

Evaluation of LiDAR-based canopy trait estimation in Midwestern row crops

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Abstract

Stand count, the number of plants per unit ground area, and leaf area index (LAI), the ratio of leaf area to ground area, are critical traits for crop research but are traditionally measured using labor-intensive methods. While new sensing technologies are being developed, quantifying improvement in measurement efficiency and data quality, relative to traditional techniques, is lacking. In this study, we use light detection and ranging (LiDAR) to generate 3D scans of corn (*Zea mays*) and soybean (*Glycine max*) plots and evaluate two computational methods: A gap fraction approach to estimate LAI and a persistent homology algorithm to estimate stand count by detecting structural peaks in the canopy. Validation experiments and statistical comparisons of bias and variance demonstrate that LiDAR-derived LAI estimates in corn are comparable in quality to those from established instruments. However, in soybean, the LiDAR method performs poorly, likely due to dense canopies limiting light penetration and structural differentiation. Stand count estimations in corn closely match manual counts, with the added benefit of full-plot coverage and significantly faster data collection. In soybean, stand count estimates are unreliable under dense canopy conditions. These results offer practical guidance for the use of LiDAR in field phenotyping and highlight both its current capabilities and limitations. While a trade-off between speed and precision remains, particularly in high-density canopies, LiDAR's scalability and multi-trait potential make it a promising tool for high-throughput breeding programs. Continued improvements in LiDAR hardware and algorithm design may further enhance measurement accuracy and extend applicability across crops and growth stages.

Abbreviations: LAI, leaf area index; LiDAR, light detection and ranging.

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Plain Language Summary

Measuring the number of plants in a field and the amount of leaf area helps researchers judge crop growth, but common methods are slow and labor intensive. We tested whether a cart-mounted laser scanner technology, called light detection and ranging (LiDAR), could measure plant number and leaf area in corn and soybean as well as standard field methods. In corn, LiDAR plant counts closely matched manual counts, and LiDAR leaf-area estimates were generally similar in quality to established instruments. LiDAR also covered whole plots and collected both traits in a single scan. In soybean, the dense canopy blocked the laser and made both measurements unreliable. These results show that LiDAR can provide fast, repeatable measurements of several crop traits when plants are distinct and gaps remain visible, but performance declines in dense canopies. The study also shows why new field sensors should be tested for both accuracy and repeatability before widespread use.

1 | INTRODUCTION

Phenomics tools have the potential to accelerate crop breeding by increasing the number of measurable traits across more crop varieties than traditional methods allow (Zhao et al., 2019). Realizing this potential requires developing and validating new capabilities to produce high-quality data tailored to plant breeders' needs (D. M. Deery & Jones, 2021). This process typically involves selecting a sensor, designing trait-estimation algorithms, and validating those estimates against established methods. Stand count, the number of plants per unit row length, is valuable for interpreting plot-level biomass variation, helping disentangle the confounding influence of plant number versus plant performance (Shi et al., 2015). Stand count can also aid in interpreting crop stress responses; for example, salt tolerance may be evaluated by counting plants that germinate under saline conditions (Ahmed et al., 2024). Similarly, leaf area index (LAI), the ratio of leaf area to ground area (m^2/m^2), is crucial for breeders and ecosystem modelers. Key physiological processes such as transpiration, light interception, and photosynthesis are directly influenced by LAI (Huang et al., 2015; Lochocki et al., 2022; Morakinyo & Lam, 2016).

Traditional methods for determining stand count and LAI are time-consuming, limiting measurements across space (e.g., total number of plots) and time (frequency of measurements). Traditionally, stand count is obtained manually by counting plants over a known row length. The gold-standard method for LAI involves harvesting all plants in a row segment, removing and measuring the leaves, and calculating LAI from total leaf area. Less destructive approaches use hemispherical photography or canopy analyzers, which estimate LAI based on visible sky within the canopy using established light-penetration models. Though implementation varies, most require several in-canopy readings and subse-

quent processing. These methods are faster than harvesting but still labor intensive, taking several minutes per measurement (Bréda, 2003). Since stand count and LAI are architectural traits, accurate three-dimensional (3D) reconstruction of the plant canopy could enable their computational estimation. Light detection and ranging (LiDAR) offers a promising high-throughput solution to 3D canopy imaging and is widely used in plant phenomics to study growth and structure (Bailey & Mahaffee, 2017; D. Deery et al., 2014; Jimenez-Berni et al., 2018; Madec et al., 2017; Siebers et al., 2018, 2024). LiDAR emits light pulses that reflect off surfaces and return to the sensor; by measuring time of flight relative to sensor position, detailed 3D point clouds are generated (Rosell et al., 2009). While these point clouds capture plant structure, they do not inherently include trait data (Rosell Polo et al., 2009/2), necessitating specialized algorithms to extract meaningful information.

Persistent homology is well-suited for identifying geometric features in 3D data (Edelsbrunner & Harer, 2008). It not only detects the most prominent or densest peaks but also evaluates their persistence relative to surrounding peaks, enabling it to filter out noise. Thus, it offers a novel approach for estimating stand count. As persistent homology algorithms have not previously been used for counting plants in LiDAR data, rigorous analysis is necessary to assess and validate its performance. Additionally, several methods have been compared for determining LAI, with previous studies having demonstrated agreement among several traditional measurement techniques, with each exhibiting design-specific tradeoffs (Wilhelm et al., 2000). LAI estimation using LiDAR coupled with a gap fraction algorithm has been proposed previously (McGrath et al., 2023); however, it has not yet been evaluated alongside traditional measurement techniques.

This study uses LiDAR technology to estimate stand count and LAI in two major crops, corn (*Zea mays*) and soybean

(*Glycine max*), aiming to statistically compare these methods with conventional ones. We apply a persistent homology algorithm, providing a novel method for estimating stand count from LiDAR data. Stand count is derived from LiDAR point clouds by detecting individual plants as clusters of points. The cloud is divided into vertical columns, and the number of points per column is used to create a two-dimensional density map. Peaks in this map, which indicate areas of higher point concentration, correspond to plant stems. This approach simulates a bird's-eye view of the canopy overlaid with a grid to identify dense regions. Our analysis also provides updated bias and variance comparisons of LAI, which overcome the limitations with traditional comparative statistics (Goodwin & Leech, 2006; Taffé, 2021). We predict that LiDAR-based methods will perform best in canopies with clearly separated plants and well-defined gaps. This research aims to advance the utility of LiDAR-based measurements of LAI and stand count in plant phenotyping and to advance adoption of these techniques in breeding and agronomic applications.

2 | MATERIALS AND METHODS

2.1 | Field sites, experimental design, and data collection

The experiment consisted of 12 soybean plots (*Glycine max* var. LD11-2070) and 15 corn plots (*Zea mays* var. DKC58 34RI) planted on June 7, 2023. Each plot consisted of four rows that were 3.05 m (10 ft) long, with 76 cm spacing between rows. Corn was planted at 15.2 cm spacing within rows, corresponding to a target maximum density of approximately 35,000 plants acre⁻¹. Soybean was planted at 4 cm spacing within rows, corresponding to a target seeding density of approximately 133,000 seeds acre⁻¹. These densities are within commercially relevant planting ranges for corn and soybean production and research systems. On August 16, 2023, nine of the 15 corn plots were manually thinned to remove 25%, 50%, or 75% of plants, creating target densities of approximately 26,000, 17,500, and 8700 plants acre⁻¹, respectively. A similar thinning treatment was applied to soybean on September 8, 2023, creating target post-thinning seeding-density equivalents of approximately 100,000, 66,000, and 33,000 seeds acre⁻¹, respectively. Six corn plots and three soybean plots were left unthinned as maximum-density controls.

The experiment was conducted as a completely randomized design, with corn and soybean analyzed separately. For corn, 15 plots were assigned to four density treatments: unthinned control plots ($n = 6$) and plots thinned by 25%, 50%, or 75% of the initial plant stand ($n = 3$ per thinning treatment). Soybean was initially planted with six unthinned control plots to mirror the corn design; however, three of these plots had poor

emergence and were excluded before analysis because they did not represent the intended maximum-density treatment and could not be reliably assigned to a controlled thinning treatment. Therefore, the final soybean analysis included 12 plots assigned to four density treatments: Unthinned control plots ($n = 3$) and plots thinned by 25%, 50%, or 75% of the initial plant stand ($n = 3$ per thinning treatment). The larger number of planted control plots was included to provide additional measurements at the maximum planting density, where occlusion effects were expected to be greatest, and to ensure sufficient usable plots in the event of uneven emergence or establishment. No formal blocking structure was used; therefore, plot was treated as the experimental unit, and repeated measurements within each plot were used to estimate method variance. Measurements were made within the plot area, with stand-count measurements focused on the two center rows to reduce border effects.

LiDAR point clouds were collected using a 2D LiDAR sensor (Hokuyo UST-10LX, Hokuyo Automatic Co., Ltd.) and a rotary encoder (Yumo E6B2-CWZ3E, Yumo Automation) mounted on a modified garden cart (Gorilla Carts; Figure 1). The LiDAR sensor was mounted 18 cm above the ground (Figure 1). The system was powered by a 20 V lithium-ion battery, and data from the LiDAR and encoder were transmitted wirelessly to a laptop for storage and processing. Point clouds were generated by synchronizing timestamps from the LiDAR and encoder to calculate x, y, and z coordinates for each point. Additional detail on the electrical enclosure and major electronic components is provided in Figure S1.

A feature of the cart system was that data collection was organized around a predefined plot list rather than continuous whole-field mapping. Before scanning, the operator loaded a plot sequence corresponding to the order in which plots would be measured in the field. For each plot, the operator initiated data collection at the plot boundary and stopped collection after reaching the end of the plot. This produced raw scan files that were already associated with a known plot identity and approximate plot extent. As a result, subsequent processing did not require segmentation of a continuous field-scale point cloud into individual plots. Instead, each scan could be constrained computationally to the plot region and to the crop rows nearest the LiDAR sensor before trait extraction. This operator-guided acquisition strategy reduced post-processing complexity while maintaining plot-level control of where each scan began and ended.

Stand count and LAI were measured multiple times per plot on August 21 for corn and September 21 for soybean to assess method variance. Five trained individuals independently assessed stand count using three methods: Meter sticks, fast-paced LiDAR scans, and slow-paced LiDAR scans. Each method was applied five times per plot. "Fast-paced" refers to a typical walking speed while pulling the cart, approximately 0.5–1 m s⁻¹, whereas "slow-paced" scans were collected at

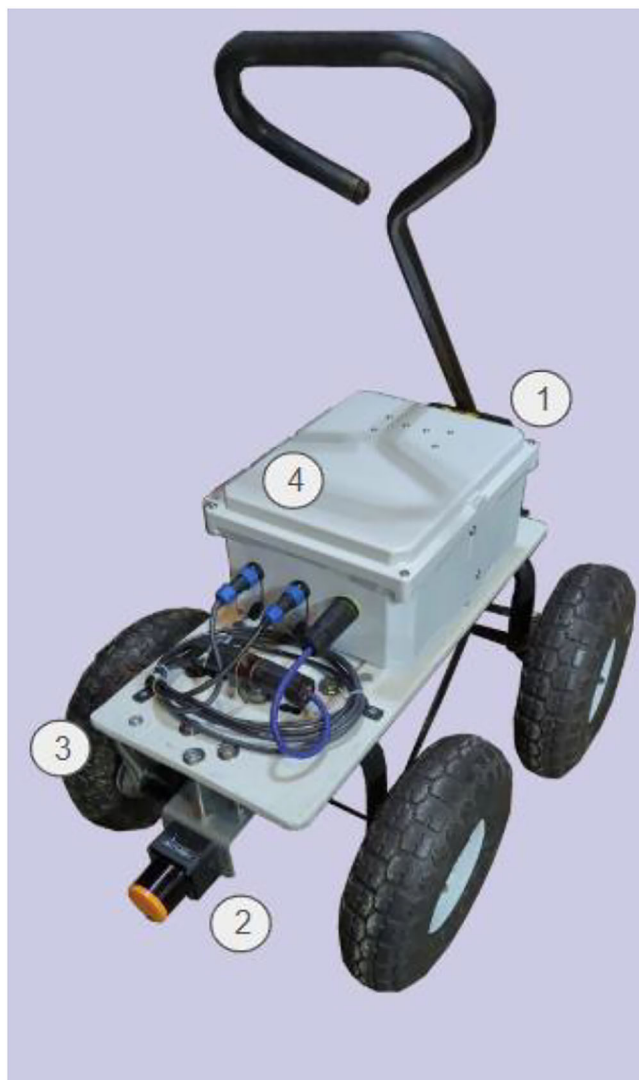


FIGURE 1 A light detection and ranging (LiDAR)-based 3D scanning system. The system was powered by a 20 V lithium-ion battery (1). A 2D scanning LiDAR (Hokuyo UST-10LX, Hokuyo Automatic Co., Ltd.) was mounted to the cart 18 cm above the ground (2). The distance traveled was measured using a rotary encoder (3, E6B2-CWZ3E, Yumo Automation) connected to the wheel with a timing belt. A wireless access point (TP-Link EAP 110, TP-Link Technologies Co., Ltd.) was housed in an enclosure. The access point transmitted data, which were stored on a laptop wirelessly connected to the cart. A waterproof enclosure (4) housed the access point and an Arduino Uno microcontroller (Arduino S.r.l.), which communicated with the LiDAR and encoder.

less than 0.5 m s^{-1} . The meter-stick method relied on a 1 m ruler placed parallel to the two center rows at a random distance from the front edge of the plot. All plants along the 1 m transect were counted, with one end of the transect considered inclusive and the other end exclusive to reduce edge-effect bias.

LAI was measured using four instruments: the LAI-2200 (LI-COR Environmental), AccuPAR (METER Group), Sun-

Scan (Delta-T Devices Ltd.), and both fast- and slow-paced LiDAR scans. LiDAR-based LAI was estimated using gap fraction analysis. Five people were trained to collect LAI measurements in the thinned corn and soybean plots. Timestamps from the instrument data files were used to estimate how long each person took to complete all measurements for each crop. The same raw LiDAR and encoder data were used for stand count and LAI estimation.

2.2 | Algorithm application

LiDAR-derived traits were generated after data collection using an offline Python processing pipeline (Figure 2). The processing pipeline separated the raw scan data into two simultaneous analysis branches. For LAI estimation, LiDAR range and angle measurements were used directly in a gap-fraction analysis and did not require generation of a 3D point cloud. For stand-count estimation, LiDAR and encoder data were synchronized to generate plot-level 3D point clouds, which were then filtered to the relevant plot region and crop rows nearest the LiDAR sensor before persistent homology analysis.

LAI was calculated from the LiDAR data following the gap-fraction approach of McGrath et al. (2023). The Hokuyo LiDAR sensor collected data across a 270° field of view; LAI estimation used a 180° subset of each scan, corresponding to returns extending 90° to either side of the sensor in the canopy-facing portion of the scan. Returns were grouped into 15° view-angle bins, with observations from equivalent angles on opposite sides of the sensor pooled for each bin. Individual returns were classified as either canopy interceptions or gaps based on return distance. Returns within 30 m of the sensor were classified as canopy interceptions, whereas returns greater than 30 m, or returns with no detected object within this range, were classified as gaps. Gap fraction was calculated for each angle bin as the number of gap observations divided by the total number of observations in that bin, and these angle-specific gap fractions were used to estimate LAI.

A simplified persistent homology algorithm was then applied to detect peaks in the two-dimensional point-density representation. Persistent homology was implemented using the `imagepers.py` module for topological peak detection, adapted from Huber's Python implementation for persistent homology in two-dimensional images (Huber, 2018). The algorithm assigns each peak a "birth" and "death" height. The birth height represents the initial appearance of a peak, while the death height marks when it merges with a taller neighboring peak. This process can be visualized as submerged mountains in a sea with receding water levels: As the water level drops, individual peaks emerge, and as it continues to recede, smaller peaks merge with taller neighboring peaks.

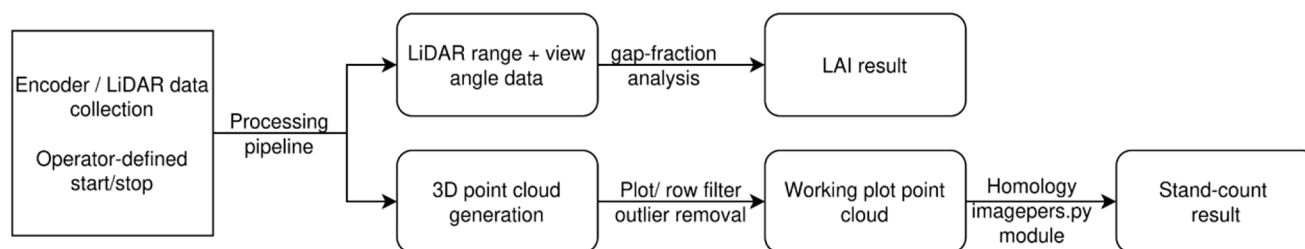


FIGURE 2 Overview of light detection and ranging (LiDAR) data collection and processing workflow. Synchronized encoder and LiDAR data were collected as plot-level scans using operator-defined start and stop positions. The processing pipeline separated the data into two analysis branches. LAI was estimated from LiDAR range and angle data using gap-fraction analysis. Stand count was estimated from a 3D point cloud after plot and row filtering, outlier removal, and persistent homology analysis implemented in the imagepers.py module.

The persistence of a peak, defined as the difference between its birth and death heights, measures how long it remained distinct and therefore how topologically significant it was in the density representation.

Areas around plant stems included points from both the stem and surrounding leaves, producing density peaks with high persistence. In contrast, smaller density peaks from leaves or noise generally had lower persistence because they merged quickly with neighboring peaks. The maximum height in each scan was normalized to 1, and peaks with persistence greater than 0.35 were counted as individual plants. Because the x - z coordinates of each peak were retained, detected plant locations could be visualized in the 3D point cloud.

A custom z -axis filtering step was applied to reduce dense bands of points caused by temporary slowing of the cart. Because the LiDAR scanned at a fixed frequency, slower cart movement caused repeated scans to be collected over nearly the same ground position, creating artificially dense point bands that could be counted as multiple persistent peaks from the same plant location (Figure S2). Points near the base of the canopy were projected into a two-dimensional density representation by dividing the x - z plane, parallel to the ground, into grid cells. Along the x -axis, grid cells were 2 cm wide; along the z -axis, each individual LiDAR scan formed a cell. Because the LiDAR scanned at regular time intervals, variation in cart speed resulted in uneven spacing among scans along the z -axis. This grid defined vertical columns in the x - z plane, and point density was calculated as the number of points within each column.

2.3 | Statistical analysis of bias and variance

The mean of all measurements was calculated for each crop, plot, and measurement method. Bias between methods was defined as the difference in mean values for each pair of methods. To evaluate bias, these differences were plotted against the mean of both methods for each plot. Plots were visually inspected to determine whether bias appeared to correlate

with the mean. If no such correlation was observed, biases were pooled, and an overall mean bias was tested for significant deviation from zero using a two-tailed, two-sample t -test with a significance level of $\alpha = 0.05$.

For each plot and method, the standard deviation of the repeated measurements was calculated and plotted against the corresponding mean. These plots were visually assessed for correlation between standard deviation and mean. In all cases, a correlation was observed, indicating that variances could not be pooled across plots. Consequently, for each plot, the ratio of variances between methods was tested for significant deviation from one using a two-tailed F -test at $\alpha = 0.05$.

3 | RESULTS

3.1 | Persistent homology estimations of plant number correlated well with manual counts

LiDAR and encoder data were combined to produce 3D point clouds of the crop rows. In corn, the thinning treatments produced visually distinct canopy structures, with progressively larger gaps between plants as thinning intensity increased (Figure 3). The persistent homology algorithm identified peaks in point density near the base of the canopy, corresponding to likely plant locations, and these detected peaks were used to estimate stand count.

In corn, Pearson correlations between repeated manual stand counts and repeated fast- and slow-paced LiDAR stand-count estimates were greater than 0.9 (Figure 4A: fast, $r = 0.92$; Figure 4D: slow, $r = 0.93$). Plot-level bias between LiDAR and manual estimates increased with stand density, with undercounting most pronounced in plots with more than four plants per linear meter (Figure 4B,E). Fast LiDAR estimates were not significantly more variable than manual counts in any plot. In contrast, manual counts had significantly greater variance than corresponding slow LiDAR estimates in four plots (Figure 4F).

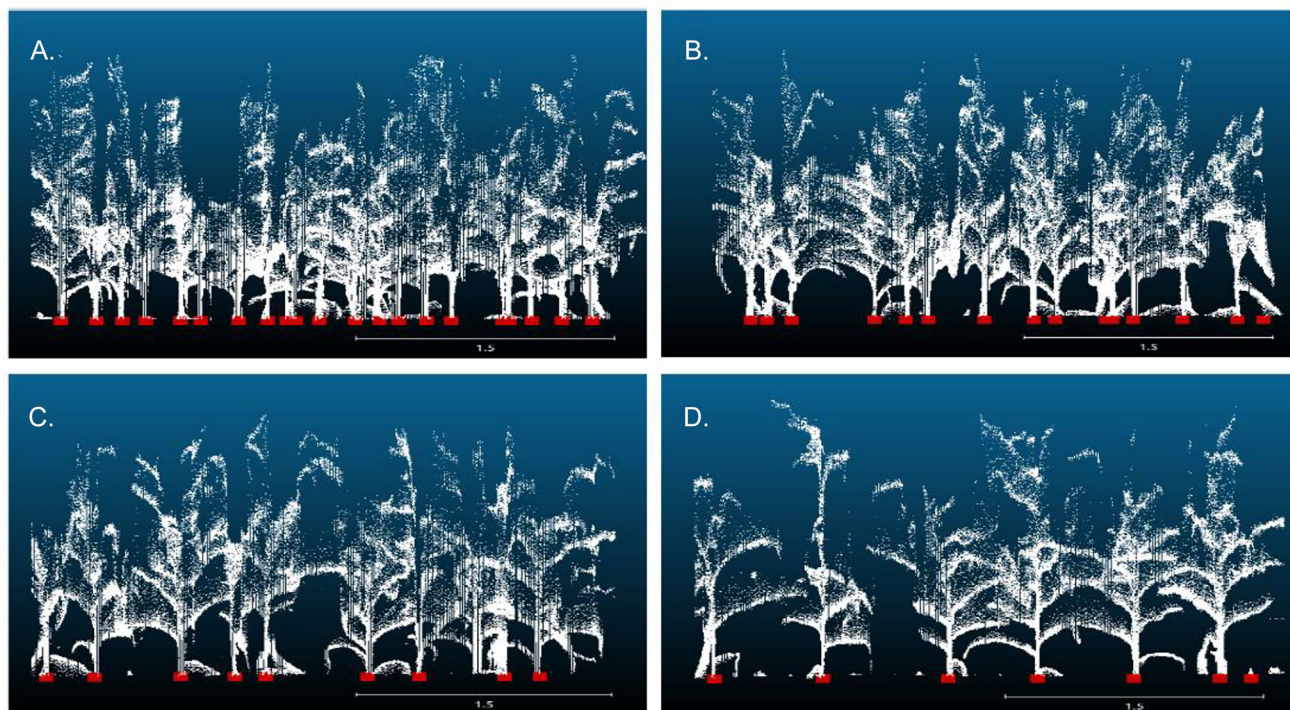


FIGURE 3 Example light detection and ranging (LiDAR) scan showing one row from corn plots thinned at 0% (A), 25% (B), 50% (C), and 75% (D). Red points at the base of each image indicate peak locations identified by the persistent homology algorithm. Scale bar shown in meters.

In soybean, Pearson correlations between repeated manual stand counts and repeated LiDAR stand-count estimates were much lower for both fast-paced ($r = 0.59$; Figure 5A) and slow-paced scans ($r = 0.58$; Figure 5D). Plot-level bias between LiDAR and manual estimates increased with stand density, indicating greater overestimation at higher plant densities (Figure 5B,E). Fast LiDAR estimates were not significantly more variable than manual counts in any plot (Figure 5C), and slow LiDAR estimates were similarly not significantly more variable than manual counts (Figure 5F). Across the range of manually counted soybean stand densities, LiDAR returned similar stand-count estimates despite differences in manual counts.

3.2 | Leaf area index

In corn, all measurement methods correlated well with the LAI-2200, with r values exceeding 0.8 (Table 1). The AccuPAR was the only instrument biased relative to the LAI-2200, underestimating LAI by an average of 0.25 units (Figure S3b). The SunScan and both LiDAR scan speeds were more precise than the LAI-2200 at low LAI values. LiDAR scanning was the fastest method overall: Fast scans required about one-quarter of the time, and slow scans less than half the time, of that needed to complete LAI-2200 measurements (Table 1).

In soybean, SunScan and AccuPAR estimates also correlated well with those from the LAI-2200 (Table 1). However,

all instruments showed bias compared to the LAI-2200. SunScan was less variable than the LAI-2200 in two of the 12 plots, and AccuPAR was less variable in one plot. As with corn, LiDAR scanning was the fastest method, with fast scans requiring roughly a quarter of the time, and slow scans less than half the time, of that needed for the LAI-2200 (Table 1).

In corn, the methods differed in both their central tendency and spread across the thinning treatments (Figure 6). In corn, AccuPAR was more precise than the LAI-2200 in plots with 75% thinning ($p = 0.03$) but had equivalent precision at other thinning levels. Fast and slow LiDAR scans were less precise than the LAI-2200 in control plots ($p = 0.004$ and $p = 0.002$, respectively) and more precise in plots with 50% thinning ($p = 0.01$ and $p = 0.02$; Figure 6).

In soybean, all LAI meters were biased relative to the LAI-2200 (Table 1; Figure 7; Figure S4). SunScan was more precise than the LAI-2200 in control plots and plots with 75% thinning. Both LiDAR scanning speeds were less precise than the LAI-2200 in control plots.

4 | DISCUSSION

In corn, LiDAR-derived stand counts correlated well with manual counts, though slight underestimation was observed in denser plots. Fast-paced LiDAR scans were as precise as manual counts, while slow scans were even more precise at lower densities. Both methods had limitations. Manual counts

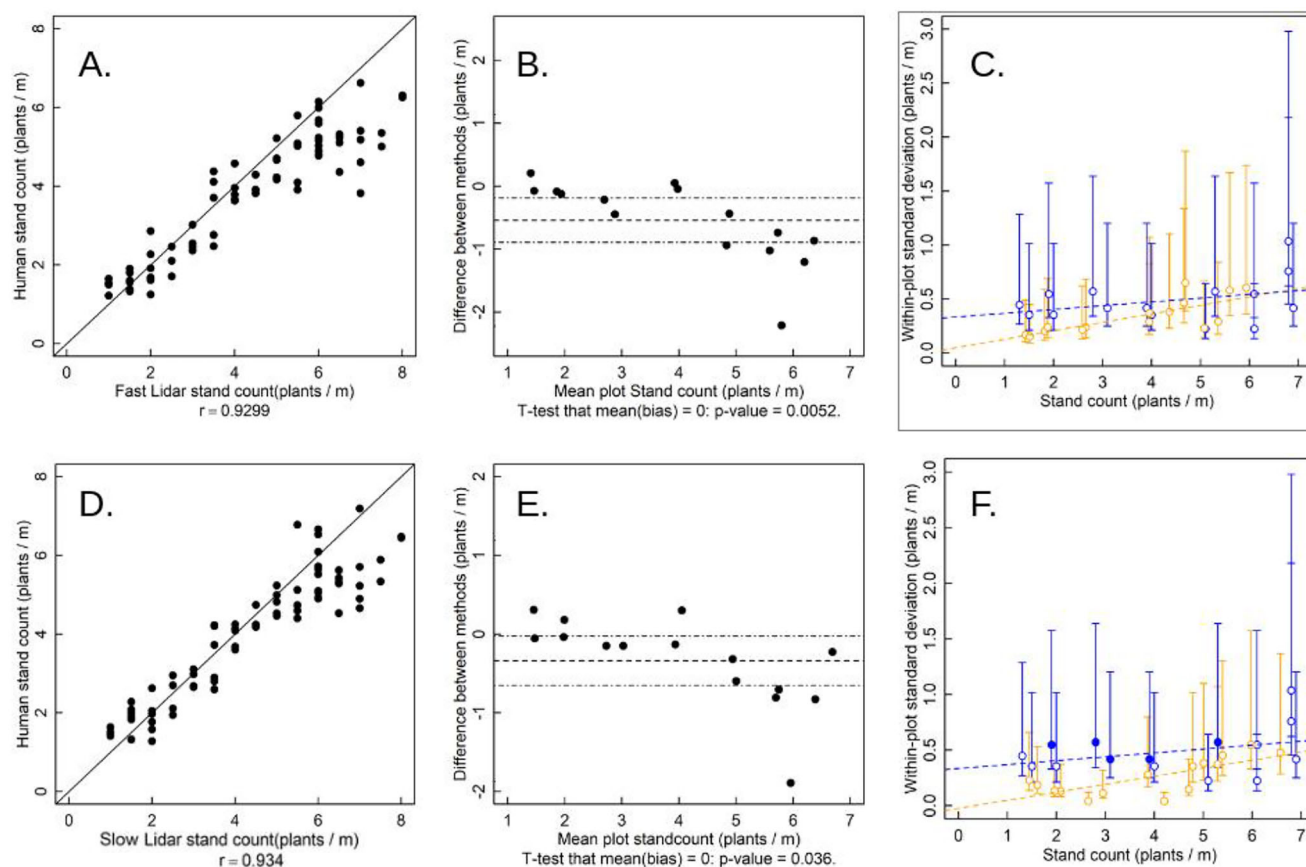


FIGURE 4 Correlation (A, D), bias (B, E), and standard deviation (C, F) between hand-counted and light detection and ranging (LiDAR)-estimated stand counts (plants/m) in corn. Data were collected from 15 plots thinned at 0%, 25%, 50%, and 75%. Bias plots show the mean of five repeated measurements per method (dots), mean bias (dashed line), and 95% confidence limits of the bias (dashed-dotted line). Standard deviation plots compare manual counts (blue symbols) with LiDAR estimates (orange symbols) using two-tailed *F*-tests. Filled symbols indicate significantly greater variance in that method compared to the other method within the same plot ($p < 0.05$). Dashed lines in variance plots are least-squares regressions shown for visualization only.

TABLE 1 Summary of statistical comparisons between leaf area index (LAI) measurement methods and the LAI-2200. Each method is evaluated for bias and variance relative to the LAI-2200.

Crop	Method	<i>r</i>	Bias	Variance	Time (measurement time / LAI2200 measurement time)
Corn	Accupar	0.88	$p < 0.01$	Equivalent	0.76
	Sunscan	0.87	$p = 0.35$	More precise at low LAI	0.94
	LiDAR—fast	0.83	$p = 0.34a$	More precise at low LAI	0.23
	LiDAR—slow	0.81	$p = 0.36^*$	More precise at low LAI	0.41
Soy	Accupar	0.89	$p < 0.001$	Equivalent	0.64
	Sunscan	0.83	$p < 0.001$	Equivalent	0.71
	LiDAR—fast	0.63	$p < 0.001$	Less precise	0.27
	LiDAR—slow	0.72	$p < 0.001$	Less precise	0.62

Note: Correlation coefficient (*r*) and bias are for comparisons between the listed methods relative to the LAI-2200. Variance is reported as either greater, less, or equivalent compared to the LAI-2200. Time is the measurement time expressed as a ratio of the total time taken by each method relative to the LAI-2200.

Abbreviation: LiDAR, light detection and ranging.

*Slope of the bias varies across the range of LAI values.

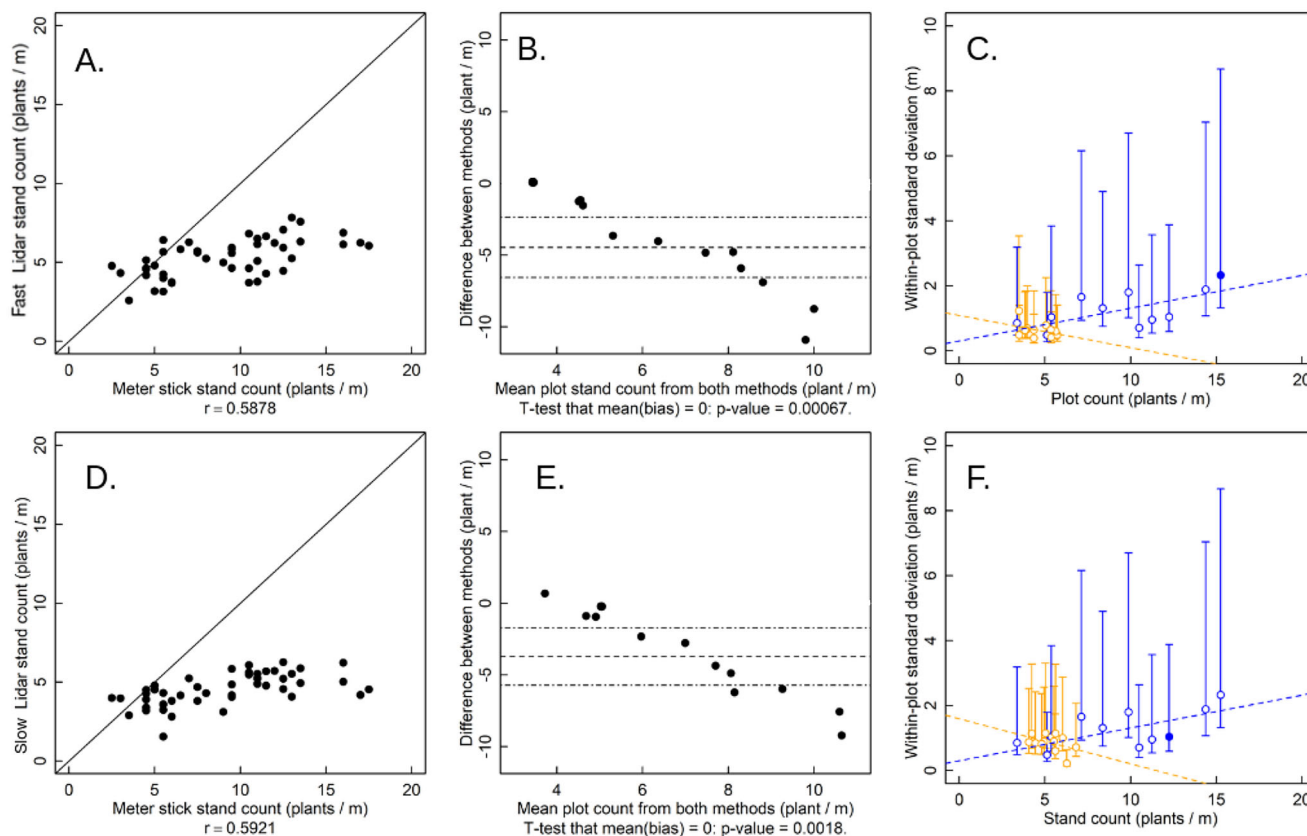


FIGURE 5 Correlation (A, D), bias (B, E), and standard deviation (C, F) between hand-counted and light detection and ranging (LiDAR)-estimated stand counts (plants/m) in soybean. Data were collected from 12 plots thinned at 0%, 25%, 50%, and 75%. Bias plots show the mean of five repeated measurements per method (dots), mean bias (dashed line), and 95% confidence interval of the bias (dashed-dotted line). Standard deviation plots compare manual counts (blue symbols) with LiDAR estimates (yellow symbols) using two-tailed *F*-tests. Filled symbols indicate significantly greater variance in that method compared to the other within the same plot ($p < 0.05$). Dashed lines in panels C and F are least-squares regressions shown for visualization only.

may have lacked precision due to nonrandom placement of the meter stick, as people making the measurements may have avoided sparse areas, and only 1 m of row is evaluated. By contrast, LiDAR scans cover the full plot length, which could increase precision but disagree with manual counts. LiDAR accuracy, however, depended on scan quality. In both fast and slow scans, one outlier plot showed an undercount of two plants per square meter. Visual inspection of the point cloud revealed fallen leaves obscuring stalks, causing the algorithm to incorrectly merge several plants into one.

Bias between methods is not inherently problematic, especially when comparing treatments, since consistent bias cancels out when calculating treatment differences. Without a true reference standard, one method is not necessarily “correct.” Nonetheless, it is informative to consider why two methods might differ and assess whether the causes are meaningful. Here, manual counts within the bounded meter-stick area were likely very accurate; variability may have stemmed from where the measurement stick was placed. Because plot density was largely uniform and the measurement protocol was relatively simple, any human counting bias was likely

small. As such, the manual count may be considered the best available estimate of the true value. LiDAR undercounting in dense plots suggests reduced detection accuracy under those conditions. Still, for many researchers, the reduced measurement time for LiDAR and potential for multiple phenotypes may outweigh these small differences, particularly when relative comparisons between plots are sufficient. Additionally, in many practical applications of stand-count phenotyping, the primary goal is to identify plots with reduced plant density rather than to recover an exact census of every plant. Under this use case, the strong correspondence between manual counts and LiDAR estimates in low density corn-plots suggests that the method is well suited for detecting treatment- or genotype-associated differences in lower densities.

Multiple phenotypes can be extracted from a single LiDAR scan. In previous studies, this LiDAR cart has been validated for measuring height and biomass, in addition to LAI and stand count estimation (McGrath et al., 2023; Siebers et al., 2024). Consistent with those prior applications, the processed LiDAR output tables shared with the supplemental data for this study include all available traits, including

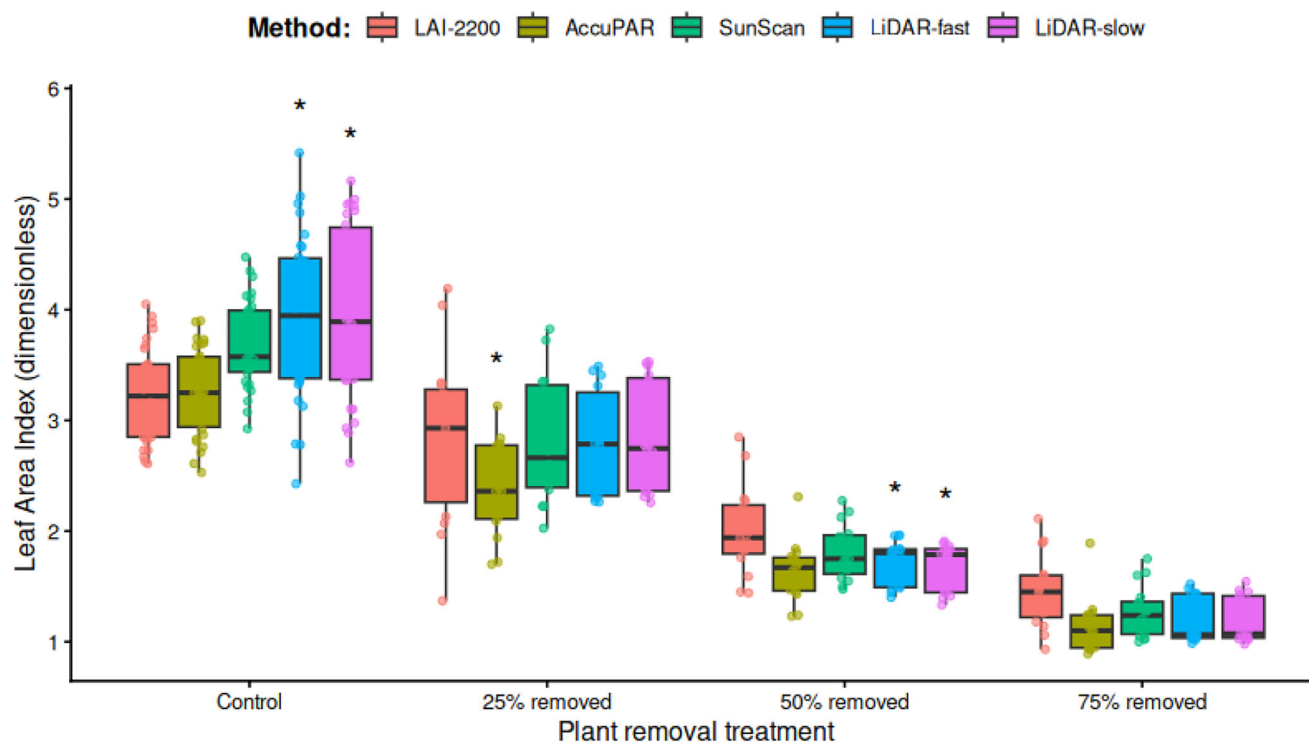


FIGURE 6 Leaf area index (LAI) measurements in corn across plant-removal treatments and measurement methods. Plant-removal treatments indicate the percentage of plants manually removed from each plot after establishment; control plots were not thinned. Corn treatments included six control plots and three plots each with 25%, 50%, or 75% of plants removed. LAI is dimensionless and was measured using the LAI-2200, AccuPAR, SunScan, fast-paced light detection and ranging (LiDAR) scans, and slow-paced LiDAR scans. Boxplots show all repeated LAI measurements for each method within each plant-removal treatment. Within each treatment, the variance of each method was compared with the variance of the LAI-2200 using a two-tailed F -test. Asterisks indicate methods with variance significantly different from the LAI-2200 within the same treatment ($p < 0.05$).

height, voxel count, convex hull volume, number of points, and scanned area. The analyses presented here focused on LAI and stand count. This capacity is important when weighing method tradeoffs: A single-purpose instrument may provide a precise estimate of one trait, whereas a LiDAR scan produces a reusable point cloud from which multiple traits can be extracted. Therefore, differences in variance for any single trait should be considered alongside the ability to generate multiple phenotypes, measurement speed, and the reanalysis potential of LiDAR-based phenotyping.

Future versions of the LiDAR cart may benefit from automation. Fully autonomous data collection would further reduce labor requirements, particularly if navigation, plot identification, and data quality control can be performed reliably in dense row-crop canopies. However, full autonomy is not required for the approach to be useful. In this system, operator-guided scanning provided an important practical advantage: the user knew the experimental design, initiated and stopped scans at known plot boundaries, and generated plot-level files that required less post-processing and metadata collection.

A practical development path for this system is to continue using the cart to collect validated plot-level phenotyping data

while improving ease of operation. In the near term, power-assisted movement may provide a larger practical benefit than full autonomy by reducing operator effort while retaining user control over plot identity, scan start and stop positions, and field data quality. Once reliable autonomous navigation becomes available for dense row-crop environments, those capabilities could be incorporated into a platform with already validated LiDAR-derived trait outputs. This approach allows phenotyping data collection to continue now, rather than delaying biological measurement until fully autonomous field operation is available.

In soybean, LiDAR-based stand count estimations were unsuccessful using our system. The canopy was too dense for the persistent homology algorithm to resolve individual plant peaks. Although variability was low, this reflected consistent overestimation rather than true precision—the algorithm produced similar counts regardless of actual plant number. Scans were conducted during early pod development, when the canopy was particularly dense. However, early in the season (e.g., post-emergence), or late in the season when leaves have senesced, soybean canopies may be sparse enough for the algorithm to work effectively. Furthermore, higher resolution, multi-band LiDAR systems that include

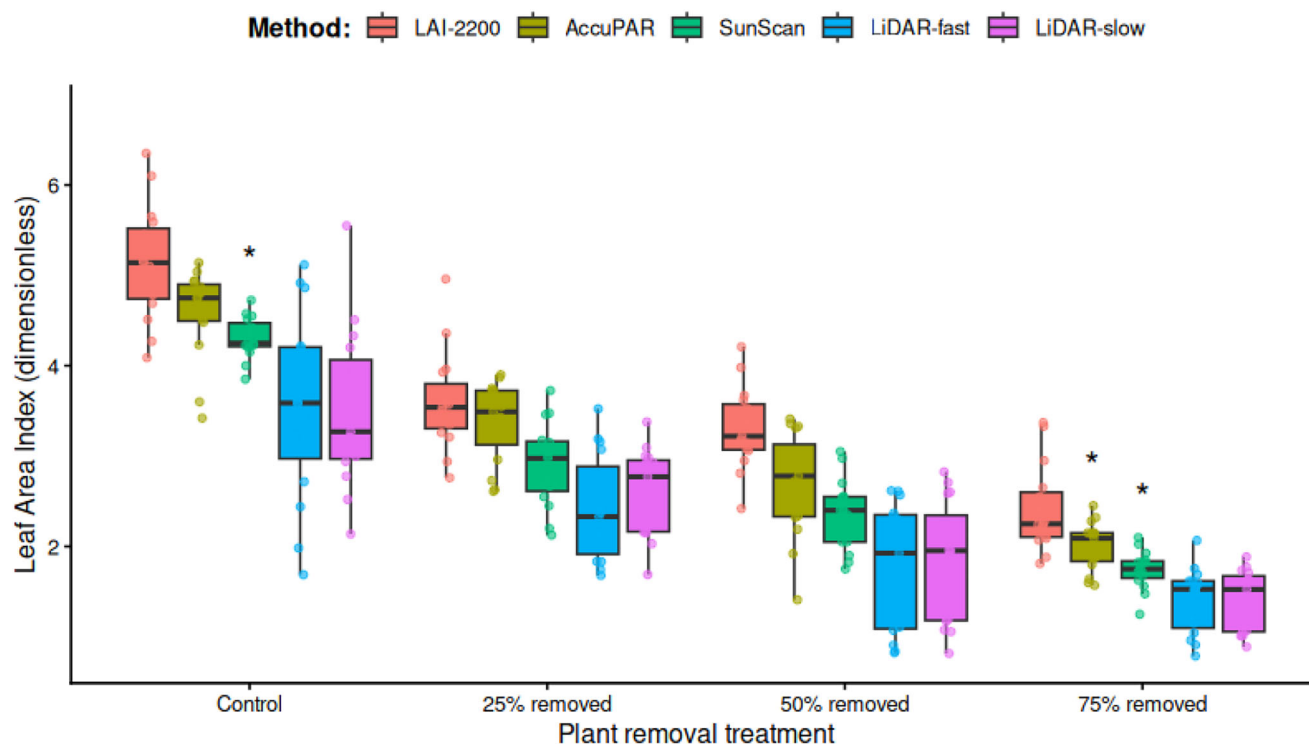


FIGURE 7 Leaf area index (LAI) measurements in soybean across plant-removal treatments and measurement methods. Plant-removal treatments indicate the percentage of plants manually removed from each plot after establishment; control plots were not thinned. Soybean treatments included three control plots and three plots each with 25%, 50%, or 75% of plants removed. LAI is dimensionless and was measured using the LAI-2200, AccuPAR, SunScan, fast-paced light detection and ranging (LiDAR) scans, and slow-paced LiDAR scans. Boxplots show all repeated LAI measurements for each method within each plant-removal treatment. Within each treatment, the variance of each method was compared with the variance of the LAI-2200 using a two-tailed F -test. Asterisks indicate methods with variance significantly different from the LAI-2200 within the same treatment ($p < 0.05$).

several measurement channels might help overcome this limitation.

Previous studies evaluated different LAI measurement approaches using ANOVA, comparing measurements to destructive sampling (Wilhelm et al., 2000). These analyses typically assess bias while assuming equal variances between instruments. Precision is often more critical than bias. An instrument may systematically over- or underestimate LAI, and that may be acceptable if the effect is consistent. However, when other factors such as cost, speed, and ease of use are equal, more precise tools increase statistical power and improve detection of treatment effects. Greater precision may also reduce the sampling effort needed to detect biologically meaningful differences.

One obstacle to adopting new instruments is uncertainty about how their precision compares under specific conditions. Correlation analysis alone can be misleading, as variability may originate from either method. In this study, LAI correlation plots showed scatter, and occasional bias but variance analysis revealed that all instruments had similar precision in corn, except at the highest LAI values where LiDAR precision decreased. Unlike correlation coefficients, variance

estimates can be compared across studies. For example, if a new LiDAR-based LAI method is developed, its precision could be benchmarked against the values reported here. Though LiDAR was not the most precise method overall, it was by far the fastest, again offering a potential compromise between speed and precision.

Reduced precision at high LAI and the inability to count plants in soybean canopies indicate a broader limitation of LiDAR-based measurements in very dense canopies. In these conditions, LiDAR beams may be intercepted by lower canopy leaves and stems before reaching the upper canopy, limiting canopy penetration. This can result in few or no detected gaps for LAI estimation and a lack of distinct density peaks for stand-count estimation. Improvements in LiDAR hardware could help address these limitations. Multi-beam LiDAR sensors scan at multiple angles simultaneously and may improve canopy coverage, while a wider field of view could allow the sensor to capture canopy structure from additional viewing directions. Narrower beam widths could also increase the likelihood that beams pass through small canopy gaps, improving gap detection for LAI and point-cloud resolution for stand count. However, beam width is

not commonly reported by manufacturers and may not be a major design priority for many current LiDAR applications. Regardless of the number, orientation, or width of LiDAR beams, dense canopies impose a physical limit on any single sensing perspective, whether measurements are collected from above or below the canopy. Future work may therefore benefit from fusing complementary data streams, such as mobile ground-based LiDAR with above-canopy UAV imagery, UAV-based LiDAR, structure-from-motion point clouds, or LiDAR measurements from cable-based phenotyping platforms.

For LAI estimation, one potential way to improve LiDAR-based gap-fraction algorithms is to better exploit the fact that LiDAR measures distance. The gap-fraction approach used here treats returns beyond 30 m as gaps and shorter returns as canopy interceptions, making the method comparable to optical gap-fraction approaches. However, unlike hemispherical lens methods, LiDAR also records the distance to each intercepted canopy element. Future algorithms could use this distance information, along with beam angle and known plot dimensions, to restrict LAI calculations to the three-dimensional volume of the experimental plot. This plot-constrained approach could reduce the influence of neighboring rows, border plants, or open space outside the plot, and may be especially useful in small-plot row-crop experiments where the experimental unit is much smaller than the sensing range of the LiDAR or other instrument used to estimate leaf area.

This study highlights the mixed performance of LiDAR in measuring stand count and LAI across corn and soybean. In soybean, LiDAR was ineffective due to dense canopies. In corn, it performed comparably to established methods. While precision decreased at high plant density, the dramatic increase in speed and the ability to measure multiple traits may justify its use in many applications. Moreover, LiDAR remains an evolving technology. With improved sensors and algorithms, it may become even more competitive. The three commercial canopy analyzers produced slightly different mean LAI values, as expected from design differences, but showed consistent responses to changing plot density and comparable precision. Therefore, from a statistical power standpoint, these instruments are functionally equivalent. LiDAR, while fast and multifunctional, is currently limited by its precision in dense canopies.

AUTHOR CONTRIBUTIONS

Matthew H. Siebers: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; supervision; validation; writing—original draft; writing—review and editing. **Peng Fu:** Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing—

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data can be found at <https://doi.org/10.5061/dryad.h1893201g>. The dataset includes raw data used to estimate measurement variance, LAI measurements from each instrument, manual and LiDAR-based stand counts, and processed LiDAR point clouds and output tables. The processed LiDAR data include multiple point-cloud-derived traits, including LAI, stand count, plant height, voxel count, convex hull volume, number of points, and scanned area.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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