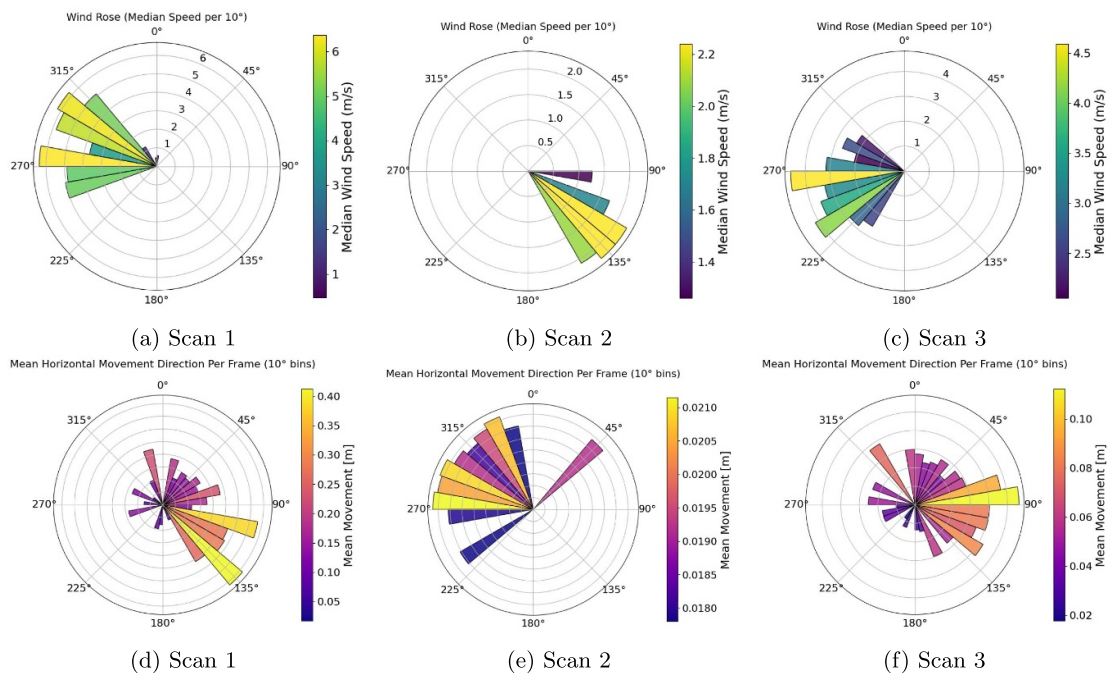
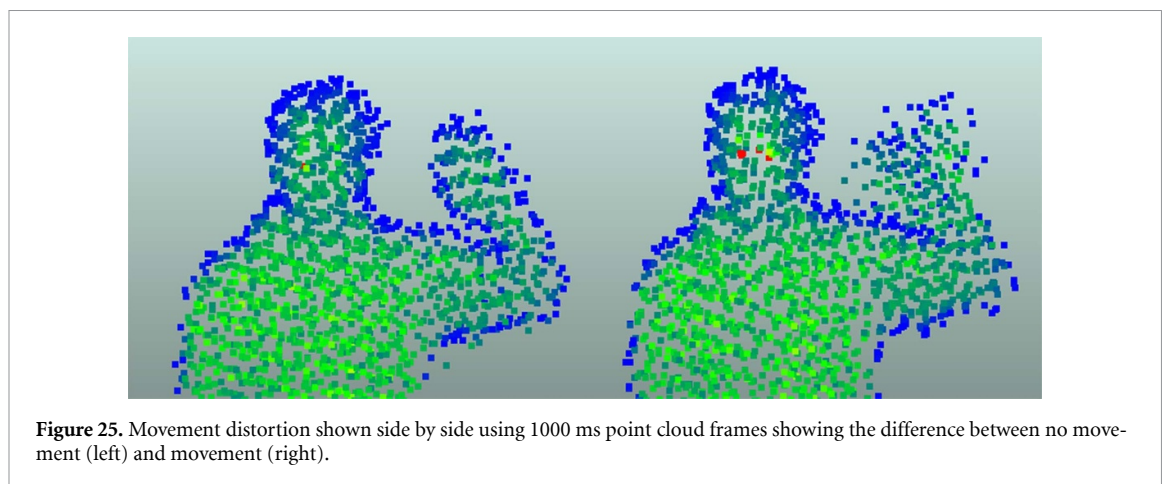
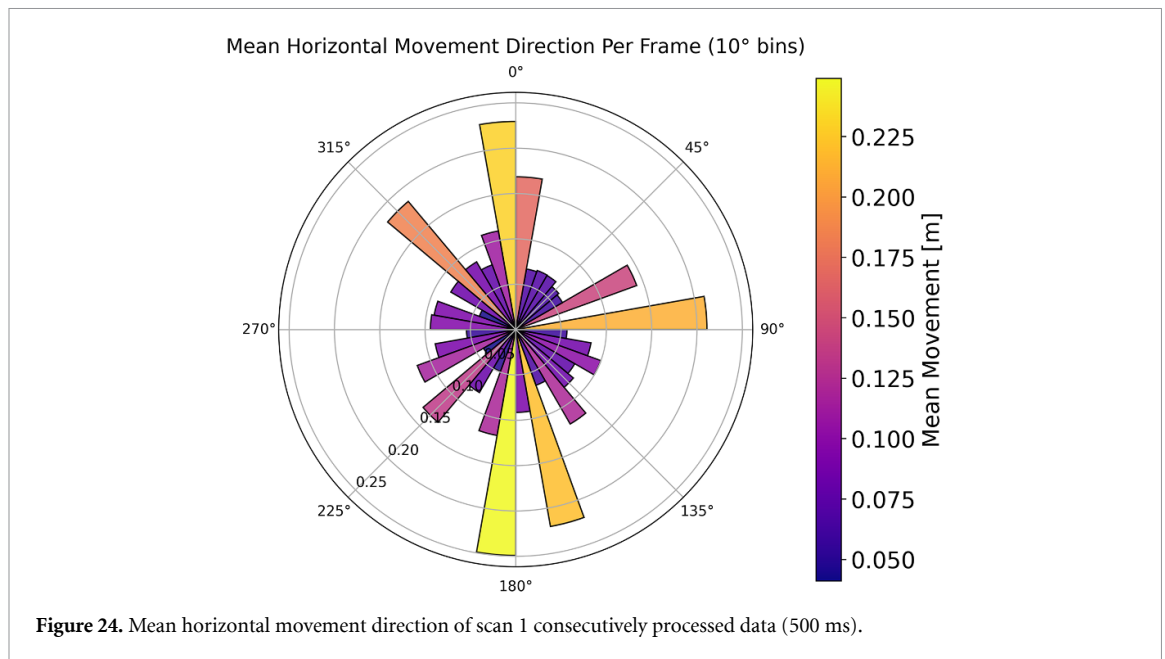


Figure 23. Top row: wind rose plots indicating the median speed and wind direction during a scan (0° = North, 180° = South). Bottom row: Mean horizontal movement direction (0° = North, 180° = South).

The non-uniformity of the scan pattern, with the FOV centre accumulating points substantially faster than the outer rings (figure 8), is found to be an important feature that can be exploited for applications of rapidly varying dynamic scenes. The regional coverage analysis demonstrates that it can be exploited by positioning the target in the central FOV and accepting reduced outer edge coverage. This leads to effective sampling rates of up to 5 Hz becoming achievable for small targets (figure 10).



5.2. Key parameters and motion quantification

Key parameters for motion detection are: (i) Reference frame, (ii) Integration time, (iii) PlantMove parametrization.

Considering choice of reference frame: comparative registration, where all scans are referenced to a single baseline scan, does achieve directional plots that are correlated to time-lagged wind direction. These can be used for studying wind vs tree motion. It does however require a careful baseline selection. If this baseline is chosen as one the extreme movements, the magnitudes of change will be overestimated. Future work could negate this by using a single baseline scan, obtained during low-wind conditions with little movement. Consecutive registration is recommended for analysing branch movement as function of time, where it is expected that a branch displaces, reacting on increasing wind force, while it will bounce back when wind force is dropping. On the other hand, comparative registration is more suitable for quantifying cumulative displacement, like estimating the amplitude of movement of branches in different locations in a large tree.

Considering integration time: The AVIA's achievable temporal resolution (1–2 Hz) limits its ability to capture high-speed or short term dynamics. Motion occurring within the 500–1000 ms frame interval leads to distorted geometries or 'motion blur', as shown in figure 25. The comparison between 500 ms and 1000 ms frame durations illustrates the trade-off to be made when using the AVIA: shorter integration times increase temporal resolution and reduce motion blur within each frame, but deliver fewer points per frame and therefore lower completeness and registration reliability. The optimal frame duration is not a fixed value but depends on three factors: the angular size of the target relative to the

FOV, the wind-driven oscillation frequency of the target, and the minimum point density required by PlantMove for stable registration.

For the narrow-leaved ash in Scan 1 (figure 15) which is relatively small and occupies mainly the central FOV region, 500 ms frames give sufficient coherence for reliable PlantMove registration. For the larger birch in Scan 3 (figure 16) 500 ms frames produces more fragmented canopy representations and reduces Plantmove registration stability. This size-dependent behaviour is specified with the regional coverage analysis. A target that fits within the inner 50% of the FOV will be well sampled even at 500 ms, while a target that extends to the FOV edges will not.

The parameter selection diagram (figure 10) provides a guidance for using these observations in practice. Given a target's approximate extent in the FOV, an operator can read off the frame duration required to achieve a specified coverage threshold, and therefore the maximum achievable sampling rate. However, it needs to be assessed in future work, what the minimum point density is for PlantMove (Wang *et al* 2022) registration on a given tree type, since this threshold sets the lower bound on useful frame duration independently of coverage. Establishing this threshold would require controlled experiments with known, independently measured displacements.

Considering PlantMove parametrization: motion blur in time-segmented point clouds may affect PlantMove results. Because each frame accumulates points over 500–1000 ms, any branch or leaf that moves during that integration window is recorded at a smeared position rather than its true instantaneous location. PlantMove does not model this within-frame motion as it treats each point cloud as a static geometry, so what it effectively measures is displacement between two time-averaged states rather than two instantaneous snapshots. Displacements are therefore likely underestimated during high-motion frames, where fast-moving canopy elements are spatially blurred in both the source and target clouds. Shorter frame durations reduce this effect but at the direct cost of point density.

The PlantMove algorithm's noise sensitivity requires careful tuning of the de-noising parameter: too much smoothing suppresses small-amplitude branch motion, while insufficient smoothing creates registration artefacts in the displacement fields. This balance is complicated by the non-uniform point density of AVIA's scan pattern, since sparsely sampled peripheral regions are more susceptible to noise-driven registration errors than the densely sampled FOV centre. The parameters (de-noise, dsp and k) were determined by iterative trial and error, optimizing for computational time and visual output quality, without formal validation against independent displacement measurements. This limits the reproducibility and generalizability of the results: parameter sets that perform well on one tree type or scan density may not transfer directly to other configurations. Tuning and validation through use of, for example, virtually scanned dynamic scenes (Weiser and Höfle 2025) can, in future work, optimize and generalize this parameter selection. With three trees of different species this study is exploratory in scope, the reported wind–motion correlations and displacement patterns are thus also indicative. Larger and more diverse samples are needed to establish robustness across species and canopy structures.

5.3. Comparison to other sensors

The AVIA's effective temporal sampling range of 1–2 Hz for tree-sized objects is difficult to achieve with most common larger TLS systems. Traditional TLS systems, with scan times of several minutes per scene, are entirely unable to resolve wind-driven oscillations. At the other extreme, high-speed LiDARs designed for automotive applications typically operate at higher frequencies, but produce repetitive scan patterns that are poorly suited to vegetation objects with complex, irregular geometry. Video-based and photogrammetric methods can achieve high frame rates but recover only 2D and/or require favourable lighting. The results show that the fast non-repetitive scanning pattern of the Livox AVIA, thus, makes it a unique tool for monitoring dynamic objects from a static viewpoint.

5.4. Outlook

This study showed how to assess wind-induced heterogenous canopy movement using a workflow exploiting Livox AVIA data. The AVIA, operating in continuous mode, acquires a space-time array of range measurements, which is split in point clouds corresponding to a suitable time interval, of, say, 1 s. In this study, one single AVIA was used. As a consequence, tree movement was only monitored from one single view-point. A logical next step would be to employ e.g. three different AVIA's, simultaneously monitoring a tree from three different view-points. This would allow to almost fully capture 3D tree movement in response to wind forcing. From a methodological point of view, it would be interesting to simultaneously use the workflow in this paper, focussing on canopy, with the workflow in Chau *et al* (2022), focussing on trunk and branches. This is expected to improve understanding of the combined response of woody and leafy parts of a tree on wind forcing, as branch parts partly move as whole, and partly move individually. A remaining challenge is posed by the tree induced self occlusions, which, even

with different view-points, will somehow hamper full 3D sampling. This self-occlusion can also influence the applicability of the workflow on other types of trees, with denser crowns. In future work, the transferability of the workflow to other types of trees, with varying crown, stem and leaf characteristics should be tested.

Furthermore, the reported displacement magnitudes have not been benchmarked against independent high-accuracy reference measurements (e.g. total station or optical motion tracking). Quantitative error metrics for absolute displacement accuracy are therefore not yet available. The physically consistent patterns observed in this study support the validity of the measured motion but do not establish absolute accuracy. Independent validation using such reference techniques, or in combination with the VLS-4D approach mentioned above, is thus an important direction for future work.

Likewise, no uncertainty budget is assessed within the workflow. Displacement uncertainty arises from a combination of range precision (< 2 cm at 20 m, section 2.2), tree movement during scanning (movement is location and wind dependent, while impact depends on integration time), registration sensitivity to local point density and movement during integration time, as well as PlantMove parameter choice (section 3.2.2). These factors have not yet been quantified for the displacement estimates. Characterizing this combined uncertainty, alongside the ground-truth validation noted above, remains an important direction for future work.

6. Conclusions and recommendations

This study demonstrates that a compact, low-cost, non-repetitive LiDAR sensor can be repurposed from a static mapping instrument into a stationary high-frequency 3D motion recorder for wind-driven tree canopy dynamics. Such function is not offered by traditional TLS or 2D video-based methods. The key methodological step which allows this is the temporal segmentation of the sensor's continuous scan stream into short point-cloud frames. This, combined with PlantMove-based registration converts a stream of frames into physically interpretable displacement fields of branch movement.

Characterization of the non-repetitive scan pattern showed that FOV coverage develops more slowly and less uniformly than specified. However, this non-uniformity can be exploited: trees confined to the central FOV can be sampled at effective rates up to 5 Hz, compared to roughly 1 Hz for full-FOV coverage. Applying 500 ms and 1000 ms frame durations to three trees confirmed this size-dependent trade-off between temporal resolution and spatial completeness, and showed that consecutive-frame registration is preferable for tracking incremental motion, while comparative (reference-frame) registration better suits cumulative displacement estimation.

The resulting motion fields capture physically consistent behaviour, where displacement increased with canopy height, and horizontal displacement generally aligned opposite to wind direction, especially in stronger wind conditions. After accounting for a several-second wind-to-motion lag, displacement correlated positively with wind speed in the scan with the strongest forcing (Pearson $r = 0.64$), though this relationship was weaker or absent in the lower-wind scans.

Together, temporal framing combined with PlantMove processing enables the Livox AVIA to quantify wind-driven tree dynamics at effective sampling rates of 1–2 Hz, positioning it as a compact and cost effective option for close range (< 100 m) dynamic monitoring between traditional TLS and current lightweight automotive LiDAR systems. For future work, multi-sensor configurations combining multiple AVIA units would allow improved spatial coverage and cross-validation of motion estimates. Additional anemometers could be used to obtain more wind measurements and would reduce uncertainty in anemometer to tree 'lag' estimations. Finally, integration with complementary sensors, such as cameras, would enable a better contextual analysis of dynamic environmental processes.

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Data availability statement

Python and Matlab code for processing the Livox AVIA output into temporal segments, and estimating displacements can be found at <https://doi.org/10.5281/zenodo.21823530> (de Jong *et al* 2026a). The original PlantMove Matlab implementation is found at <https://doi.org/10.5281/zenodo.6388906> (Wang 2022).

The data that support the findings of this study will be openly available following an embargo at the following URL/DOI: <https://doi.org/10.5281/zenodo.19884296> (de Jong *et al* 2026b).

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Author contributions

Thomas de Jong—Methodology, data acquisition, data analysis, writing; Daan Hulskemper—Supervision, writing, supplementary material; Roderik Lindenbergh—Conceptualization, supervision, writing.

Supplementary data

Short videos demonstrating tree movement are available as supplementary data.

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