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

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leaf angle distributions were known, and in the field for an isolated tree and 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

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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
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

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

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

Some recent work has begun 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
 120 searched for hits (Fig. 1a and Table 1). If the $(i + 1, j)$ and $(i + 1, j + 1)$ were
 121 both also hits, the (i, j) , $(i + 1, j)$, and $(i + 1, j + 1)$ points were connected

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 (θ_i, φ_j) , $(\theta_{i+1}, \varphi_j)$, $(\theta_{i+1}, \varphi_{j+1})$ points and the (θ_i, φ_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.

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

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

133 where $\mathbf{n} = (n_x, n_y, n_z)$ is the normal vector, and $\mathbf{a}$ and $\mathbf{b}$ are two vectors

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.

134 defining the sides of the triangle which are found by looking up the (x, y, z)
 135 coordinates at each vertex (Table 2). The sign convention of the $\mathbf{a}$ and $\mathbf{b}$ vectors
 136 should be defined such that the calculated normal vectors are consistent (e.g.,
 137 as in Fig. 2).

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

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

140 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
 245 correspond to multiple hits were automatically discarded, as they are assumed
 246 to be points on the edge of a leaf that will result in erroneous hit points as
 247 discussed previously in Sect. 2.1.1. More generally, if a LiDAR unit was used
 248 that could record multiple hits per pulse, the nearest hit location should be used
 249 in the triangulation.

250 3.2. Synthetic scan data

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

266 A $1 \times 1 \times 1 \text{ m}^3$ volume of disks was considered that was 3 m away from the
 267 simulated scanner and situated on the ground (Fig. 4a). The scanner location
 268 was 0.5 m above the ground. Disks with a radius of 5 cm were inserted into the
 269 volume with a uniform random position. The elevation and azimuthal angles of
 270 the disks were chosen by drawing from a uniform distribution. The performance
 271 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 ($\pi(0.05)^2 \text{ m}^2$),

the one-sided area density of the cases were 0.063, 0.021, 0.50, 0.98, and 1.70 m^2/m^3 . Since the random component means that results will change for each realization, 20 independent realizations were generated for each disk density.

3.3. Field sites

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

The tree was divided into three vertical levels, with four azimuthal zones at each level. The first vertical level began at 0.76 m from the ground to limit interference by grass and weeds, with each vertical level being 1.07 m tall. This left approximately 2 m of leaves above the top zone that were not measured since they could not be reached using the available equipment. The azimuthal zones faced each of the four cardinal directions. Manual measurements of inclination and azimuthal angle were performed on 50 randomly chosen leaves using a digital inclinometer and compass. The normal vector was taken to begin on the adaxial surface and emanate away from the leaf. Since all leaves had some degree 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
 326 row-parallel direction, and all measurements at a given height were aggregated
 327 together. Two LiDAR scans were performed that were separated by 5 m in the
 328 row-parallel direction, which were co-registered using common objects in the
 329 scene. The scanner was placed in the middle of the row, which meant that it
 330 was roughly 1 m from the nearest vegetation.

331 In the validation experiments, vegetation was first scanned with the LiDAR
 332 at three different densities: $N_{\Theta} \times N_{\Phi} = 1708 \times 4064$, 2135×5080 , and 3415×8120 .
 333 For later reference, the resolutions of these scans will be respectively referred
 334 to as ‘low’, ‘mid’, and ‘high’. The distance between adjacent scan points on
 335 a surface oriented normal to the scan direction can be roughly estimated as
 336 $\Delta s \approx r \Delta \theta$, where r is the distance from the scanner. Note that strictly speaking
 337 this is only the distance between points in the θ direction, as the spacing in the
 338 φ direction is a function of the scan zenithal direction. For the low and high
 339 resolution scans, $\Delta \theta$ is 1.6 mrad and 0.82 mrad, respectively. This means that
 340 the closest leaf hit points for the tree (about 2 m away) have a spacing that
 341 ranges from about 3 mm to the width of the leaf (~ 10 cm) depending on
 342 leaf orientation. For the furthest leaf hit points (about 6 m away), the hit
 343 point spacing ranges from about 1 cm to the width of the leaf. When the high
 344 resolution scan was used, these values are reduced by about a factor of 2. Based
 345 on these estimations, L_{max} was chosen to be 5 cm. For this value, erroneous
 346 triangles connecting leaves spaced at larger than 5 cm will be eliminated. This
 347 does mean that there may be some triangles on leaves within a few degrees
 348 parallel with the scan direction that will be undesirably eliminated.

349 The scan rate was set to 122K points/second, which, considering the scan
 350 pattern, means that it takes around 0.05 sec to scan two adjacent azimuthal
 351 directions, thus this is the time to scan the four adjacent points needed to
 352 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
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-

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.

383 individual 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 $45\text{-}90^\circ$. 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 $45\text{-}90^\circ$, 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
433 low. A significant number of obstructed or nearly parallel disks could also cause
434 errors to be very large. As disk density was further increased, results became

435 more consistent. In these cases a substantial fraction of disk area is consistently
 436 obstructed, but there are enough samples in view to obtain a good approxima-
 437 tion of the PDF. In examining several of the individual PDFs, we found that
 438 the first θ_L bin was consistently under predicted. This bin corresponds to leaves
 439 inclined nearly parallel to the scan direction. It should be noted, however, that
 440 depending on the position of the leaves relative to the scanner, the first θ_L bin
 441 may not always correspond to leaves nearly parallel to the scan direction.

442 4.2. *Isolated tree*

443 A visualization of individual hit points colored by their RGB color value is
 444 shown in Fig. 6a. The visualizations revealed that leaves located in the outer-
 445 lower portion of the tree tended to be oriented closer to vertical. Qualitatively,
 446 leaves in the upper portion of the tree were generally more horizontal. Average
 447 leaf azimuth tended to point along the shortest path length leading to the outer
 448 edge of the crown.

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

458 These trends are intuitively consistent with configurations that are likely
 459 to maximize solar interception. For an unobstructed solar collector at the ge-
 460 ographical location of the tree, the optimal normal direction is nearly South-
 461 facing with an inclination of about 35° (Lave and Kleissl, 2011). Leaves in the

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.

upper crown (which were less obstructed) had normals that skewed toward the South and were most likely to be inclined at 30-35° (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 from the sides. Thus, one may intuitively expect leaf orientations to bias toward the row-normal directions and be inclined closer to vertical. It should be reiterated that the tops of the “upper” zones were not located at the top of

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.

489 vegetation, but rather there was still a significant amount of vegetation above
 490 the upper zones. As a result, there was little difference in the PDFs of leaf
 491 inclination between the upper and lower zones. The distribution of azimuthal
 492 angles is slightly more uniform for the upper zones, which is consistent with
 493 results for the isolated tree.

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

510 The LiDAR and manual measurements of leaf azimuth showed similar trends,
 511 but quantitative agreement was not particularly good. Both the manual and
 512 LiDAR measurements show peaks in the PDFs in the row-normal directions.
 513 However the peaks in the manually measured PDFs are much more pronounced.
 514 This can also be explained by the curvature of the leaves. Although the average
 515 leaf orientation is most likely to be in the row-normal directions, any curvature

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).

in the leaves will give contributions to the off-normal directions. This means that the prominence of the peaks is likely to be reduced if the contributions of all parts of the leaves are considered.

4.4. Effect of scan resolution

The effect of the scan resolution was examined by comparing the low, medium, and high density scans. The PDFs obtained from the low resolution LiDAR scans previously shown in Figs. 9 and 10 are compared against the PDFs formed 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 highest possible density and systematically discard points from the scan such that this requirement is met.

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).

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

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

ity 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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604 or the Agricultural Research Service of any product or service to the exclusion
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743		azimuthal direction (e.g., North is on the North side of the tree).	
744		Rows correspond to the volume's vertical level (z_1 is lowest, z_3 is	
745		highest). N denotes the number of samples (i.e., triangles) that	
746		comprise the density function.	29

747	10	Probability density functions of leaf azimuthal angle for 12 vol-	
748		umes within an isolated tree. Note that $\varphi_L = 0$ is North, $\varphi = 90^\circ$	
749		is East, etc. Solid lines represent the manually measured prob-	
750		ability density functions (50 samples per zone). Columns corre-	
751		spond to the volume's azimuthal direction (e.g., North is on the	
752		North side of the tree). Rows correspond to the volume's verti-	
753		cal level (z_1 is lowest, z_3 is highest). N denotes the number of	
754		samples (i.e., triangles) that comprise the density function. . . .	30
755	11	Visualization of the three-dimensional distribution of leaf orienta-	
756		tion in the vineyard ($L_{max} = 5$ cm). Triangles are colored based	
757		on their computed (a) inclination angle, and (b) azimuthal an-	
758		gle. The view shown in the figure is approximately South-facing	
759		(180°). Spheres denote each of the two individual scan locations.	31
760	12	Probability density functions of leaf orientation within a vine-	
761		yard. Note that the vineyard rows run North-South ($\varphi = 0, 180^\circ$).	
762		Solid lines represent the manually measured probability density	
763		functions (200 samples per zone). (a),(b) correspond to the up-	
764		per zones, and (c),(d) correspond to the lower zones. N is the	
765		total number of samples used to construct the probability den-	
766		sity function (i.e., the number of triangles in either the upper or	
767		lower volumes).	33

768	13	Probability density functions of leaf inclination angle for 12 vol-	
769		umes within an isolated tree for varying scan resolutions: ‘low’	
770		(solid lines), ‘mid’ (dashed lines), and ‘high’ (dotted lines). Note	
771		that $\theta_L = 0$ and $\theta_L = 90^\circ$ correspond to horizontal and ver-	
772		tical leaves, respectively. Columns correspond to the volume’s	
773		azimuthal direction (e.g., North is on the North side of the tree).	
774		Rows correspond to the volume’s vertical level (e.g., z_1 is lowest,	
775		z_3 is highest).	35
776	14	Probability density functions of leaf azimuthal angle for 12 vol-	
777		umes within an isolated tree for varying scan resolutions: ‘low’	
778		(solid lines), ‘mid’ (dashed lines), and ‘high’ (dotted lines). Note	
779		that $\varphi_L = 0$ is North, $\varphi = 90^\circ$ is East, etc. Columns correspond	
780		to the volume’s azimuthal direction (e.g., North is on the North	
781		side of the tree). Rows correspond to the volume’s vertical level	
782		(e.g., z_1 is lowest, z_3 is highest).	36