

Rapid measurement of the three-dimensional
distribution of leaf orientation and the leaf angle
probability density function using
terrestrial LiDAR scanning

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Abstract

At the plant or stand level, leaf orientation is often highly anisotropic and heterogeneous, yet most analyses neglect such complexity. In many cases, this is due to the difficulty in measuring the spatial variation of the leaf angle distribution function. There is a critical need for a technique that can rapidly measure the leaf angle distribution function at any point in space and time. A new method was developed and tested that uses terrestrial LiDAR scanning data to rapidly measure the three-dimensional distribution of leaf orientation for an arbitrary volume of leaves. The method triangulates laser-leaf intersection points recorded by the LiDAR scan, which allows for easy calculation of normal vectors. As a byproduct, the triangulation also yields continuous surfaces that reconstruct individual leaves. In order to produce a probability density function for leaf orientation from triangle normal vectors, it is critical that the proper weighting be applied to each triangle. Otherwise, results will heavily bias toward normal vectors pointed toward the the LiDAR scanner. The method was validated using artificially generated LiDAR data where the exact leaf angle distributions were known, and in the field for an isolated tree and

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a grapevine canopy by comparing LiDAR-generated distribution functions to manual measurements. The artificial test cases demonstrated the consistency of the method, and quantitatively showed that errors in the predicted leaf angle distribution functions decreased as scan resolution was increased or as the density of leaves was increased. The isolated tree field validation showed qualitatively similar trends between manual and LiDAR measurements of distribution functions. Manual measurements of leaf orientation in the vineyard were shown to have large errors due to high leaf curvature, which illustrated the benefits of the more detailed LiDAR measurement method.

Keywords: Leaf angle distribution function, Leaf orientation measurement, Plant reconstruction, Terrestrial LiDAR scanning

1. Introduction

1 It is often necessary to account for the variability in leaf orientation in mete-
2 orological, climatological, or remote sensing analyses of plant systems. Because
3 the preferred orientation of leaves is driven by solar radiation, it is not surprising
4 that the probability density function (PDF) of leaf orientation is an important
5 component of radiation transport in plant canopies. Anisotropic leaf orientation
6 generally results in anisotropic radiation transfer, which necessitates a descrip-
7 tion of leaf orientation in analysis (Ross, 1981; Myneni and Ross, 1991; Bailey
8 et al., 2014). Since leaf orientation dictates how light is reflected and scattered,
9 it is also an important consideration in the interpretation of remote sensing
10 data collected in vegetative environments (Nilson and Kuusk, 1989; Jones and
11 Vaughan, 2010). The preferred orientation of leaves also influences other pro-
12 cesses not related to radiation interception such as drag (Schuepp, 1993), particle

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13 deposition (Raupach et al., 2001), and convection (Schuepp, 1993; Bailey et al.,
14 2016).

15 Despite the known importance of leaf orientation in many environmental
16 processes, previous work has been unable to faithfully represent the spatial and
17 temporal variability of the leaf angle PDF in analyses. This is primarily due
18 to the difficulty in obtaining adequate measurements of leaf orientation, which
19 can be highly heterogeneous in space (Kull et al., 1999; Raabe et al., 2015) and
20 variable over daily and seasonal scales (Shell et al., 1974; Thanisawanyangkura
21 et al., 1997). In order to measure the leaf angle distribution function, a large
22 number of individual measurements of leaf orientation can be collected to gen-
23 erate the PDF. Manual measurement of leaf orientation is extremely tedious,
24 and can be difficult to perform in dense or tall vegetation. Manual measure-
25 ments also have many potential sources for error, as each measurement requires
26 a judgement call on the part of the individual. A passage from Norman and
27 Campbell (1989) stresses these issues: “Direct measurement of leaf angle distri-
28 butions requires much determination and extraordinary care; *let the uninitiated*
29 *beware.*”

30 The simplest and most common approach for dealing with such difficulties
31 in analyses is to remove the effects of leaf orientation and make the assumption
32 that leaves have no preferred orientation. This has been demonstrated to be a
33 poor assumption in a vast number of cases (see Pisek et al., 2013). Regardless,
34 it is an assumption that is often made out of necessity when measurements are
35 unavailable. There is clear opportunity for improvement of many meteorological
36 and climatological models, measurements, and general analyses by faithfully
37 including the effects of leaf orientation.

38 In cases where some measurement of the leaf angle distribution function is
39 desired but direct methods are not feasible, indirect methods have also been

40 developed that use a collimated source of radiation at some known orientation
 41 to infer leaf angle distributions. The most easily accessible source of collimated
 42 radiation is sunlight. By recording how sunlight is attenuated by vegetation,
 43 one can invert the well known Beer’s law for radiation interception to estimate
 44 leaf orientation (cf. [Norman and Campbell, 1989](#)). These methods are limited
 45 by the fact that all results are integrated along the path between the sun and the
 46 instrument, making it difficult to obtain three-dimensional information. They
 47 also generally require an estimation of the leaf area density (LAD), which can
 48 lead to compounding errors. A more recent indirect method that has gained
 49 popularity is to manually identify leaf angles from digital photographs ([Ryu
 50 et al., 2010](#)). This method is a bit more efficient than direct measurement, but
 51 it cannot measure leaf azimuth and only considers leaves in direct view that are
 52 approximately parallel with the camera view direction.

53 Terrestrial LiDAR scanning, which is the focus of this paper, has seen in-
 54 creasing usage in obtaining measurements of canopy structure (e.g., [Radtke and
 55 Bolstad, 2001](#); [Henning and Radtke, 2006](#); [Hosoi and Omasa, 2006](#); [Rosell et al.,
 56 2009](#); [Yang et al., 2013](#)). Terrestrial LiDAR scanners emit concentrated beams
 57 of radiation in the form of laser pulses into the spherical space surrounding the
 58 scanner. In the event that the beam hits an object, the distance to the object
 59 can be determined by analyzing the radiation reflected back to the scanner.
 60 Unlike methods utilizing the attenuation of sunlight, LiDAR can quickly ob-
 61 tain millions of data points that provide three-dimensional information about
 62 radiation attenuation from many directions, which can be inverted to provide
 63 information about canopy structure such as leaf area density ([Hosoi and Omasa,
 64 2006](#); [Béland et al., 2011](#)). One important limitation in the use of LiDAR data
 65 to measure LAD distributions is the general lack of knowledge of the behavior
 66 of the leaf angle distribution function, which plays a critical role in performing

67 such measurements.

68 Some recent work has began developing methods to measure leaf orientation
69 using LiDAR data. [Zheng and Moskal \(2012\)](#) estimated leaf normals using an
70 algorithm that fits a plane to neighboring LiDAR leaf intersection points. The
71 method performed well for small potted plants, but showed poor agreement
72 with measurements when applied to a tree in the natural environment. Their
73 method also did not properly weight leaf normals when calculating the PDF of
74 inclination, leading to a biased PDF (see Sect. 2.2). [Hosoi and Omasa \(2015\)](#)
75 manually identified leaves within LiDAR point cloud data, and used planar fits
76 to calculate and average leaf normals. This method allows easy access to the
77 entire plant, but it is comparable in effort to performing manual measurements
78 in the field. As with any manual measurement technique, there is also the po-
79 tential for user bias in results, which has not been quantified through validation
80 exercises.

81 In this work, we seek to develop and validate an algorithm that autonomously
82 calculates the three-dimensional distribution of leaf orientation in natural vege-
83 tation from LiDAR data. The ultimate goal is to rapidly generate the leaf angle
84 PDF for an arbitrarily defined volume of leaves, providing a direct measurement
85 of how the PDF changes in space and time.

86 2. Methods

87 2.1. Triangulation and calculation of surface normals

88 The LiDAR scan creates a uniform grid of sample points in spherical space.
89 Let Θ and Φ denote the range of zenithal and azimuthal directions explored by
90 the LiDAR, respectively. The number of scan points in the zenith (N_Θ) and
91 azimuthal (N_Φ) directions gives the resolution of the scan. Thus, the zenithal
92 angle between adjacent scan points is $\Delta\theta = \Theta/N_\Theta$, and the azimuthal angle is

93 $\Delta\varphi = \Phi/N_\Phi$. For each of the $N_\Theta \times N_\Phi$ scan points, the instrument reports the
 94 distance to the nearest object in the direction (θ, φ) .

95 The strategy for computing the distribution of leaf normals was to first tri-
 96 angulate laser-leaf intersection points. A successfully constructed triangular
 97 mesh along leaf surfaces would allow for easy calculation of normal vectors at
 98 the location of each triangle. Triangles are desirable because they comprise the
 99 minimum number of points necessary to compute a normal vector. This means
 100 that only three adjacent hit points are required on a given leaf to calculate a
 101 normal vector and obtain an estimate of its orientation. Standard triangulation
 102 algorithms are not applicable for discrete surfaces such as leaves. Examples are
 103 (Press et al., 2007) Delaunay triangulation which in three dimensions seeks to
 104 create tetrahedral cells and not surfaces, or the convex hull algorithm which
 105 seeks to create a continuous convex surface. There are numerous algorithms
 106 designed to reconstruct continuous solid objects from point cloud data (e.g.,
 107 Bernardini et al., 1999). Since plant leaves consist of a field of many individual
 108 surfaces, this work will develop a simpler algorithm below that is specifically
 109 designed to efficiently identify and reconstruct individual leaves without con-
 110 necting each of them together to form a single object.

111 The scan data can be stored into a two dimensional data structure (denoted
 112 as A_{ij}), where columns denote each azimuthal scan direction and rows denote
 113 each zenithal scan direction (Fig. 1a and Table 1). If the (i, j) scan point does
 114 not intersect an object (denoted as a ‘miss’), A_{ij} is set to false, whereas if the
 115 point intersects an object (denoted as a ‘hit’), A_{ij} is set to a unique identifier
 116 corresponding to the hit point. For practical purposes, a bounding box can be
 117 established that encompasses only points of interest, with all hit points lying
 118 outside of this box considered misses.

119 To triangulate the (i, j) hit point, neighboring points in the table A_{ij} were

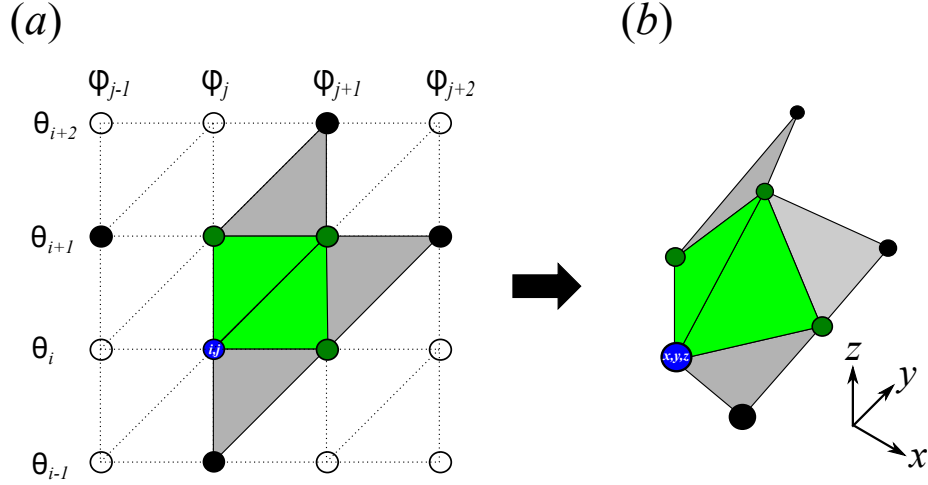


Figure 1: Visual depiction of point cloud triangulation. (a) shows how points are first triangulated using the two-dimensional grid of (θ_i, φ_j) pairs. Leaf-laser intersection points (hits) and non-intersection points (misses) are denoted respectively by closed and open circles. At any hit point, a triangulation is attempted with the $(\theta_i, \varphi_j), (\theta_{i+1}, \varphi_j), (\theta_{i+1}, \varphi_{j+1})$ points and the $(\theta_i, \varphi_j), (\theta_{i+1}, \varphi_{j+1}), (\theta_i, \varphi_{j+1})$ points. (b) shows the triangulation mapped to the (x, y, z) hit coordinates.

120 searched for hits (Fig. 1a and Table 1). If the $(i + 1, j)$ and $(i + 1, j + 1)$ points
 121 were both also hits, the $(i, j), (i + 1, j),$ and $(i + 1, j + 1)$ points were connected
 122 to form a triangle. The $(i + 1, j + 1)$ and $(i, j + 1)$ points were also searched,
 123 and if they were all hits, the $(i, j), (i + 1, j + 1),$ and $(i, j + 1)$ points were
 124 connected to form another triangle. This proceeded for $i = 1$ through $N_\Theta - 1$
 125 and $j = 1$ through $N_\Phi - 1$. A number of simple variations on this triangulation
 126 methodology are possible, such as attempting to form a triangle with the $(i, j),$
 127 $(i + 1, j),$ and $(i, j + 1)$ points if the above triangles cannot be formed. This
 128 is usually only expected to add additional triangles on the edges of leaves, and
 129 overall we have found that using these slightly more complicated triangulation
 130 methods had a minimal impact on results.

131 Once triangles have been formed, their normal vectors are simply given by

Table 1: Example table structure needed to perform the triangulation algorithm from LiDAR scan data depicted visually in Fig. 1. Mapping of hit indices in spherical grid space for all scan points. Numerical values correspond to point # (row) in Table 2.

	φ_{j-1}	φ_j	φ_{j+1}	φ_{j+2}
θ_{i+2}	0	0	7	0
θ_{i+1}	1	4	6	8
θ_i	0	3	5	0
θ_{i-1}	0	2	0	0

Table 2: Example table structure needed to perform the triangulation algorithm from LiDAR scan data depicted visually in Fig. 1. Storage of the (x, y, z) position of each hit location (misses are not stored).

point #	x	y	z
1	x_1	y_1	z_1
2	x_2	y_2	z_2
3	x_3	y_3	z_3
4	x_4	y_4	z_4
5	x_5	y_5	z_5
6	x_6	y_6	z_6
7	x_7	y_7	z_7
8	x_8	y_8	z_8

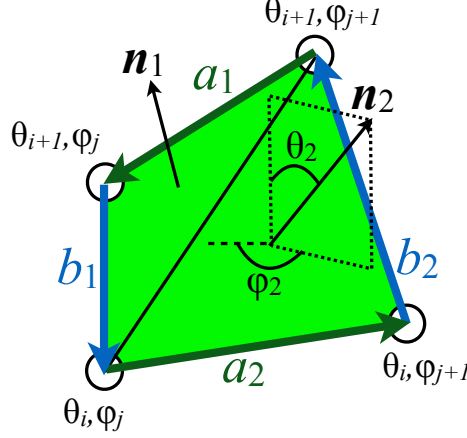


Figure 2: Schematic of the coordinate system for two adjacent triangles.

the cross product of the vectors defining any two sides of the triangle (Fig. 2)

$$\mathbf{n} = \mathbf{a} \times \mathbf{b}, \quad (1)$$

where $\mathbf{n} = (n_x, n_y, n_z)$ is the normal vector, and $\mathbf{a}$ and $\mathbf{b}$ are two vectors defining the sides of the triangle which are found by looking up the (x, y, z) coordinates at each vertex (Table 2). The sign convention of the $\mathbf{a}$ and $\mathbf{b}$ vectors should be defined such that the calculated normal vectors are consistent (e.g., as in Fig. 2).

If desired, the triangle's inclination and azimuthal angles can also be easily calculated from the normal vector as

$$\theta_L = \text{asin} \left(\frac{n_z}{|\mathbf{n}|} \right), \quad (2)$$

and

$$\varphi_L = \text{atan} \left(\frac{n_y}{n_x} \right). \quad (3)$$

141 In this work, we define φ_L to range from 0 to 360° such that it is consistent
 142 with the compass direction (0 is North, 90° is East, etc.).

143 The LiDAR cannot directly determine if a hit point corresponds to the bot-
 144 tom or top surface of a leaf. In most applications, this is not problematic, as a
 145 distinction is often not necessary between the two sides of leaves in analyses. In
 146 order to *approximately* distinguish between the sides of a leaf, we assumed that
 147 all triangles with a downward pointing normal vector ($n_z < 0$) corresponded to
 148 the abaxial side of the leaf, and that $n_z > 0$ corresponded to the adaxial side. If
 149 $n_z < 0$, the normal vector was reversed (i.e., multiplied by -1), which effectively
 150 shifted the azimuthal angle by 180° . This allowed for direct comparison with
 151 manual measurements, which generally consider the leaf normal to be pointing
 152 away from the adaxial side of the leaf.

153 2.1.1. Potential issues

154 Leaf edge effects: It is clearly undesirable to have triangles that connect the
 155 edges of adjacent leaves, i.e., the triangles should stop at the edge of a leaf.
 156 Furthermore, the laser beam has a finite diameter (generally on the order of
 157 millimeters), which means that laser hits near the edge of the leaf will partially
 158 intersect the given leaf and partially intersect another object. Depending on the
 159 LiDAR instrument, it may effectively average multiple hit locations across the
 160 beam area and therefore partial hit points bias toward a location further along
 161 the beam path.

162 Although many possible methods could be devised to deal with the above
 163 complications, a relatively simple solution was used that is based on a size
 164 thresholding methodology. If any side of the triangle was longer than some
 165 predefined threshold length L_{max} , the triangle was rejected. L_{max} should be
 166 defined such that it is significantly larger than the expected spacing between
 167 adjacent hit points on a leaf, yet significantly smaller than the expected spacing

168 between adjacent leaves. As the scan density is increased, L_{max} becomes in-
169 creasingly easier to define since the spacing between scan points decreases. It is
170 certainly possible that this thresholding procedure will not eliminate some unde-
171 sirable triangles such as when two leaves are very close to each other, however
172 such instances should be relatively infrequent unless the canopy is extremely
173 dense.

174 Noise in position measurements: The spatial locations of hit points have some
175 error due to limited instrument accuracy, usually on the order of millimeters.
176 Leaf motion due to wind also introduces some noise in the measurements. If the
177 scan resolution is extremely fine, it is possible that the characteristic dimension
178 of triangulated points can become near that of the spatial error in hit point
179 measurements. If this occurs, calculated triangle normals become very sensi-
180 tive to errors, and significant variation can be observed in the normals of two
181 adjacent triangles on the same leaf. Some noise could potentially be reduced
182 through smoothing (e.g., by weighted averaging adjacent normal vectors).

183 Woody material: In this work, no attempt was made to separate triangles as-
184 sociated with leaf and woody material. For plants with a large ratio of leaf to
185 wood area, it may be acceptable to neglect the effects of woody material due
186 to their negligible contributions. If the quantity of interest is simply net plant
187 material, the distinction between the two may not be needed. If necessary, leaf
188 and woody material could be separated using, e.g., the method of [Béland et al.](#)
189 [\(2014\)](#).

190 Occluded leaves: An inherent limitation in any optical measurement is that ob-
191 jects occluded from the view of the sensor cannot be measured. This means that
192 if there is significant heterogeneity in leaf orientation within the sampling vol-
193 ume, measurements are likely to bias towards leaves closest to the sensor. There
194 are several means of reducing this bias. One is to use sufficiently small volumes

195 that heterogeneity in leaf orientation is approximately resolved. This means
196 that any sub-sample of a volume will be representative of the entire volume.
197 Multiple scans can also be used to increase the number of samples in highly
198 occluded volumes. Adding multiple scans can introduce the potential problem
199 that some leaves within a volume may be sampled multiple times (oversampled).
200 This can be considered analogous to the problem of under-sampling some areas
201 of the volume, and means that a bias may be introduced if there is substantial
202 heterogeneity in leaf orientation within a given volume.

203 *2.2. Formulating the probability density function*

204 A problem immediately arises when trying to use the normals of the trian-
205 gulated points to form a PDF. As a leaf surface becomes increasingly inclined
206 away from the scanner location, the distance between adjacent hit points on
207 that leaf increases. The spacing between adjacent hit points is smallest when
208 the leaf normal is parallel with the laser direction, and tends toward infinity
209 as the leaf normal becomes orthogonal to the laser direction. In terms of the
210 triangulation, this means that leaves with normals closer to parallel with the
211 laser direction will have more triangles than leaves with normals closer to being
212 orthogonal to the laser direction. As a result, the computed PDF will be biased
213 toward leaves with normals that are parallel with the laser direction.

214 In order to correct for this bias, a triangle's normal should be weighted by
215 its area. There are many ways to calculate the area of an arbitrary triangle, one
216 example being Heron's formula

$$A = \sqrt{s(s - \ell_1)(s - \ell_2)(s - \ell_3)}, \quad (4)$$

217 where ℓ_1 , ℓ_2 , and ℓ_3 are the lengths of the sides of the triangle, and $s =$
218 $0.5(\ell_1 + \ell_2 + \ell_3)$.

219 The discrete leaf angle probability density function g_L is then constructed
 220 by summing the total area of triangles within each discrete angle class, and nor-
 221 malizing such that g_L integrates to unity. Regardless of the applied weighting,
 222 the method will still not account for the portion of leaves that are perfectly
 223 parallel to the laser direction, as these portions will have no hit points.

224 In cases where there is a wide range of scan zenith angles for a given volume,
 225 an additional weighting may be needed to account for varying scan point density.
 226 Because of the scan pattern of the LiDAR, there is a higher density of scan points
 227 at lower zenith angles. Thus, triangles should also be weighted by $\sin \theta_z$, where
 228 θ_z is the zenith angle of the scan point.

229 3. Validation

230 3.1. LiDAR instrument

231 In this study, the Focus^{3D} X 330 (FARO Technologies, Lake Mary, FL,
 232 USA) portable laser scanner was used to map the structure of vegetation. The
 233 scanner emits laser pulses with a wavelength of 1550 nm in a uniformly gridded
 234 pattern over a field of view of 300° in the vertical and 360° in the horizontal (i.e.,
 235 $\Theta = 150^\circ$ and $\Phi = 360^\circ$). The maximum scan resolution is $N_\Theta \times N_\Phi = 17,080 \times$
 236 $40,640$, which corresponds to an angular resolution of $\Delta\theta = \Delta\varphi = 0.009^\circ$. The
 237 beam diameter at exit is roughly 2.25 mm and diverges at a typical half angle
 238 of about 0.011° . Upon intersection with an object (range from 0.6 m up to
 239 330 m), the three-dimensional coordinates of the intersection are calculated and
 240 recorded, with a typical distance accuracy of ± 2 mm. The scanner also collects
 241 a large number of color digital photographs during the scan. This allows a
 242 mapping of the 3D hit point onto the 2D photographs, which gives an RGB color
 243 value associated with each hit point. The FARO unit records only one distance
 244 measurement per scan pulse. Any points deemed by the FARO firmware to

correspond to multiple hits were automatically discarded, as they are assumed to be points on the edge of a leaf that will result in erroneous hit points as discussed previously in Sect. 2.1.1. More generally, if a LiDAR unit was used that could record multiple hits per pulse, the nearest hit location should be used in the triangulation.

3.2. *Synthetic scan data*

Given the substantial errors expected for manual measurement of leaf orientation (e.g., Sect. 3.4), validation of the new method using field data presents a considerable challenge given that there is no ‘gold standard’ against which to compare. In order to address such problems, we formulated a novel methodology for validating the LiDAR scanning approach under ideal conditions. This involved creating synthetic LiDAR data that reproduces the scans that would be generated by the instrument described above. This methodology involved launching simulated rays from a given point and intersecting them with virtual leaves of known orientation. In this case, the virtual leaves were circular disks, which were chosen because simple ray-object intersection tests could be performed (cf. Suffern, 2007). Rays were launched in the same pattern as is done by the LiDAR instrument described above, which were intersected with each circular disk to determine the closest hit point (or that no hit occurred). The hit points were then triangulated, and the PDFs of the surface zenithal and azimuthal angles were computed.

A $1 \times 1 \times 1 \text{ m}^3$ volume of disks was considered that was 3 m away from the simulated scanner and situated on the ground (Fig. 4a). The scanner location was 0.5 m above the ground. Disks with a radius of 5 cm were inserted into the volume with a uniform random position. The elevation and azimuthal angles of the disks were chosen by drawing from a uniform distribution. The performance of the triangulation method is dependent on the chosen leaf angle distribution,

272 such that it will perform better for distributions that have more leaf area pro-
 273 jected in the direction of the scanner. A uniform distribution was chosen so that
 274 equal weights are given to all orientations to avoid favoring certain orientations.
 275 Cases were simulated that had 2^3 , 3^3 , 4^3 , 5^3 , and 6^3 disks in the volume. Given
 276 the size of the volume ($1 \times 1 \times 1 \text{ m}^3$) and the area of the disks ($\pi(0.05)^2 \text{ m}^2$),
 277 the one-sided area density of the cases were 0.063, 0.021, 0.50, 0.98, and 1.70
 278 m^2/m^3 . Since the random component means that results will change for each
 279 realization, 20 independent realizations were generated for each disk density.

280 3.3. Field sites

281 While the synthetic scan data can be used to demonstrate consistency of
 282 the method, there is still a need to perform field tests to ensure adequate per-
 283 formance in real vegetation. For this purpose, two validation experiments were
 284 performed. One was in a 6 m tall broad-leafed black cottonwood tree (*Populus*
 285 *balsamifera*) in Oregon ($44^\circ 34' 11.11'' \text{ N}$, $123^\circ 14' 47.53'' \text{ W}$). The other was
 286 in a 2 m tall grapevine canopy (*Vitis vinifera*) near the isolated tree ($44^\circ 33'$
 287 $53.06'' \text{ N}$, $123^\circ 14' 40.17'' \text{ W}$). The vines were trained to grow on a vertical
 288 shoot position (VSP) trellis system, with a row spacing of 2.5 m. These two
 289 sites were chosen because they represented the range of possible leaf inclination
 290 classes, and were small enough to allow for the collection of direct measurements
 291 without the use of special equipment such as scaffolding. In both plants, the
 292 characteristic leaf dimension was on the order of 10 cm, with some leaves as
 293 large as 15-20 cm.

294 The tree was divided into three vertical levels, with four azimuthal zones at
 295 each level. The first vertical level began at 0.76 m from the ground to limit
 296 interference by grass and weeds, with each vertical level being 1.07 m tall. This
 297 left approximately 2 m of leaves above the top zone that were not measured since
 298 they could not be reached using the available equipment. The azimuthal zones

299 faced each of the four cardinal directions. Manual measurements of inclination
 300 and azimuthal angle were performed on 50 randomly chosen leaves using a
 301 digital inclinometer and compass. The normal vector was taken to begin on the
 302 adaxial surface and emanate away from the leaf. Since all leaves had some degree
 303 of curvature, an ‘average’ leaf normal direction was estimated and measured.
 304 Four individual LiDAR scans of the tree were performed at each of the cardinal
 305 directions (which faced each zone), and co-registered together using the built-in
 306 GPS and inclinometer and refined by aligning common objects in the scene.
 307 The scanner was placed at roughly 2 meters from the nearest vegetation, and
 308 was mounted on a tripod about 1.5 m tall. Due to limited resources, only 6 of
 309 the 12 zones were sampled. These 6 zones were chosen in an alternating pattern:
 310 on the first level the North-South zones, second level the East-West zones, and
 311 third level North-South zones. Once leaf orientations had been measured, all
 312 leaves in each of the 6 zones were removed and scanned using an LI-3100C leaf
 313 area meter (LI-COR, Lincoln, NE, USA) to give a rough approximation of leaf
 314 area density, which was in the range of about $0.5\text{-}1.5\text{ m}^2/\text{m}^3$ depending on the
 315 volume.

316 The vineyard was divided into 20 discrete volumes that were 0.76 m wide in
 317 the row-parallel direction. Each of these 20 volumes were divided into a lower
 318 and upper zone, resulting in 40 total zones. The lower zones started at the
 319 fruiting wire which was 0.76 m from the ground, and extended to a height of
 320 1.17 m. The upper zones started at a height of 1.17 m and extended to a height
 321 of 1.70 m which was the height of the uppermost catch wire. The top catch
 322 wire was chosen as a consistent boundary, although some vegetation extended
 323 above this height. In each of the 40 total zones, 10 manual measurements were
 324 made of leaf inclination and azimuthal angles using the same procedure as in
 325 the tree. The leaf orientation PDF was assumed to be homogeneous in the

row-parallel direction, and all measurements at a given height were aggregated together. Two LiDAR scans were performed that were separated by 5 m in the row-parallel direction, which were co-registered using common objects in the scene. The scanner was placed in the middle of the row, which meant that it was roughly 1 m from the nearest vegetation.

In the validation experiments, vegetation was first scanned with the LiDAR at three different densities: $N_\Theta \times N_\Phi = 1708 \times 4064$, 2135×5080 , and 3415×8120 . For later reference, the resolutions of these scans will be respectively referred to as ‘low’, ‘mid’, and ‘high’. The distance between adjacent scan points on a surface oriented normal to the scan direction can be roughly estimated as $\Delta s \approx r \Delta \theta$, where r is the distance from the scanner. Note that strictly speaking this is only the distance between points in the θ direction, as the spacing in the φ direction is a function of the scan zenithal direction. For the low and high resolution scans, $\Delta \theta$ is 1.6 mrad and 0.82 mrad, respectively. This means that the closest leaf hit points for the tree (about 2 m away) have a spacing that ranges from about 3 mm to the width of the leaf (~ 10 cm) depending on leaf orientation. For the furthest leaf hit points (about 6 m away), the hit point spacing ranges from about 1 cm to the width of the leaf. When the high resolution scan was used, these values are reduced by about a factor of 2. Based on these estimations, L_{max} was chosen to be 5 cm. For this value, erroneous triangles connecting leaves spaced at larger than 5 cm will be eliminated. This does mean that there may be some triangles on leaves within a few degrees parallel with the scan direction that will be undesirably eliminated.

The scan rate was set to 122K points/second, which, considering the scan pattern, means that it takes around 0.05 sec to scan two adjacent azimuthal directions, thus this is the time to scan the four adjacent points needed to construct a triangle. As a result, wind may become a factor if leaf movement

353 is substantial over this period of time. The leaf should not move faster than
354 a few cm/s, otherwise the distance moved could be comparable to the triangle
355 dimension.

356 *3.4. Estimation of errors in manual measurements*

357 Manual measurements of leaf orientation contain substantial errors that can
358 vary between the individuals that are performing the measurements. The fore-
359 most of which is that each measurement requires a judgement call by the in-
360 dividual. Any leaf has an infinite number of normals, and the measurer must
361 assign a single value (or some finite number of values). For leaves with minimal
362 curvature, this is not particularly problematic as the range of possible normals
363 on a single leaf is small. However, for leaves with substantial curvature, it is
364 not uncommon to find leaves with inclination angles that span the full range
365 of 0 to 90°. Thus, an individual's perception of the 'average' normal is quite
366 subjective.

367 For the isolated tree, leaves had minimal curvature and thus choosing a
368 representative normal vector was relatively consistent. However, the vineyard
369 leaves were highly complex, often resulting in ambiguous normal vectors. To
370 obtain some estimation of the human error in manual measurements in the vine-
371 yard canopy, several raters were asked to measure the inclination and azimuthal
372 angles of the same 20 leaves. Each rater used the same equipment, and were
373 given the same set of instructions. They were told to imagine an 'average' plane
374 passing through the leaf, whose normal vector they were to measure. They were
375 instructed to resolve any ambiguity using their best judgement.

376 The inter comparison of measurements shows a considerable amount of vari-
377 ance in some cases (Fig. 3). The standard deviation between raters for all leaves
378 was 7.3° and 14.7° for leaf inclination and azimuth, respectively. If these val-
379 ues are normalized by the range of possible values, the normalized standard

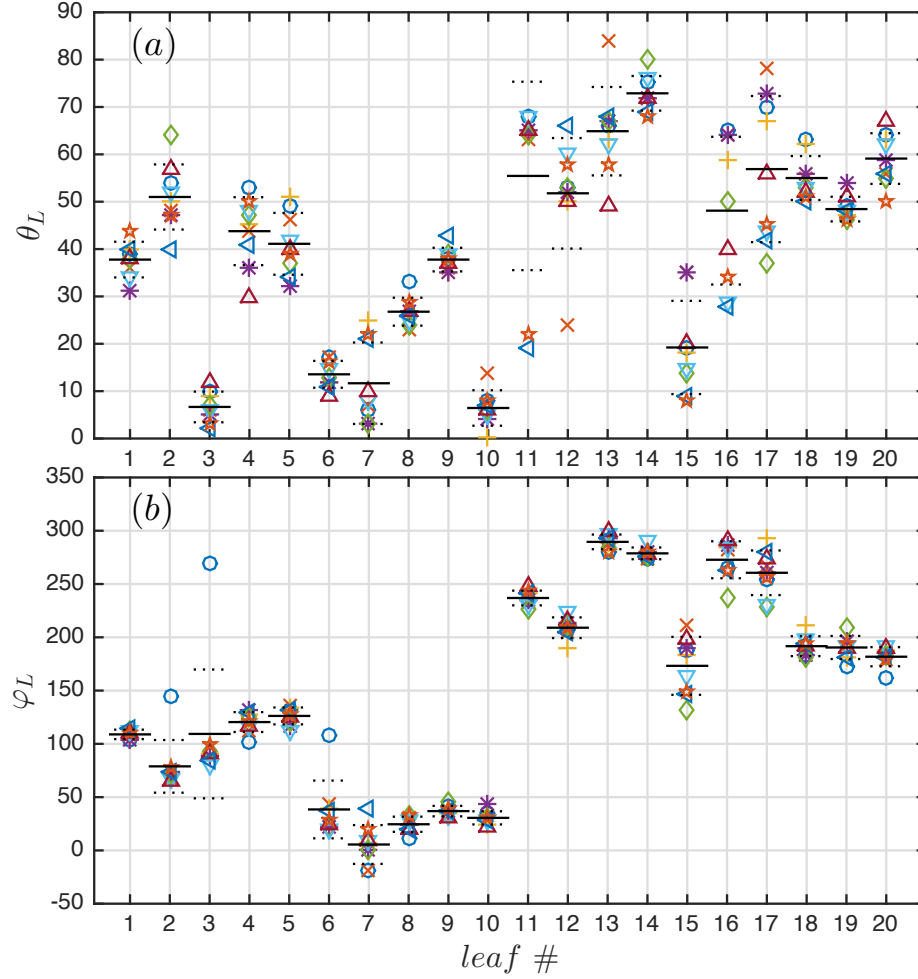


Figure 3: Assessment of error in manual measurements of leaf orientation in the vineyard canopy. Differing symbols correspond to each of the nine raters, who measured the same 20 leaves in the vineyard. Measurements are reported of the person's view of the average or representative (a) leaf inclination and (b) leaf azimuth. Solid horizontal lines denote the mean observation, and dashed horizontal lines denote ± 1 standard deviation. Note that some azimuthal measurements in (b) were shifted by 360° such that they could be visually grouped with other measurements.

380 deviations are found to be about 8% and 4% for leaf elevation and azimuth,
381 respectively.

382 Certain leaves had inclinations that appeared to be less ambiguous to in-
383 dividual raters than others, and had a standard deviation of only a couple of
384 degrees (e.g., leaves 6, 9, 19). The elevation of other leaves appeared to be
385 quite ambiguous. For example, the sampled distributions for leaves 16 and 17
386 appeared to be bi-modal. For leaf 17 about half of the group found that the leaf
387 was inclined at about 75° , while the other half found that the leaf was inclined
388 at about 40° . This result can likely be explained by the curvature of the leaves.
389 By examining the structure of grapevine leaves, we found that a ‘characteristic’
390 leaf had the two lobes nearest the petiole oriented close to vertical, the mid
391 portion of the leaf inclined at around 45° , and the lobe furthest from the petiole
392 inclined somewhere between 45 - 90° . There are certainly many exceptions to
393 this characterization, but this appeared to be the most representative view.

394 Considering the measurement of the ‘characteristic’ leaf, there are several
395 likely scenarios. First is that a rater could choose to measure the center of the
396 leaf, in which case they will likely find an inclination angle nearer to 45° . They
397 could also choose the more vertical portion of the leaf, in which case they will
398 likely find an inclination angle nearer to 90° . If the rater was to take a true
399 average of the leaf inclination, they would find an average inclination angle of
400 somewhere between 45 - 90° , most likely around 70° .

401 It appears to be quite difficult to assign an ‘average’ normal to a leaf with
402 substantial curvature. For the grapevine canopy, manual measurements are
403 likely to bias toward the center of the distribution. This underscores the need
404 for a measurement method that eliminates non-systematic bias. Some additional
405 accuracy could likely be gained by making multiple measurements on a single
406 leaf, but this significantly increases the time required to perform measurements,

407 and it still does not eliminate non-systematic bias.

408 4. Results

409 4.1. Synthetic scans

410 Synthetic scan data was generated with densities that matched the ‘low’ and
411 ‘high’ resolution scans used in the field experiments. For consistency with the
412 field experiments, L_{max} was also chosen to be 5 cm. Sample PDFs are shown
413 in Fig. 4 for 2 leaves (Fig. 4b,c) and 27 leaves (Fig. 4d,e). In the 2 leaves case,
414 disk directions were not randomly chosen, but rather were chosen such that one
415 disk had most of its area projected normal to the scanner $((\theta, \varphi) = (80^\circ, 0))$,
416 while the other disk had little area projected normal to the scanner $((\theta, \varphi) =$
417 $(10^\circ, 170))$.

418 Results are compared for cases when equal weights are incorrectly applied
419 to all triangles, and when the PDF is correctly area weighted. As expected, the
420 equally weighted PDF biases toward triangles that are closer to being orthog-
421 onal to the ray direction. We incorrectly observe that it is almost three times
422 more likely to find a triangle inclined at 10° versus 45° . When the proper area
423 weighting is applied, we obtain a computed PDF that is very close to the ex-
424 act PDF. Small errors are due to the slightly jagged nature of the triangulation
425 around the edges of the disks, and due to would-be triangles that are obstructed
426 from the view of the scanner.

427 The effects of obstructed disks was tested by varying the density of disks
428 within the volume (Fig. 5). As the density of disks within the volume increases,
429 the average error in the predicted PDF decreases. For a small number of disks
430 (e.g., 8), ‘luck’ has a considerable effect on the accuracy of the predicted PDF.
431 If, by chance, most of the disk area is unobstructed from view of the scanner
432 and there are no disks nearly parallel to the scan direction, errors were quite

low. A significant number of obstructed or nearly parallel disks could also cause errors to be very large. As disk density was further increased, results became more consistent. In these cases a substantial fraction of disk area is consistently obstructed, but there are enough samples in view to obtain a good approximation of the PDF. In examining several of the individual PDFs, we found that the first θ_L bin was consistently under predicted. This bin corresponds to leaves inclined nearly parallel to the scan direction. It should be noted, however, that depending on the position of the leaves relative to the scanner, the first θ_L bin may not always correspond to leaves nearly parallel to the scan direction.

4.2. Isolated tree

A visualization of individual hit points colored by their RGB color value is shown in Fig. 6a, and the corresponding surface triangulation is shown in Fig. 6b. The visualizations revealed that leaves located in the outer-lower portion of the tree tended to be oriented closer to vertical (Fig. 7a). Qualitatively, leaves in the upper portion of the tree were generally more horizontal. Average leaf azimuth tended to point along the shortest path length leading to the outer edge of the crown (Fig. 7b).

Calculated leaf angle PDFs provided a more quantitative depiction of trends in leaf orientation (Figs. 9 and 10). The average leaf inclination angle in the lower portion of the tree was greater than 45° , and was close to ‘erectophile’ as classified by [de Wit \(1965\)](#) (Fig. 8a). Leaf azimuthal angles tended toward the outward-facing direction of the tree crown (Fig. 8b). Moving upward along the tree, the leaf inclination PDF becomes skewed toward the horizontal orientation (planophile). Furthermore, the PDF of leaf azimuth becomes closer to uniform. In the upper crown, leaves in the East- and West-facing zones tended to have azimuthal distributions that skewed toward the South.

These trends are intuitively consistent with configurations that are likely

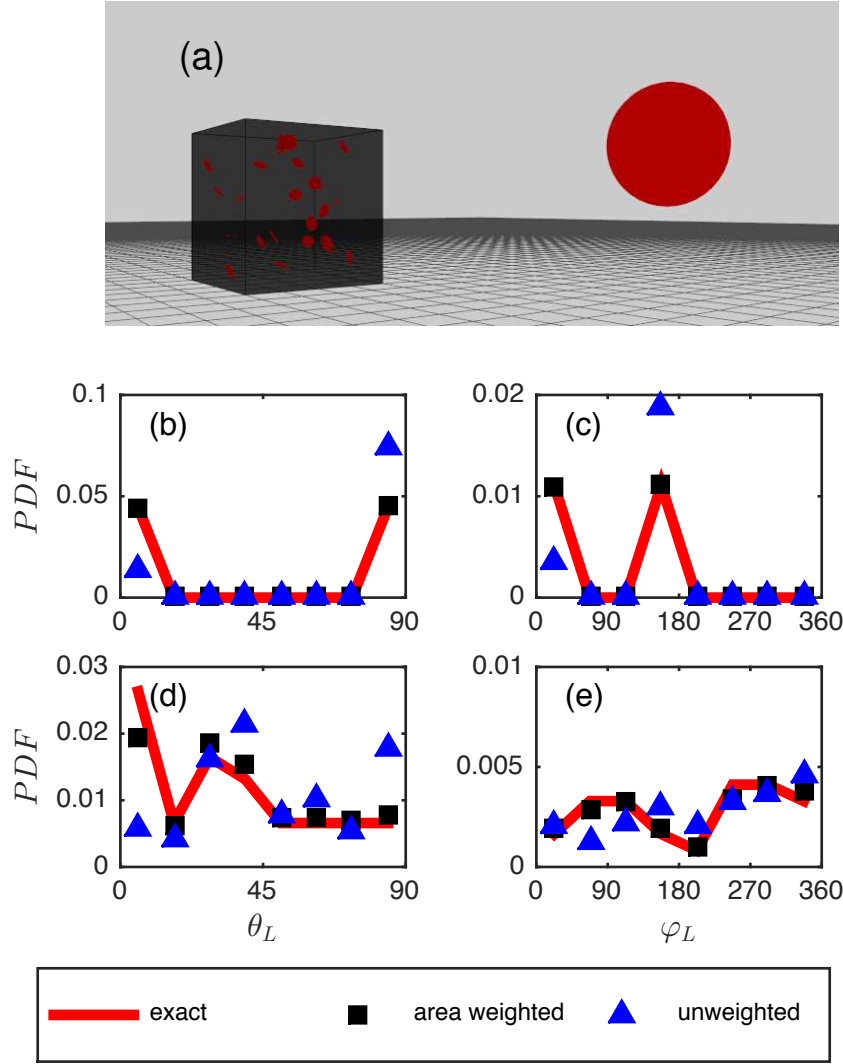


Figure 4: Illustration of triangulation methodology using synthetic LiDAR scan data. A visual depiction of the simulated scan with 64 circular disks is shown in (a). Rays are launched from the sphere, some of which intersect the disks, which are visualized using the triangulation. Probability density functions are calculated when no weighting is applied and when a proper area weighting is applied, which are compared to the ‘exact’ distributions. (b,c) 2 disks, and (d,e) 27 disks.

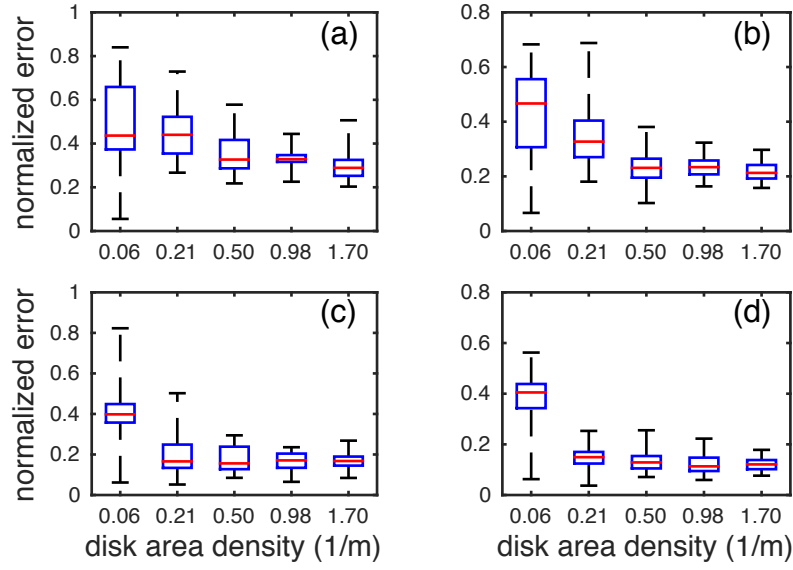


Figure 5: Box-and-whisker plots of normalized error in the PDF of (a,c) θ_L and (b,d) φ_L for the synthetic scan cases. The normalized error is defined as the root-mean-squared error between the exact PDF and the PDF formed by the triangulation methodology, which is normalized by the probability density for a uniform distribution (i.e., $1/90$ for θ_L and $1/360$ for φ_L).

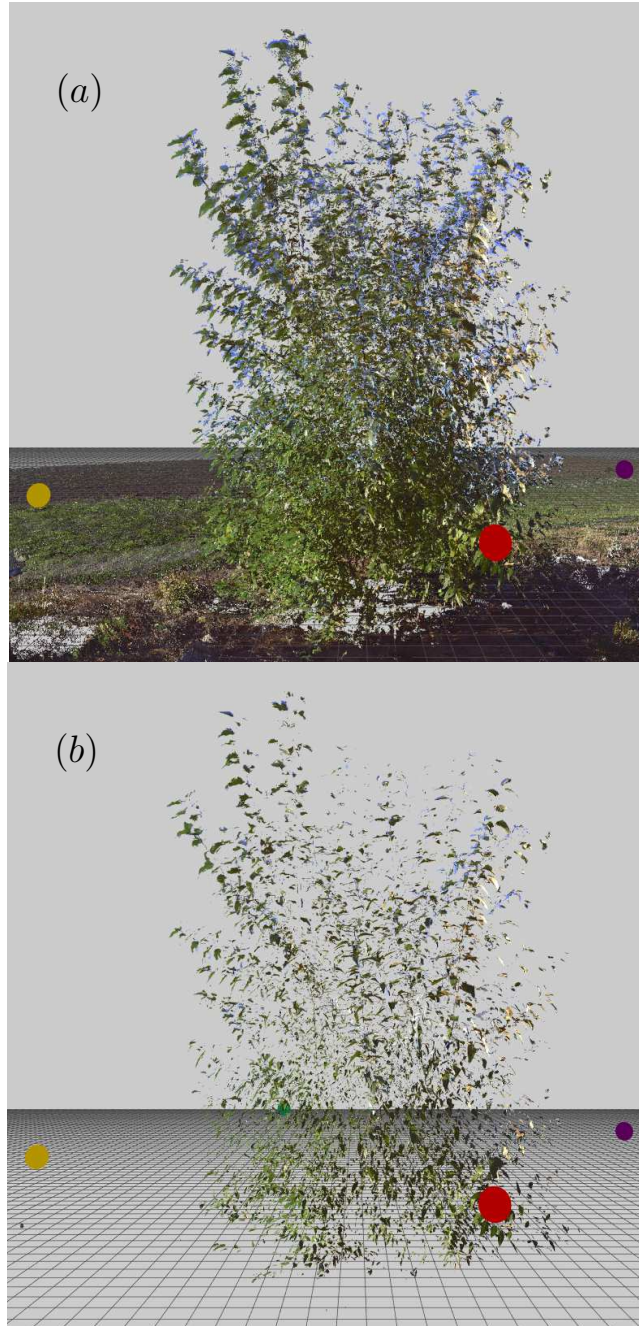


Figure 6: Leaf surface reconstruction of the isolated tree using LiDAR data (low resolution): (a) raw scan points, (b) triangulated surfaces ($L_{max} = 5$ cm, >1.3 million triangles). Spheres denote each of the four individual scan locations. Note that the surfaces of the triangles are colored by linearly interpolating the RGB values given at the vertices by the scanner.

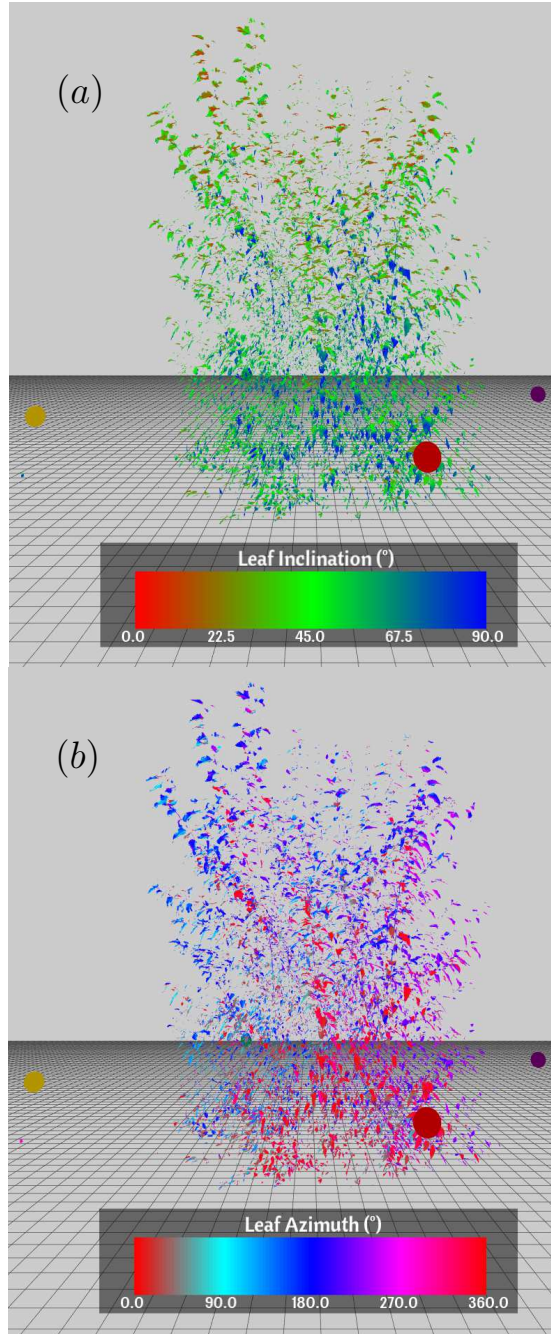


Figure 7: Visualization of the three-dimensional distribution of leaf orientation in the isolated tree. Triangles are colored based on their computed (a) inclination angle, and (b) azimuthal angle. The view shown in the figure is South-facing (180°). Spheres denote each of the four individual scan locations.

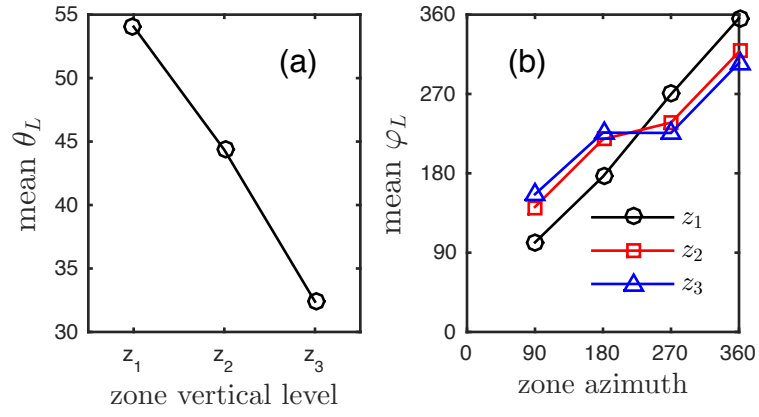


Figure 8: Variation of mean leaf orientation in space. (a) Mean leaf inclination angle for each vertical zone level (z_1 closest to ground, z_3 furthest from ground); (b) Linear directional mean of leaf azimuth for each azimuthal zone at each vertical zone level.

to maximize solar interception. For an unobstructed solar collector at the geographical location of the tree, the optimal normal direction is nearly South-facing with an inclination of about 35° (Lave and Kleissl, 2011). Leaves in the upper crown (which were less obstructed) had normals that skewed toward the South and were most likely to be inclined at $30\text{-}35^\circ$ (Fig. 8a), suggesting that they were oriented to maximize sunlight interception. Leaves near the ground were closer to vertical and tended to point along the shortest path length leading to the outer edge of the crown, which would appear to absorb the most sunlight given that dense leaves attenuate light from above.

Overall, good agreement was found between LiDAR and manual measurements of leaf angle distribution functions (Figs. 9 and 10), considering expected errors present in manual measurements. The manually measured PDFs contain noticeable noise, indicating that more than 50 samples per zone are likely needed for a smooth distribution. However, data is of high enough quality to show a clear trend in the PDFs, which qualitatively agrees with the PDFs obtained using the LiDAR measurement technique.

4.3. Vineyard

Visualizations of leaf orientation for the vineyard also show an intuitive trend (Fig. 11). The majority of the leaves were inclined at greater than 45° and had azimuthal angles in approximately the row-normal directions. Calculated PDFs of leaf inclination verified these qualitative observations (Fig. 12), revealing an inclination distribution that is approximately erectophile and an azimuthal distribution that biased toward the row-normal directions.

Like in the isolated tree, LiDAR measurements of leaf angle distribution functions in the vineyard appeared to be skewed toward the direction that will provide the most sunlight interception. The design of the trellis system is intended to maximize light penetration, which directly exposes leaves to sunlight

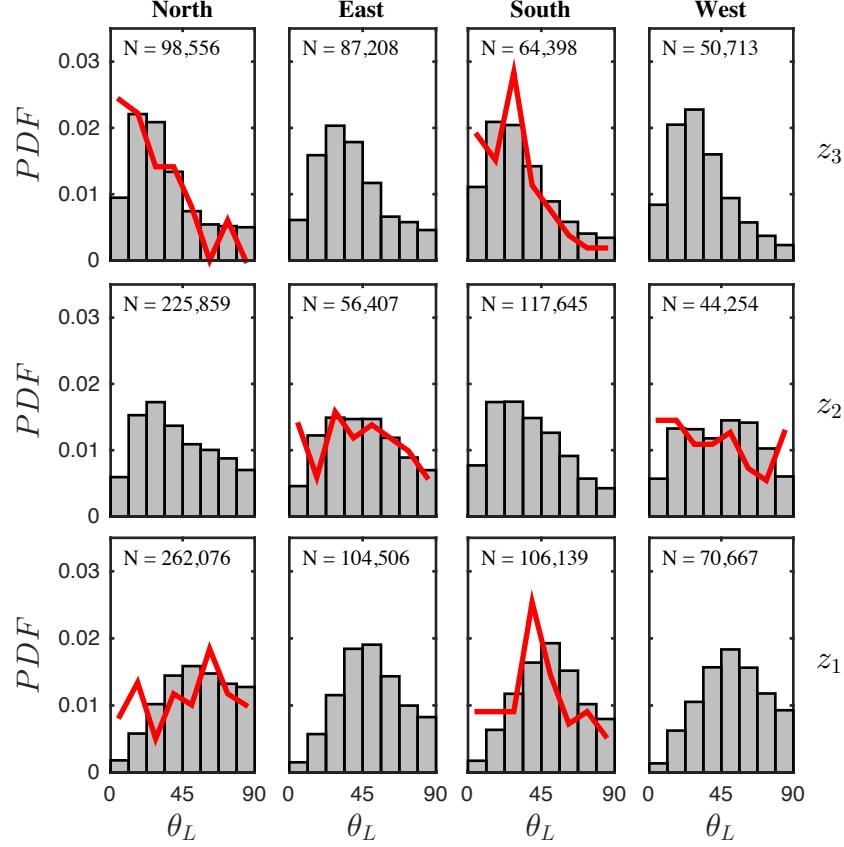


Figure 9: Probability density functions of leaf inclination angle for 12 volumes within an isolated tree. Note that $\theta_L = 0$ and $\theta_L = 90^\circ$ correspond to horizontal and vertical leaves, respectively. Solid lines represent the manually measured probability density functions (50 samples per zone). Columns correspond to the volume's azimuthal direction (e.g., North is on the North side of the tree). Rows correspond to the volume's vertical level (z_1 is lowest, z_3 is highest). N denotes the number of samples (i.e., triangles) that comprise the density function.

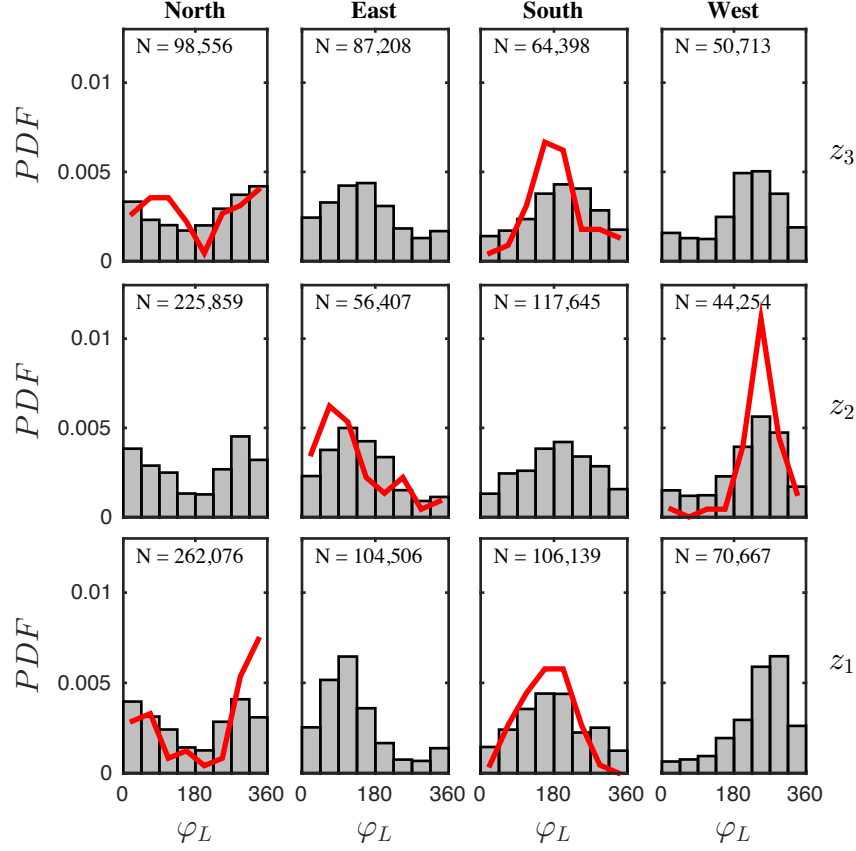


Figure 10: Probability density functions of leaf azimuthal angle for 12 volumes within an isolated tree. Note that $\varphi_L = 0$ is North, $\varphi = 90^\circ$ is East, etc. Solid lines represent the manually measured probability density functions (50 samples per zone). Columns correspond to the volume's azimuthal direction (e.g., North is on the North side of the tree). Rows correspond to the volume's vertical level (z_1 is lowest, z_3 is highest). N denotes the number of samples (i.e., triangles) that comprise the density function.

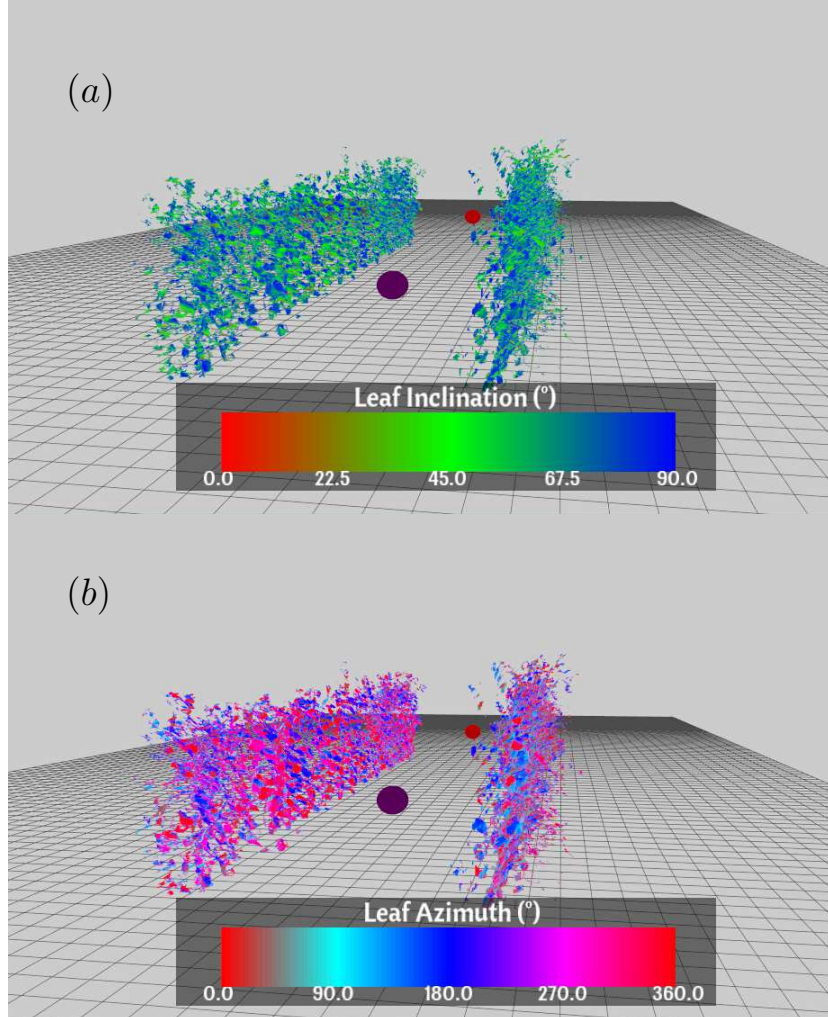


Figure 11: Visualization of the three-dimensional distribution of leaf orientation in the vineyard ($L_{max} = 5$ cm). Triangles are colored based on their computed (a) inclination angle, and (b) azimuthal angle. The view shown in the figure is approximately South-facing (180°). Spheres denote each of the two individual scan locations.

487 from the sides. Thus, one may intuitively expect leaf orientations to bias to-
 488 ward the row-normal directions and be inclined closer to vertical. It should be
 489 reiterated that the tops of the “upper” zones were not located at the top of
 490 vegetation, but rather there was still a significant amount of vegetation above
 491 the upper zones. As a result, there was little difference in the PDFs of leaf
 492 inclination between the upper and lower zones. The distribution of azimuthal
 493 angles is slightly more uniform for the upper zones, which is consistent with
 494 results for the isolated tree.

495 Agreement between LiDAR and manual measurements of leaf orientation
 496 was poor. As discussed previously, the vineyard presented some substantial
 497 challenges when performing manual measurements of leaf orientation, which
 498 was primarily due to complex leaf geometry/topography. This generally resulted
 499 in manual measurements that biased toward lower inclination angles. Indeed,
 500 the manual measurements of leaf inclination gave a more Gaussian PDF, with
 501 the peak lying between 40-60°. It is probable that the manually measured
 502 PDF contains substantial errors, and that it is unable to properly represent
 503 leaves oriented near vertical. If a qualitative comparison is performed with
 504 more rigorous data in a vineyard (e.g., [Bailey et al., 2014](#)), it appears that the
 505 LiDAR measurements agree with the expected behavior that the PDF of θ_L
 506 peaks at around 90°. The PDF of θ_L reported in [Bailey et al. \(2014\)](#) consists
 507 of much more detailed measurements that were extremely time consuming to
 508 collect. These measurements gave a PDF of θ_L that exponentially decreased
 509 away from vertical, which, along with physical intuition and the visualizations
 510 in Fig. 11a, agrees with the LiDAR measurements.

511 The LiDAR and manual measurements of leaf azimuth showed similar trends,
 512 but quantitative agreement was not particularly good. Both the manual and
 513 LiDAR measurements show peaks in the PDFs in the row-normal directions.

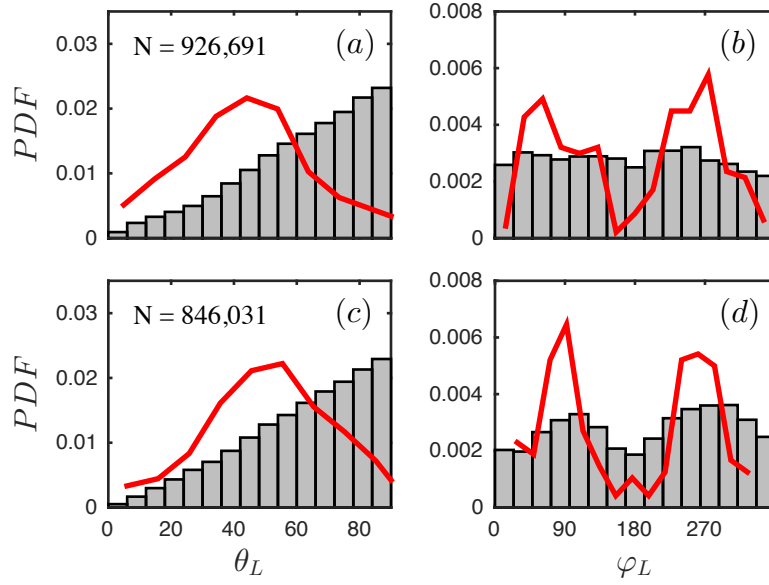


Figure 12: Probability density functions of leaf orientation within a vineyard. Note that the vineyard rows run North-South ($\varphi = 0, 180^\circ$). Solid lines represent the manually measured probability density functions (200 samples per zone). (a),(b) correspond to the upper zones, and (c),(d) correspond to the lower zones. N is the total number of samples used to construct the probability density function (i.e., the number of triangles in either the upper or lower volumes).

514 However the peaks in the manually measured PDFs are much more pronounced.
 515 This can also be explained by the curvature of the leaves. Although the average
 516 leaf orientation is most likely to be in the row-normal directions, any curvature
 517 in the leaves will give contributions to the off-normal directions. This means
 518 that the prominence of the peaks is likely to be reduced if the contributions of
 519 all parts of the leaves are considered.

520 4.4. Effect of scan resolution

521 The effect of the scan resolution was examined by comparing the low, mid,
 522 and high density scans. The PDFs obtained from the low resolution LiDAR
 523 scans previously shown in Figs. 9 and 10 are compared against the PDFs formed
 524 from the mid and high resolution scans in Figs. 13 and 14. It should also be

noted that the same length threshold value of $L_{max} = 5$ cm was used for all three resolutions. Overall, changes to the PDFs were minimal as scan resolution was varied, indicating that the technique is relatively robust for a range of scan densities. Visual inspection showed that for the mid and high resolution scans, there was some noise in calculated normals due to errors in measured hit point locations, although this did not seem to affect the PDFs. Similar observations were found for the vineyard, although not shown for brevity.

5. Summary

This work presents and validates a method that can rapidly measure the three-dimensional distribution of leaf orientation using terrestrial LiDAR scanning data. The LiDAR instrument is placed near the plant to be measured and used to generate a cloud of millions of discrete points that give the distances to various objects surrounding it.

A probability density function (PDF) of leaf orientation can then be computed for any arbitrary volume of vegetation using the triangle normals. It is critical that each normal be correctly weighted in terms of its contribution to the PDF, otherwise the PDF will bias toward normals that are parallel to the ray directions. The PDF should be formed by summing the triangle areas corresponding to discrete bins of $\delta\theta$ or $\delta\varphi$ and normalizing such that the density function integrates to unity.

Primary assumptions and limitations of the technique are:

1. It was assumed that the scan density is such that the characteristic triangle dimension is much smaller than the characteristic leaf dimension and leaf separation dimension, but much larger than the error in the LiDAR distance measurement. The scan density and distance from vegetation should be adjusted to meet this requirement. Alternatively, one could scan at the

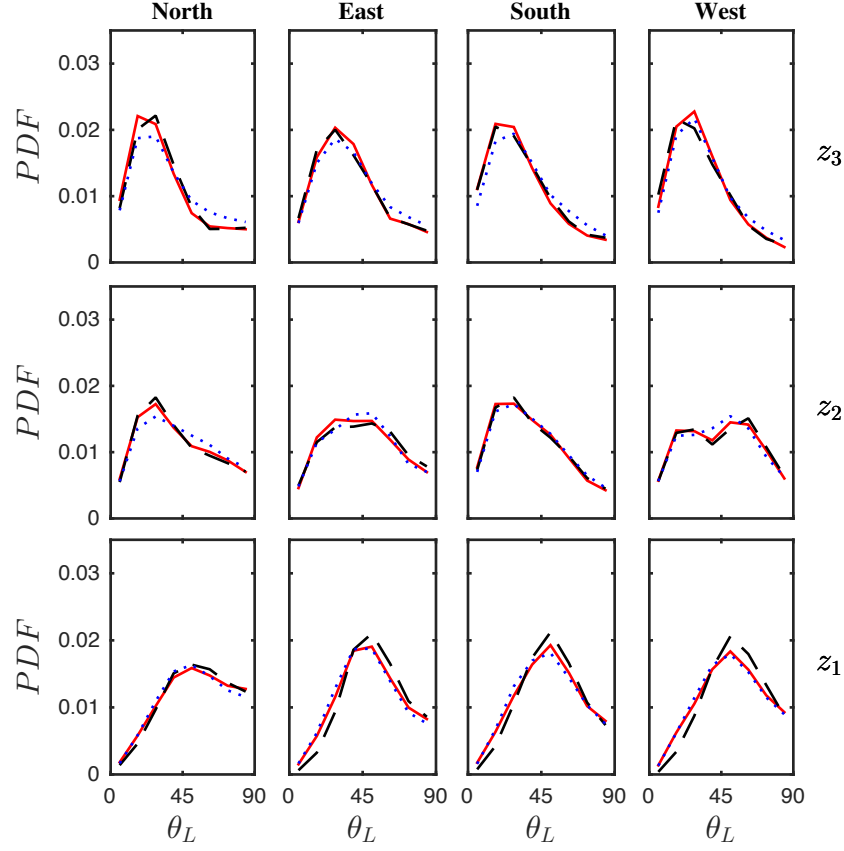


Figure 13: Probability density functions of leaf inclination angle for 12 volumes within an isolated tree for varying scan resolutions: ‘low’ (solid lines), ‘mid’ (dashed lines), and ‘high’ (dotted lines). Note that $\theta_L = 0$ and $\theta_L = 90^\circ$ correspond to horizontal and vertical leaves, respectively. Columns correspond to the volume’s azimuthal direction (e.g., North is on the North side of the tree). Rows correspond to the volume’s vertical level (e.g., z_1 is lowest, z_3 is highest).

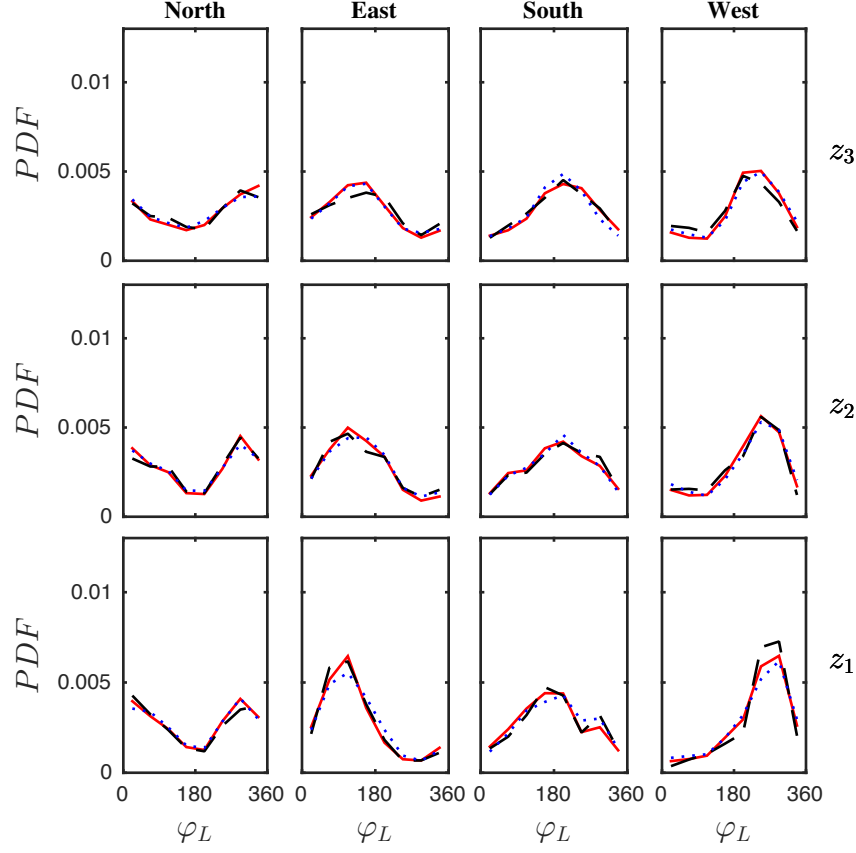


Figure 14: Probability density functions of leaf azimuthal angle for 12 volumes within an isolated tree for varying scan resolutions: ‘low’ (solid lines), ‘mid’ (dashed lines), and ‘high’ (dotted lines). Note that $\varphi_L = 0$ is North, $\varphi = 90^\circ$ is East, etc. Columns correspond to the volume’s azimuthal direction (e.g., North is on the North side of the tree). Rows correspond to the volume’s vertical level (e.g., z_1 is lowest, z_3 is highest).

- 551 highest possible density and systematically discard points from the scan
552 such that this requirement is met.
- 553 2. The triangulation algorithm was assumed to adequately remove the effects
554 of partial hits by choosing an L_{max} value that is sufficiently small. Points
555 could also be filtered using the reflectance of the hits or using an edge
556 detection algorithm.
- 557 3. It was assumed that the woody area is small compared to leaf area, or
558 that a distinction between the two is not necessary. If desired, one could
559 use an algorithm to separate hit points corresponding to wood and leaf
560 material (e.g., [Béland et al., 2014](#)).
- 561 4. Leaves that are completely obstructed from the view of the laser are not
562 measured. Thus, measured leaf orientations are likely to bias toward leaves
563 that are not occluded from the view of the scanner. This can be overcome
564 to some degree by using multiple scanner locations, however it is an in-
565 herent limitation of LiDAR (and other optical) measurements in general.
- 566 5. Scans should be performed in minimal wind conditions to reduce noise in
567 distance measurements.

568 Because of the considerable error in field measurements of leaf orientation,
569 the method was demonstrated to be consistent using synthetic scan simulations.
570 These simulations demonstrated the consistency of the method overall, and were
571 used to quantify errors in an ideal situation. It was found that errors in the
572 estimated leaf angle PDF decreased with increasing scan density and as leaf
573 density increased. The methodology was validated in the field by comparing
574 LiDAR-generated measurements to manual measurements in an isolated tree
575 and in a grapevine canopy. Qualitative agreement between manual and LiDAR
576 measurements for the isolated tree was good, and demonstrated the feasibility of

the LiDAR technique. Agreement between manual and LiDAR measurements in the grapevine canopy was relatively poor, which was attributed to the quality of the manual measurements. Replicant measurements demonstrated large biases in manual measurements when leaf shape/topography was complex. However, behavior of the LiDAR measurements in the vineyard intuitively agreed with visual observations as well as previously published data. It is likely that the LiDAR measurements are at least as accurate, if not more accurate than manual measurements, yet the LiDAR measurements give much more detailed information in a fraction of the time.

Future work should continue to evaluate the limitations and trade-offs of the LiDAR measurement method. The future applications of the method in advancing our understanding of plant physics are vast. Numerous modeling and analytical techniques could be improved by incorporating detailed information related to leaf orientation, ranging from applications in remote sensing to turbulent flow physics. The technique can be used to improve LiDAR measurements of leaf area density distributions by providing the correct projected leaf area fractions. There is also opportunity to analyze the temporal behavior (e.g., heliotropic motion) of leaf orientation by performing many LiDAR scans separated in time.

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605 or the Agricultural Research Service of any product or service to the exclusion
606 of others that may be suitable.

607 **References**

- 608 Bailey, B.N., Overby, M., Willemsen, P., Pardyjak, E.R., Mahaffee, W.F., Stoll,
609 R., 2014. A scalable plant-resolving radiative transfer model based on opti-
610 mized GPU ray tracing. *Agric. For. Meteorol.* 198-199, 192–208.
- 611 Bailey, B.N., Stoll, R., Pardyjak, E.R., Miller, N.E., 2016. A new three-
612 dimensional energy balance model for complex plant canopy geometries:
613 Model development and improved validation strategies. *Agric. For. Meteorol.*
614 218-219, 146–160.
- 615 Béland, M., Baldocchi, D.D., Widlowski, J.L., Fournier, R.A., Verstraete, M.M.,
616 2014. On seeing the wood from the leaves and the role of voxel size in de-
617 termining leaf area distribution of forests with terrestrial lidar. *Agric. For.*
618 *Meteorol.* 184, 82–97.
- 619 Béland, M., Widlowski, J.L., Fournier, R.A., Côté, J.F., Verstraete, M.M., 2011.
620 Estimating leaf area distribution in savanna trees from terrestrial LiDAR.
621 *Agric. For. Meteorol.* 151, 1252–1266.
- 622 Bernardini, F., Mittleman, J., Rushmeier, H., Silva, C., Taubin, G., 1999. The
623 ball-pivoting algorithm for surface reconstruction. *IEEE Trans. Vis. Comp.*
624 *Graph.* 5, 349–359.
- 625 de Wit, C.T., 1965. *Photosynthesis of Leaf Canopies*. Agricultural Research
626 Report 663. Wageningen. 57 pp.

627 Henning, J.G., Radtke, P.J., 2006. Ground-based laser imaging for assessing
628 three-dimensional forest canopy structure. *Photogramm. Eng. Remote Sens.*
629 72, 1349–1358.

630 Hosoi, F., Omasa, K., 2006. Voxel-based 3-D modeling of individual trees for
631 estimating leaf area density using high-resolution portable scanning lidar.
632 *IEEE Trans. Geosci. Remote Sens.* 40, 3610–3618.

633 Hosoi, F., Omasa, K., 2015. Estimating leaf inclination distribution of broad-
634 leaved trees in each part of the canopies by a high-resolution portable scanning
635 lidar. *J. Agric. Meteorol.* 71, 136–141.

636 Jones, H.G., Vaughan, R.A., 2010. *Remote Sensing of Vegetation: Principles,*
637 *Techniques, and Applications.* Oxford University Press, Oxford, UK. 400 pp.

638 Kull, O., Broadmeadow, M., Kruijt, B., Meir, P., 1999. Light distribution and
639 foliage structure in an oak canopy. *Trees* 14, 55–64.

640 Lave, M., Kleissl, J., 2011. Optimum fixed orientations and benefits of tracking
641 for capturing solar radiation in the continental United States. *Renew. Energy*
642 36, 1145–1152.

643 Myneni, R.B., Ross, J., 1991. *Photon-Vegetation Interactions: Applications in*
644 *Remote Sensing and Plant Ecology.* Springer. 582 pp.

645 Nilson, T., Kuusk, A., 1989. A reflectance model for the homogeneous plant
646 canopy and its inversion. *Remote Sens. Environ.* 27, 157–167.

647 Norman, J.M., Campbell, G.S., 1989. Canopy structure, in: Pearcy, R.W.,
648 Ehleringer, J., Mooney, H.A., Rundel, P.W. (Eds.), *Plant Physiological Ecol-*
649 *ogy: Field Methods and Instrumentation.* Chapman & Hall, New York, pp.
650 301–326.

651 Pisek, J., Sonnentag, O., Richardson, A.D., Ottus, M.M., 2013. Is the spherical
 652 leaf inclination angle distribution a valid assumption for temperate and boreal
 653 broadleaf tree species? *Agric. For. Meteorol.* 169, 186–194.

654 Press, W.H., Teukolsky, S.A., Vetterling, W.T., Flannery, B.P., 2007. *Numerical
 655 Recipes: The Art of Scientific Computing*. Cambridge University Press,
 656 Cambridge, U.K. 1256 pp.

657 Raabe, K., Pisek, J., Sonnentag, O., Annuk, K., 2015. Variations of leaf inclina-
 658 tion angle distribution with height over the growing season and light exposure
 659 for eight broadleaf tree species. *Agric. For. Meteorol.* 214–215, 2–11.

660 Radtke, P.J., Bolstad, P.V., 2001. Laser point-quadrat sampling for estimating
 661 foliage-height profiles in broad-leaved forests. *Can. J. For. Res.* 31, 410–418.

662 Raupach, M.R., Woods, N., Dorr, G., Leys, J.F., Cleugh, H.A., 2001. The
 663 entrapment of particles by windbreaks. *Atmos. Env.* 35, 3373–3383.

664 Rosell, J.R., Llorens, J., Sanz, R., Arnó, J., R.-D., M., Masip, J., Escolà, A.,
 665 Camp, F., Solanelles, F., Gràcia, F., Gil, E., Val, L., Planas, S., Palacín, J.,
 666 2009. Obtaining the three-dimensional structure of tree orchards from remote
 667 2D terrestrial LIDAR scanning. *Agric. For. Meteorol.* 149, 1505–1515.

668 Ross, J., 1981. *The Radiation Regime and Architecture of Plant Stands*. Dr.
 669 W. Junk Publishers, The Hague, The Netherlands. 424 pp.

670 Ryu, Y., Sonnentag, O., Nilson, T., Vargas, R., Kobayashi, H., Wenk, R., Bal-
 671 docchi, D.D., 2010. How to quantify tree leaf area index in an open savanna
 672 ecosystem: A multi-instrument and multi-model approach. *Agric. For. Mete-
 673 orol.* 150, 63–76.

674 Schuepp, P.H., 1993. Tansley review no. 59. leaf boundary layers. *New Phytol-
 675 ogist* 125, 477–507.

676 Shell, G.S.G., Lang, A.R.G., Sale, P.J.M., 1974. Quantitative measures of leaf
677 orientation and heliotropic response in sunflower, bean, pepper and cucumber.
678 Agric. Meteorol. 13, 25–37.

679 Suffern, K.G., 2007. Ray Tracing from the Ground Up. A K Peters/CRC Press,
680 Boca Raton, FL. 784 pp.

681 Thanisawanyangkura, S., Sinoquet, H., Rivet, P., Cretenet, M., Jallas, E., 1997.
682 Leaf orientation and sunlit leaf area distribution in cotton. Agric. For. Meteorol.
683 86, 1–15.

684 Yang, X., Strahler, A.H., Schaaf, C.B., Jupp, D.L.B., Yao, T., Zhao, F., Wang,
685 Z., Culvenor, D.S., Newnham, G.J., Lovell, J.L., Dubayah, R.O., Wood-
686 cock, C.E., Ni-Meister, W., 2013. Three-dimensional forest reconstruction
687 and structural parameter retrievals using a terrestrial full-waveform lidar in-
688 strument (Echidna®). Remote Sens. Env. 135, 36–51.

689 Zheng, G., Moskal, L.M., 2012. Leaf orientation retrieval from terrestrial laser
690 scanning (TLS) data. IEEE Trans. Geosci. Remote Sens. 50, 3970–3979.

691 **List of Figures**

692 1 Visual depiction of point cloud triangulation. (a) shows how
693 points are first triangulated using the two-dimensional grid of
694 (θ_i, φ_j) pairs. Leaf-laser intersection points (hits) and non-intersection
695 points (misses) are denoted respectively by closed and open cir-
696 cles. At any hit point, a triangulation is attempted with the
697 $(\theta_i, \varphi_j), (\theta_{i+1}, \varphi_j), (\theta_{i+1}, \varphi_{j+1})$ points and the $(\theta_i, \varphi_j), (\theta_{i+1}, \varphi_{j+1}),$
698 $(\theta_i, \varphi_{j+1})$ points. (b) shows the triangulation mapped to the
699 (x, y, z) hit coordinates. 7

700	2	Schematic of the coordinate system for two adjacent triangles. . .	9
701	3	Assessment of error in manual measurements of leaf orientation	
702		in the vineyard canopy. Differing symbols correspond to each of	
703		the nine raters, who measured the same 20 leaves in the vineyard.	
704		Measurements are reported of the person's view of the average or	
705		representative (a) leaf inclination and (b) leaf azimuth. Solid hor-	
706		izontal lines denote the mean observation, and dashed horizontal	
707		lines denote ± 1 standard deviation. Note that some azimuthal	
708		measurements in (b) were shifted by 360° such that they could	
709		be visually grouped with other measurements.	19
710	4	Illustration of triangulation methodology using synthetic LiDAR	
711		scan data. A visual depiction of the simulated scan with 64 cir-	
712		cular disks is shown in (a). Rays are launched from the sphere,	
713		some of which intersect the disks, which are visualized using the	
714		triangulation. Probability density functions are calculated when	
715		no weighting is applied and when a proper area weighting is ap-	
716		plied, which are compared to the 'exact' distributions. (b,c) 2	
717		disks, and (d,e) 27 disks.	23
718	5	Box-and-whisker plots of normalized error in the PDF of (a,c) θ_L	
719		and (b,d) φ_L for the synthetic scan cases. The normalized error	
720		is defined as the root-mean-squared error between the exact PDF	
721		and the PDF formed by the triangulation methodology, which is	
722		normalized by the probability density for a uniform distribution	
723		(i.e., $1/90$ for θ_L and $1/360$ for φ_L).	24

724	6	Leaf surface reconstruction of the isolated tree using LiDAR data	
725		(low resolution): (a) raw scan points, (b) triangulated surfaces	
726		($L_{max} = 5$ cm, >1.3 million triangles). Spheres denote each of	
727		the four individual scan locations. Note that the surfaces of the	
728		triangles are colored by linearly interpolating the RGB values	
729		given at the vertices by the scanner.	25
730	7	Visualization of the three-dimensional distribution of leaf orien-	
731		tation in the isolated tree. Triangles are colored based on their	
732		computed (a) inclination angle, and (b) azimuthal angle. The	
733		view shown in the figure is South-facing (180°). Spheres denote	
734		each of the four individual scan locations.	26
735	8	Variation of mean leaf orientation in space. (a) Mean leaf in-	
736		clination angle for each vertical zone level (z_1 closest to ground,	
737		z_3 furthest from ground); (b) Linear directional mean of leaf az-	
738		imuth for each azimuthal zone at each vertical zone level.	27
739	9	Probability density functions of leaf inclination angle for 12 vol-	
740		umes within an isolated tree. Note that $\theta_L = 0$ and $\theta_L = 90^\circ$	
741		correspond to horizontal and vertical leaves, respectively. Solid	
742		lines represent the manually measured probability density func-	
743		tions (50 samples per zone). Columns correspond to the volume's	
744		azimuthal direction (e.g., North is on the North side of the tree).	
745		Rows correspond to the volume's vertical level (z_1 is lowest, z_3 is	
746		highest). N denotes the number of samples (i.e., triangles) that	
747		comprise the density function.	29

748	10	Probability density functions of leaf azimuthal angle for 12 vol-	
749		umes within an isolated tree. Note that $\varphi_L = 0$ is North, $\varphi = 90^\circ$	
750		is East, etc. Solid lines represent the manually measured prob-	
751		ability density functions (50 samples per zone). Columns corre-	
752		spond to the volume's azimuthal direction (e.g., North is on the	
753		North side of the tree). Rows correspond to the volume's verti-	
754		cal level (z_1 is lowest, z_3 is highest). N denotes the number of	
755		samples (i.e., triangles) that comprise the density function. . . .	30
756	11	Visualization of the three-dimensional distribution of leaf orienta-	
757		tion in the vineyard ($L_{max} = 5$ cm). Triangles are colored based	
758		on their computed (a) inclination angle, and (b) azimuthal an-	
759		gle. The view shown in the figure is approximately South-facing	
760		(180°). Spheres denote each of the two individual scan locations.	31
761	12	Probability density functions of leaf orientation within a vine-	
762		yard. Note that the vineyard rows run North-South ($\varphi = 0, 180^\circ$).	
763		Solid lines represent the manually measured probability density	
764		functions (200 samples per zone). (a),(b) correspond to the up-	
765		per zones, and (c),(d) correspond to the lower zones. N is the	
766		total number of samples used to construct the probability den-	
767		sity function (i.e., the number of triangles in either the upper or	
768		lower volumes).	33

769	13	Probability density functions of leaf inclination angle for 12 vol-	
770		umes within an isolated tree for varying scan resolutions: ‘low’	
771		(solid lines), ‘mid’ (dashed lines), and ‘high’ (dotted lines). Note	
772		that $\theta_L = 0$ and $\theta_L = 90^\circ$ correspond to horizontal and ver-	
773		tical leaves, respectively. Columns correspond to the volume’s	
774		azimuthal direction (e.g., North is on the North side of the tree).	
775		Rows correspond to the volume’s vertical level (e.g., z_1 is lowest,	
776		z_3 is highest).	35
777	14	Probability density functions of leaf azimuthal angle for 12 vol-	
778		umes within an isolated tree for varying scan resolutions: ‘low’	
779		(solid lines), ‘mid’ (dashed lines), and ‘high’ (dotted lines). Note	
780		that $\varphi_L = 0$ is North, $\varphi = 90^\circ$ is East, etc. Columns correspond	
781		to the volume’s azimuthal direction (e.g., North is on the North	
782		side of the tree). Rows correspond to the volume’s vertical level	
783		(e.g., z_1 is lowest, z_3 is highest).	36