FRONT MATTER

Title

From Selfies to Science – Precise 3D Leaf Measurement with iPhone 13 and Its Implications for Plant Development and Transpiration

Authors

1. Gabriel Bar-Sella[1], Matan Gavish[2], Menachem Moshelion[1]*
Plant Sciences and Genetics in Agriculture, The Robert H Smith Faculty of Agriculture, Food and Environment, The Hebrew University of Jerusalem, Jerusalem 9190401, Israel.
2. School of Computer Science and Engineering, Hebrew University of Jerusalem, Jerusalem, srael
*Address correspondence to: menachem.moshelion@mail.huji.ac.il

Abstract

Advanced smartphone technology has unified sophisticated, cost-effective sensors, broadening access to high-precision data acquisition. This study aimed to validate the hypothesis that the iPhone 13-Pro camera, in conjunction with its LiDAR technology, can accurately extract information such as the surface area of maize leaves (*Zea mays*). 3D point cloud models enabled remote, non-destructive trait data collection, and four methods for 3D canopy area extraction were compared to assess their relation with wole-plant transpiration rates. The experimental findings demonstrated a robust correlation (R^2=0.88, RMSE=62.45) between manually scanned surface area and the iPhone 3-dimentional estimated plant surface area. Furthermore, the study revealed that the ratio of stem to total plant surface area is 11.6% (R^2=0.91, RMSE=30.20). Utilizing this ratio for predicting canopy surface area from total plant surface area resulted in a significant correlation (R^2=0.89) with the measured canopy. The mobile iPhone's surface area measurement tool offers a significant advantage by providing the capability to scan the entire plant surface area. This contrasts with the projected leaf area index measurements taken by most commercial top canopy scanners, which are unable to penetrate the canopy like manual measurements do. An additional advantage of the real size surface measurement of the whole canopy is its high correlation (R^2=0.83) with the whole canopy transpiration rate, as was measured using a gravimetric system on the same scanned plants. This study presents a novel method for analyzing 3D plant traits with a portable, accurate, and affordable tool, enhancing selection processes for plant breeders and advancing agricultural practices.

MAIN TEXT

1. Introduction

The current global population of 7.7 billion people is expected to reach 9.8 billion by 2050 [1, 2], leading to increase in worldwide food demand. Moreover, due to the negative impact of climate change on the agriculture production and crop yields [3, 4, 5], new technological devices and approaches are required to be utilized, in order precisely manage the limited resources and optimize crop yields by accurately monitor plants physiological and developmental responses to their environment [6]. Major advancement in genomic technologies together with the dramatic reduction in their prices, mark genomics usage more feasible. Plant phenomics has exhibited significant promise in enhancing agricultural productivity through the systematic examination of plant physiological traits, such as morphology, colors, size, dimensions, texture, and various other attributes.

The plant vegetative growth phase, particularly its leaves, plays a pivotal role in the growth and optimal productivity of plants. Leaves serve as the primary organs for photosynthesis, where carbohydrates are synthesized. Furthermore, leaves facilitate transpiration, the process of water evaporation from the plant into the atmosphere, enabling the upward movement of water and minerals from the soil. By quantifying leaf characteristics and monitoring their growth, valuable anatomical and physiological insights can be acquired. For instance, measuring parameters such as leaf length, area, and color distribution along the height profile can provide indicators of developmental stage, chlorophyll content, deficiencies and more. When combined with functional traits like transpiration rate and photosynthesis, a comprehensive understanding of the plant's condition at any given moment can be obtained.

Manual measurement of these attributes is time-consuming, inefficient, and potentially harmful to plants. Alternatively, utilizing specialized devices is costly and necessitates suitable infrastructure [7]. However, the rapid technological advancement of smartphones together with low cost made it possible to employ various sensors to collect plant data with high accuracy. For instance, the Apple iPhone 13 Pro smartphone is equipped with three high-quality cameras and a Light Detection and Ranging (LiDAR) scanner. The LiDAR technology allows non-distractive, distant measurement through laser beam illumination and facilitates the creation of a three-dimensional model of the subject being scanned, from which data and traits can be extracted. Utilizing these iPhone capabilities offers a simpler and more affordable alternative to existing market products, thus making it an appealing choice for plant dynamics studies and parametric modelling.

The aim of this research was to test the hypothesis that accurate information, such as surface area, can be extracted from maize leaves (Zea mays) using the iPhone 13 Pro camera with LiDAR

technology. This information would enable the calculation of diagnostic indicators for the plant while constructing a three-dimensional model that serves as a viable alternative to manual measurements. Thus, we generated three-dimensional models of cultivated maize that served as representative plant models for leaf measurements.

In this research we aimed to:

- Test the iPhone 13 Pro as a new research tool, estimate its reliability and plant level data acquisition precision in the agriculture sector.
- Conduct weekly 3D scanning of maize plants that were grown under. controlled and monitored conditions.
- Create 3D point cloud database of maze plants.
- Automate the process of plant organs segmentation of the point clouds to extract leaves and whole plant surface area and compare these traits to transpiration and growth data.

2. Materials and Methods

Experimental Design

The experimental and technical design of the study is presented in Fig. 1.

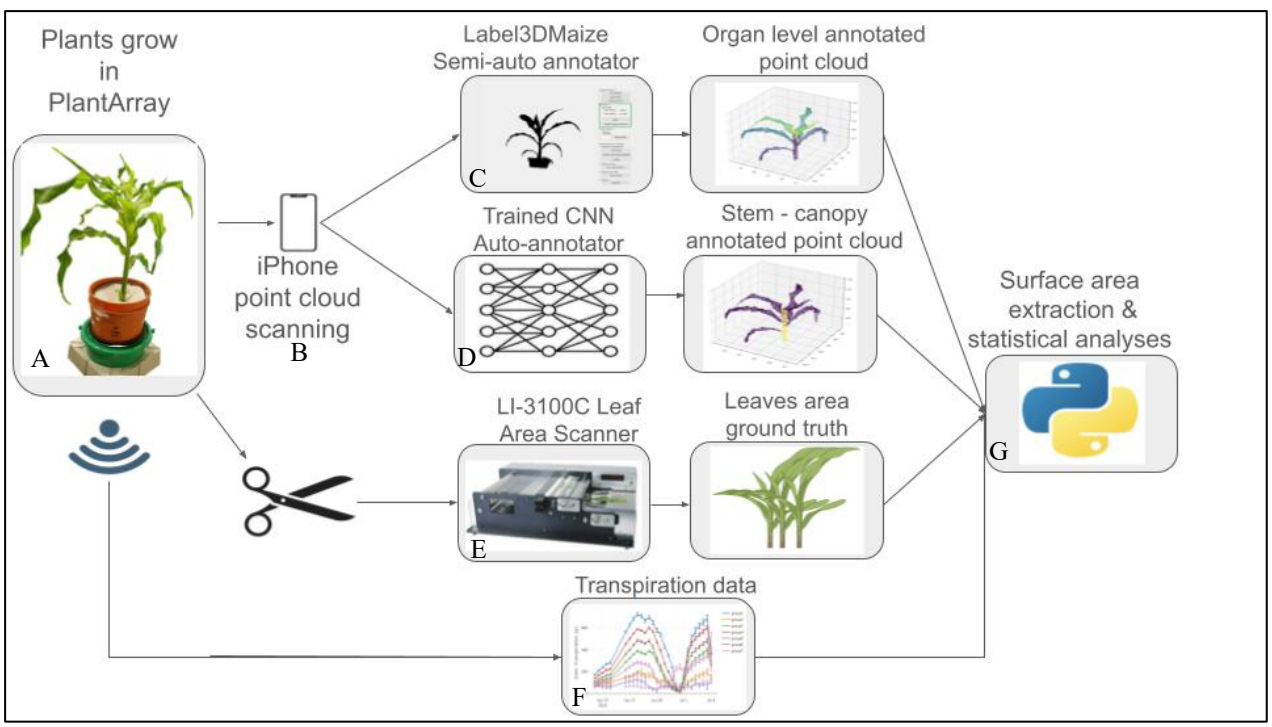


Figure 1 – Overview of the experimental and technical design of the study.
A) Maize plants were grown in PlantArray system, while transpiration data was constantly collected. B) Weekly 3D scanning of the plants conducted using iPhone to generate point clouds. The point clouds went through different annotation methods, including C) Label3DMaize software

that was used to annotate each leaf separately in the point clouds, D) pre-trained CNN model to segment and annotate stem and canopy points separately. E) Leaves of scanned plants where cut and scanned using the LI-3100C scanned to produce ground truth data and corelated to F) the whole canopy transpiration rate. G) Python based algorithm was used to extract leaves surface area from the point clouds and conduct statistical analyses.

Statistical Analysis

Statistical analyses were employed using Python 3.10.9 [15] through Jupyter Notebook version 6.5.2 [16]. Linear regressions were fit using the "LinearRegression" function of "scikit-learn" package [17]. One-way ANOVA test was conducted using the "scipy" package's "f_oneway" function [18]. The Python packages "pandas" [19] and "numpy" [20] were used to arrange the data before plotting. The Python packages "matplotlib", "seaborn" [21] were used for data visualization. All statistical code and data files needed are available to download at https://github.com/gavrielbs/3D_Corn_Phenotype.

PlantArray System by Plant-DiTech LTD

PlantArray is a high-throughput, multi-sensor physiological phenotyping gravimetric platform. This plant phenotyping system performs quick plant screening based on precise physiology traits measurements that are great indicators for yield potential with proven high correlation to field yield results.

EQ1: %Error formula

$$\%Error = \left|\frac{Observed - Expected}{Expected}\right| * 100$$

Amazon EC2 For CNN model

Linux machine hosted on Amazon AWS running on Amazon Linux OS with all the needed dependencies to run the PointCNN model. The machine included CUDA9, a parallel computing platform, Python V3.6, Tensorflow V1.6, Tesla GPU K80 and NVIDIA driver version 384.98.

Polycam 3D Scanner App, LiDAR, 360 by Polycam Inc.

The app allows 2 types of scanning modes – LiDAR and Photo mode. We found that the LiDAR mode (utilizing the LiDAR sensor) is better for spatial scanning with when less accuracy needed, while the Photo mode suites objects scanning is much more precise (Therefore, all the data presented in this study utilize this option). After scanning is done, a '.xyz' point cloud file was exported from the app, and then manually edited (using CloudCompare) to keep only the maize plant without the pot and surroundings (Fig. 2).

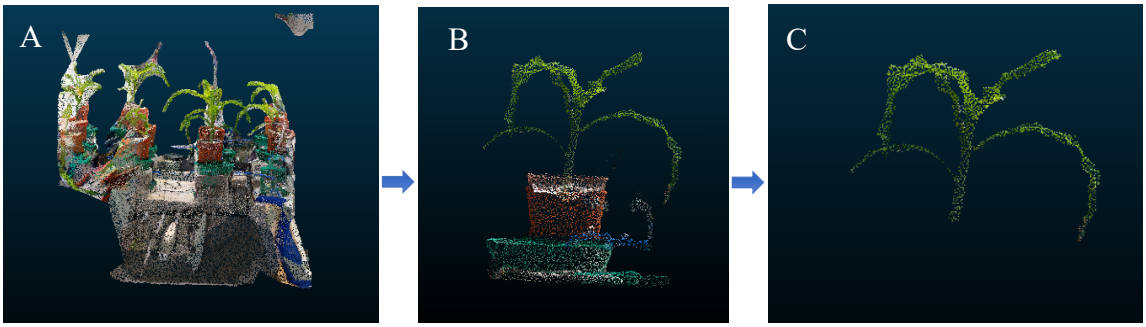


Figure 2 – Point cloud editing process stages.
Initial point cloud exported from the Polycam app. B) Point cloud with surroundings excluded. C) Final point cloud file of a maize plant with stem and leaves only.

LI-3100C Area Meter Leaf Scanner

Rugged bench-top instrument designed to quickly digitize the area, length, and width of leaves. It features two transparent conveyer belts that rotate to move leaves across a scanning bed. This instrument is ideal for rapidly measuring large quantities of harvested leaves. The LI-3100C records the area of individual leaves and quickly computes cumulative area for a group of leaves, making it easy to compare treatments or experimental groups.

CloudCompare

An open source software for processing and annotating 3D point cloud files.

Alpha Shapes algorithm for surface area computation

The alpha shapes is a generalization of a convex hull, a computational geometric approach used for defining and analyzing complex shapes within point cloud data or sets of data points in Euclidean space. The algorithm takes its name from the parameter ‘alpha’, a parameter that influences the shape of the generated alpha shape. The basic idea behind the Alpha Shapes algorithm is to construct a series of nested shapes that represent the varying levels of connectedness between neighboring points. When the alpha parameter is decreased, the shapes gradually forming an increasingly complex boundary that encompasses the given data points. The Python package Open3D implements this algorithm to construct a triangle mesh from an unstructured point cloud while performing surface reconstruction. The surface is constructed by triangles, allowing the calculation of its area by using and summing the Heron’s formula for each triangle.

Heron's formula for calculating the area of a triangle

$$A = \sqrt{s(s-a)(s-b)(s-c)}$$

Where A is the triangle area; a, b and c represents the length of the triangle sides and s is computed as $0.5 * (a + b + c)$.

Growing conditions for the maize plants

Maize plants grew in a room under controlled conditions over the period of 4 weeks.

- Daily Average RH : 44.015%
- Daily Average Temperature : 22.196 (C)
- Daily Average PPFD : 475.818 ($\frac{\mu mol}{m^2 * s}$)

Label3DMaize

An interactive corn plant point cloud segmentation and annotation software. The software selects the top and bottom stem points in the maize point cloud and adjusts the corresponding radius both via manual interaction. The median region growing method is then applied to achieve automatic segmentation and labelling of the maize stem and leaves. Suppose the connection area between the stem and leaves is not accurately annotated. In that case, the toolkit provides a fine segmentation function that allows correction of the misclassified points through simple manual interaction.

Semicircular scanning

Each plant was scanned by moving the iPhone in a semicircular motion along the vertical axis. This process ensured that all leaves were scanned from both their upper and lower surfaces. Additionally, the iPhone was rotated around the plant, capturing data from 360 degrees along the horizontal axis (Fig. 3)

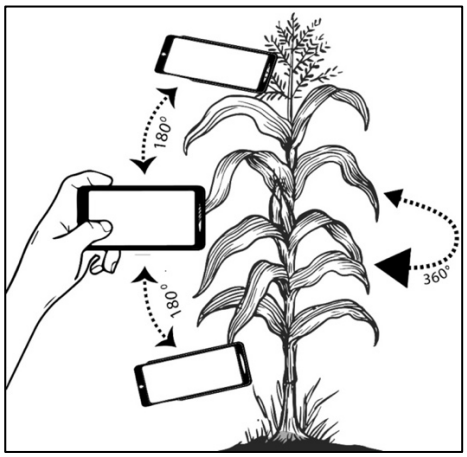


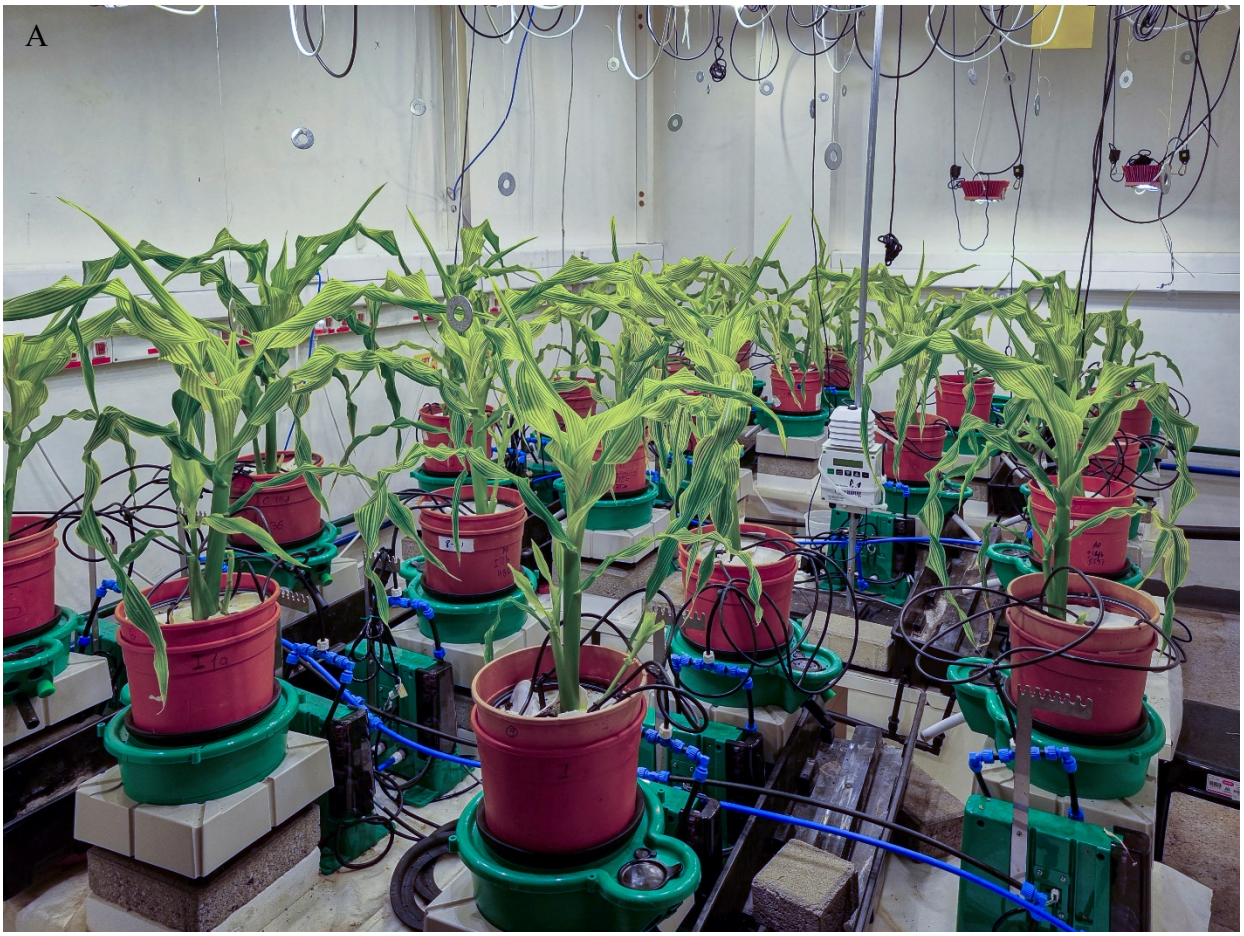
Figure 3 – Demonstration of scanning process of a maize plant from all different angles to

capture all details.

3. Results

Testing the scanner with a maize leaf

To assess the capabilities of the iPhone scanner, a comparative analysis was conducted between the actual surface area of a single leaf (determined using the LI-3100C Area Meter Leaf Scanner, Materials) and the calculated surface area derived from a manually segmented point cloud (Using CloudCompare, Materials) of a maize leaf using the Alpha Shapes algorithm from the Open3D Python package. The Alpha Shapes algorithm constructs a mesh consisting of triangles, allowing the calculation of its area by summing the area of each triangle (Fig. 4; Materials). Manual measurements of the leaf surface area averaged 34.625± 1.11(cm^2) (n=4, technical replicates), while the iPhone's calculated surface area using an alpha parameter value of 0.6 was 71.022 (cm^2). As the doubling in size arises because the script calculation includes both the adaxial and abaxial sides. Multiplying the LI-3100C 's measured surface by a factor of two to fit the iPhones' calculated one, resulted in a percentage error of 2.5% (calculated using the percent error formula, see EQ1), thus confirming the accuracy of the scanning process and the effectiveness of the surface reconstruction method.



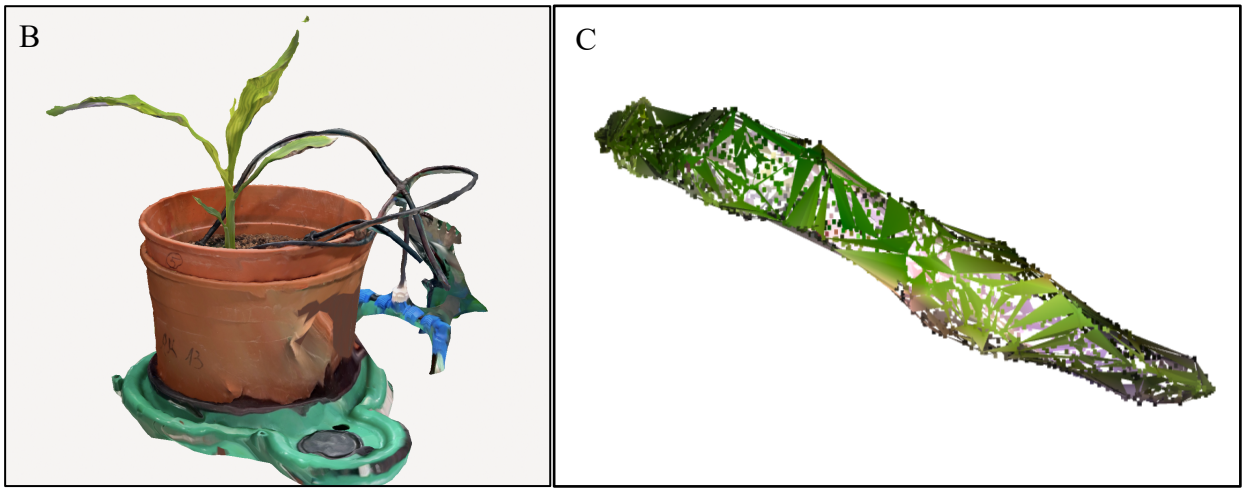


Figure 4 - Evaluating iPhone accuracy for maize leaf 3D scanning and surface area measurement. A) 4 weeks old maize plants in a controlled growing room. Each plant is placed inside a separate lysimeter. B) Potted, whole plant scanning, presented as point cloud of a single maze, C) Surface constructed point cloud of a segmented leaf No.3, taken from B. The surface is constructed by triangles.

Single leaf level point cloud analysis

A comparison between the actual surface area and the estimated surface area of multiple leaves (n=90, biological repetitions) was conducted using linear regression analysis. The actual surface area of each leaf was measured using the LI-3100C Area Meter Leaf Scanner, and then averaged (n=3, technical replicates). This averaged value was then multiplied by a factor of two to align it with the iPhone's estimated surface area. The linear equation derived from the regression analysis was Y = 1.036X + 44.354. The analysis revealed a high R^2 value of 0.88 and a significant correlation with a p-value less than 0.01. (Fig. 5).

For data collection, Maize plants (hybrid line HMX59Y5832) were grown for 4 weeks in a controlled environment using the Plant Array system (Materials) where individual discrete plants' daily transpiration rates were continually collected (Fig. 4A). The iPhone scanner was employed to generate 13 point clouds of maize plants at 4 weeks of age. Each plant was scanned in a semicircular movement along vertical axis, ensuring all leaves were scanned both adaxially and adaxially, and around the plant, covering 360 degrees along horizontal axis (Materials). Subsequently, stem and individual leaves of each plant were semi-automatically segmented and labeled using the Label3DMaize app (Miao et al., 2021, Fig. 5; Materials). A Python algorithm (Materials) was then utilized to analyze the point clouds and extract the surface area of each leaf. Mean and standard deviation metrics were computed for the measured and calculated surface areas of each leaf, with respect to their chronological appearance along the stem, across all plants (Table 2).

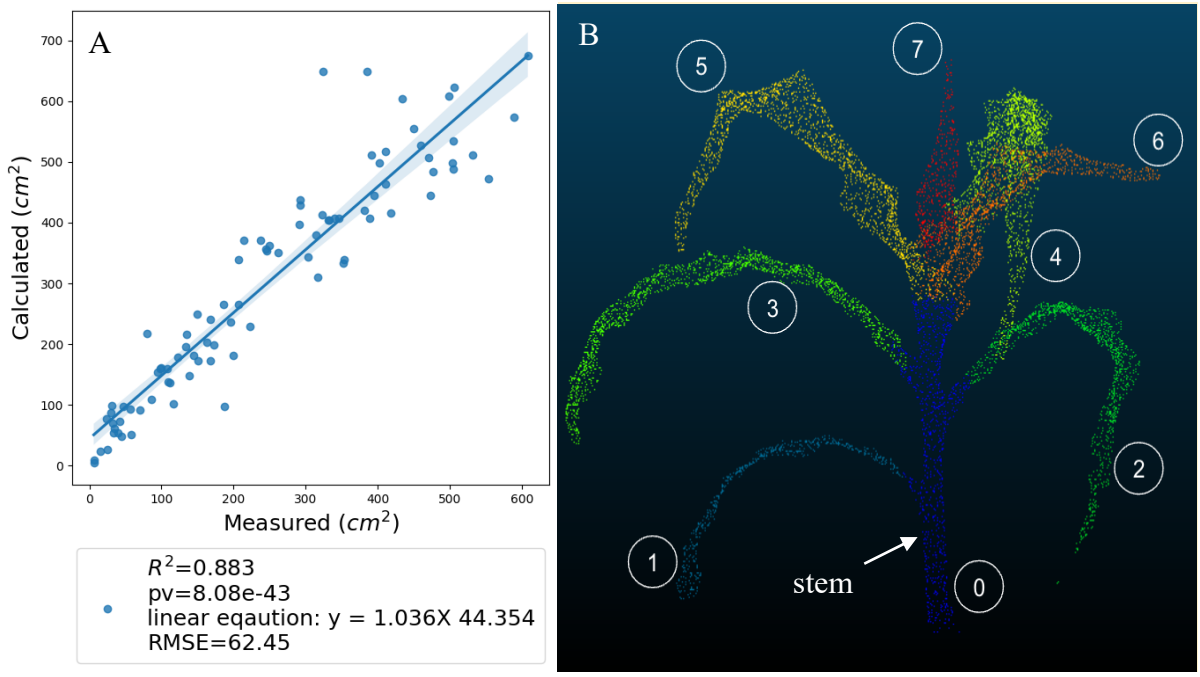


Figure 5 – Comparative analysis of direct surface area measurements and computational extractions from point cloud data in maize leaves. A) Correlation between the manual surface area measurements and calculated ones, generated using the iPhone's 3D scans. Shaded areas represent 95% confidence intervals of regression line. B) Annotated point cloud of a maize plant No.6 with an arrow pointing at the stem. Each leaf is colored separately and numbered according to its appearance along the stem (e.g. 1) from the bottom.

Organ	Organ No.	Plant No.6 iPhone Estimated Area (cm^2)	Plant No.6 LI-3100C Measured Area (cm^2)	Plant No.6 Leaf %Error	Cross iPhone Estimated Mean (cm^2)	Cross iPhone Estimated std (cm^2)	Cross LI-3100C Measured Mean (cm^2)	Cross LI-3100C Measured Std (cm^2)	Mean Cross %Error	N
Stem	0	338.52	N/A	N/A	247.75	±108.83	N/A	N/A	N/A	15
Leaf	1	171.83	150.58	14.11%	152.33	±79.76	120.58	±67.5	36.79%	15
Leaf	2	380.12	314.97	20.68%	321.07	±137.84	251.02	±121.64	32.76%	15
Leaf	3	499.00	504.10	1.01%	474.26	±171.37	385.63	±154.09	32.33%	15
Leaf	4	573.04	588.93	2.70%	460.59	±175.96	412.78	±161.33	18.69%	15
Leaf	5	526.58	460.15	14.44%	334.44	±162.56	282.19	±142.63	29.75%	15
Leaf	6	437.39	292.75	49.41%	209.95	±146.63	149.42	±94.97	67.745	13
Leaf	7	136.76	111.76	22.36%	105.65	±44.34	51.06	±34.08	170.16%	7

Table 2: Detailed representation of measurements areas multiplied by 2, as shown in the regression graph for assessing measurement repeatability.

Column "Organ No." represents each leaf's chronological number as shown in Figure 3B. Columns "Plant No.6 iPhone Estimated Area" and "Plant No.6 LI-3100C Measured Area" show the data for plant shown in Figure 3B and "Plant No.6 Leaf %Error" represents the %error between these columns. Columns "Cross iPhone Estimated Mean" and "Cross iPhone Estimated Std" represent the mean and std values of calculated area of each leaf's chronological number, across all plants (Example – row number 2 represents the data for leaf No.1, most bottom leaf of each plant). Columns "Cross LI-3100C Measured Mean" and "Cross LI-3100C Measured Std" represent the mean and std values of measured area of each leaf's chronological number, across all plants.

Simplified whole canopy level point cloud analysis

The method above required us to distinguish and separate the stem from the entire surface area, which proved to be a challenging task, therefore, the aim of this analysis was to compare the iPhone's estimated and LI-3100C's measured surface area of the entire maize canopy. Instead of segmenting the stem and canopy prior to comparison (as explained above), a regression analysis was conducted to establish a relationship factor between stem and total plant surface area. This approach enabled the prediction of canopy area based on the total plant surface area (Materials - Table 1). For this analysis, data of semi-automatically segmented and labeled maize point clouds (n=14, segmented using Label3DMaize; Materials) was used, yielding a highly favorable R^2 value of 0.91 and a significant correlation with a p-value less than 0.01. The resulting linear equation from the regression analysis was Y = 0.116X - 8.863 (Fig. 6A), showing that the stem area is less than 11.6% of the plant total area at this stage of growth.

Subsequently, utilizing the linear equation for stem area prediction, the surface area of the entire canopy for each plant was calculated by subtracting the predicted stem area from the whole plant area. Comparing the predicted surface area of the whole canopy with the measured surface area (calculated as the sum of the leaf surface areas for each plant) resulted in a R^2 value of 0.89 and a significant correlation with a p-value less than 0.01 (Fig. 6 b).

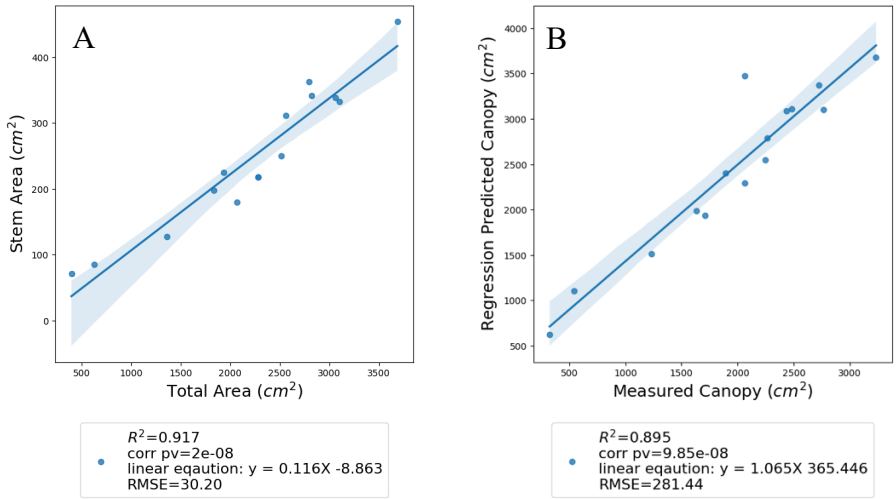


Figure 6 – Predicting the whole canopy area of maize point cloud using stem area. Regression analysis was used: A) To predict stem area from plant total area. Using the resulted linear equation, the canopy area was predicted for each plant separately. B) The predicted canopy area was compared to the measured canopy area of each plant.

Simplified whole canopy level point cloud analysis using CNN model

Convolutional Neural Network (CNN) is a type of artificial neural network that is primarily used in image processing, computer vision, and other applications that involve spatial inputs. In this approach, we tested a trained CNN model for automatic stem and leaf segmentation for the maize point clouds (Ao et al., 2021) to distinguish between canopy and stem points, for the comparison of calculated whole canopy area with measured area. The model was designed to be executed on two separate platforms: Amazon Linux EC2 with Tesla K80 GPU and Amazon EC2 Windows Server 2022 to perform point cloud segmentation and stem extraction, respectively. For the segmentation, the first step of the model was down-sampling each point cloud into 2048 points, to suit the limitation of PointCNN the model was based on. The down-sampled point cloud was then tested by the model, resulting with initial segmentation of stem and leaf points. For the stem extraction, a 3D cylinder was fitted by the random sample consensus (RANSAC) algorithm around the stem segmented points (based on a given stem radius), considering that the maize stem grows vertically. The fitted cylinder position was then used to extract stem points in the initial point cloud, where points within the cylinders were labeled as stems and those left outside the cylinders as leaves. Each point cloud underwent stem extraction three times, each time with a different radius parameter value (0.01, 0.02 and 0.03 m) for the 3D cylinder fitting, resulting with a total of 39 point clouds (2 of the 15 files could not be tested) with a varying degrees of successful segmentation achieved (Fig. 7, Materials - Table 2). Canopy area was calculated for each point cloud based on the leaf segmented points. Regression analysis was then conducted for each plant's measured canopy area against its calculated canopy area, derived from the predicted canopy of the CNN model (represented by purple points in Figure 5, indicating leaf-labeled points). All three regressions exhibited a strong R^2 values above 0.94 and a significant correlation with a p-value less than 0.01 (Fig. 8). On the graphs, green dots signify point clouds with successful stem segmentation, while red dots represent unclassified point clouds, containing only leaf-labeled points. In the latter case, the entire plant surface area was calculated as the canopy area (Materials - Table 2). The significant correlations observed, irrespective of stem and canopy separation, suggest that at this stage of plant growth, the stem area may not be relevant.

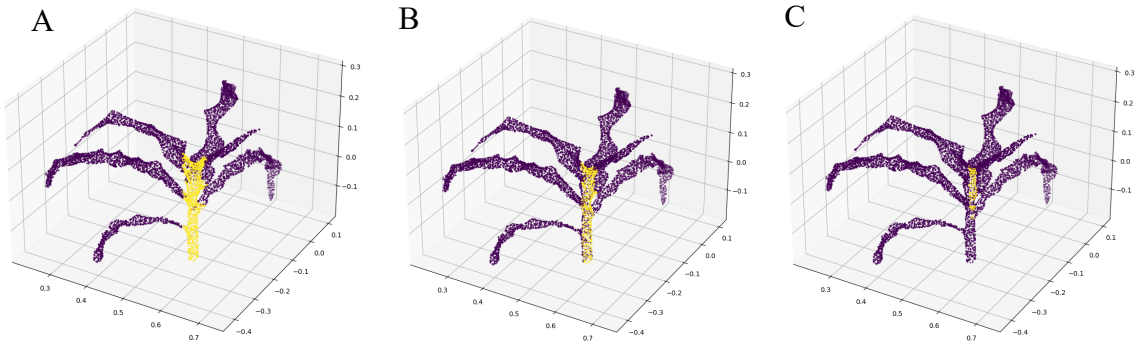


Figure 7 –Impact of stem radius on maize canopy prediction accuracy.
A) Fully segmented stem (yellow points) and leaves (purple points) using radius = 0.03m. B) Partially segmented stem points using radius = 0.02m, sporadic leaf labeled points in the stem. C) unsuccessful stem segmentation – almost all points (included the stem points) are labeled as leaf, using radius = 0.01m.

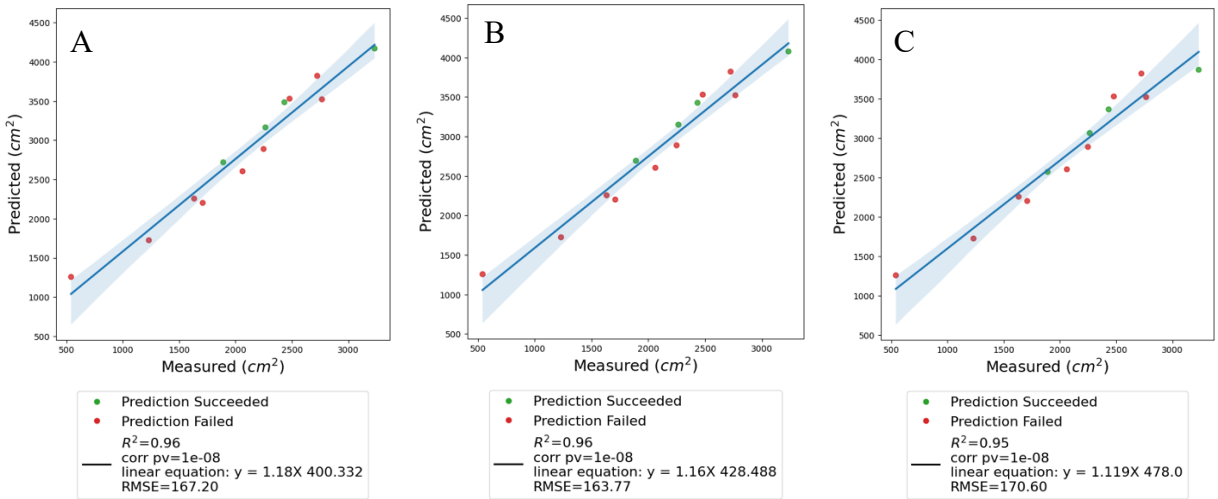


Figure 8 – Comparison between canopy areas resulted by the CNN and the measured ones.
Regression analysis for predicted canopy area by 3 radius parameter values: A) 0.01m, 0.02m and C) 0.03m respectively) against measured area. Green dots represent full successful stem segmentation point clouds, red dots represent point clouds with only leaf labeled points.

Comparing daily transpiration rate to canopy areas

Subsequently, we conducted a comparison between the daily transpiration rate of each plant, on a single date, and their respective calculated canopy areas derived from the different approaches mentioned earlier. The daily transpiration rate data was collected separately for each plant using the PlantArray system (methods, Fig. 4). Correlations between daily transpiration rate and labeled canopy area, total area and regression factor canopy area resulted with a significant correlation with a p-value less than 0.01 and R^2 values of 0.73, 0.72 and 0.76 respectively. Correlating the daily transpiration rate against canopy areas predicted using the CNN model, yielded significant

correlation with a p-value less than 0.01 and R^2 values of 0.76, 0.76, and 0.75 for testing with different radius parameter values of 0.01 (m), 0.02 (m) and 0.03 (m) respectively (Fig. 9). Additionally, to further support our findings, a One-Way ANOVA test was conducted to evaluate the differences in canopy area between the different approaches described above. The results indicated no significant difference in canopy area calculations with a p-value of 0.079 (Fig. 10). These results confirmed that the total plant area, which is the easier to calculate and produce, can be utilized as an alternative to calculating the canopy area separately.

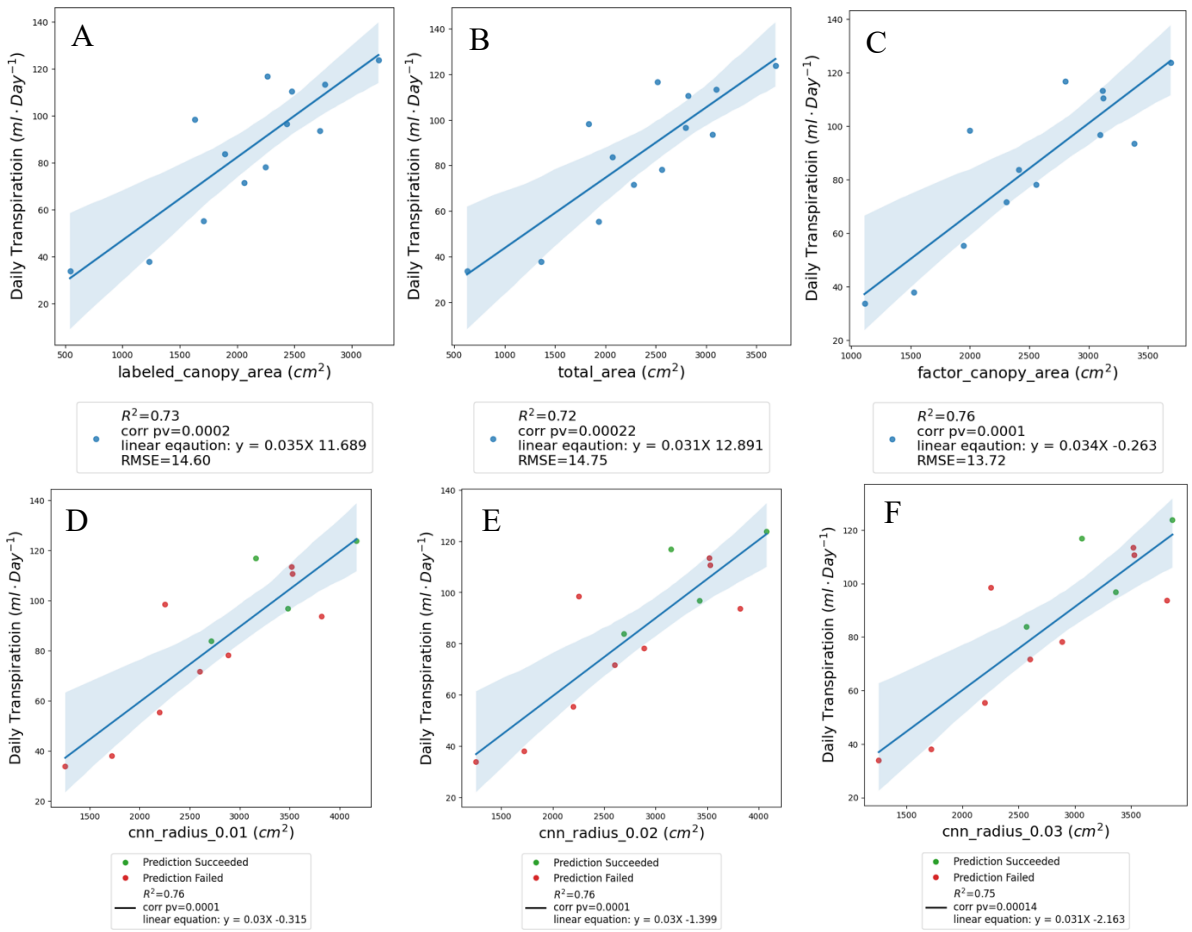


Figure 9 – Comparing transpiration rate against canopy area predicted from different approaches. Daily transpiration linear regressions against: A) Semi-automatic labeled canopy area. B) Total area (stem+canopy). C) Predicted canopy by stem factor. D) CNN model radius = 0.01. E) CNN model radius = 0.02. F) CNN model radius = 0.03.

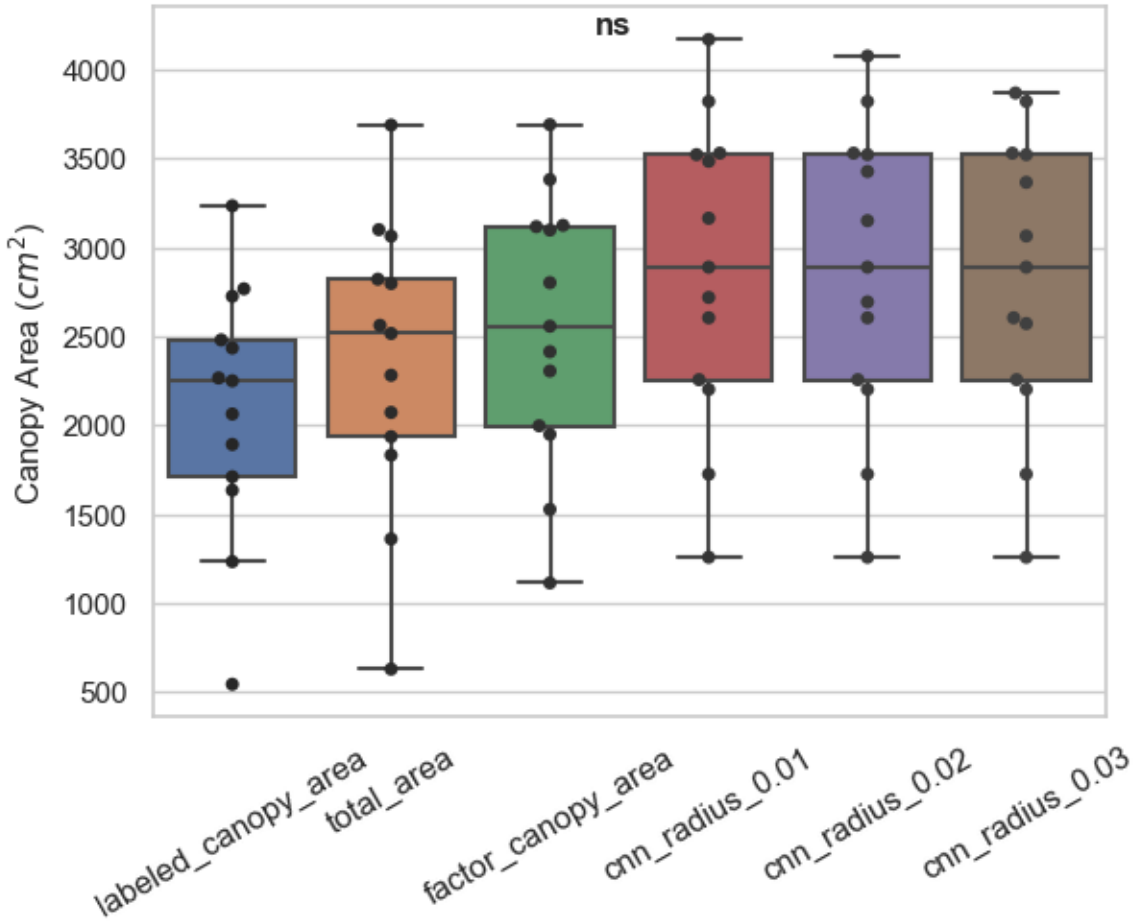


Figure 10 – One-Way ANOVA test results for different transpiration predictors.
Surface area distribution among different approaches. No significant difference between the approaches.

Detecting growth and daily transpiration rate over time

Throughout the 4-weeks growing phase of the plants, starting from the 2nd week, weekly 3D scans were carried out individually for each plant (on the dates 2023-02-15, 2023-02-23 and 2023-02-28). From each scan, the whole plant surface area was computed to assess the growth rate (Fig. 11A). Concurrently, the daily transpiration rate ($\frac{ml}{day}$) was recorded continuously and separately for each plant using the Plant Array system (Fig. 11B). The decision was made to use the transpiration rate from '2023-02-26' instead of '2023-02-28', as on the latter date, the plants were harvested for leaf measurements and transpiration data collection was interrupted. A comparative analysis of these features using linear regression revealed a highly significant correlation with a p-value less than 0.01 and a R^2 value of 0.83 (Fig. 12). This strong correlation between the plant's growth rate, determined from the whole plant surface area, and the daily transpiration rate demonstrates the interrelation between plant development and water loss through transpiration.

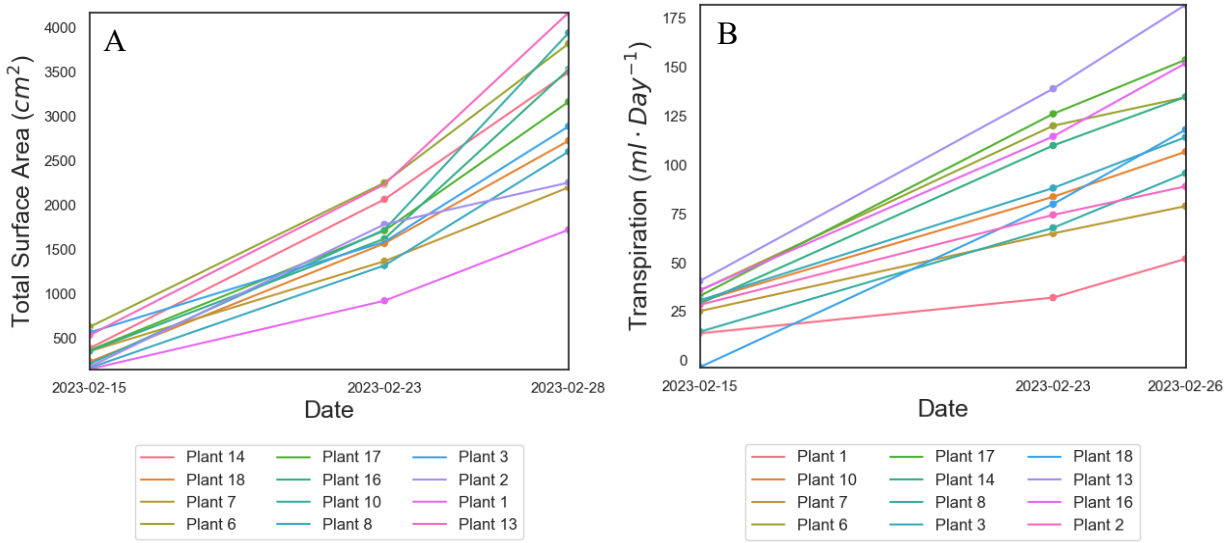


Figure 11 – Change in plants' surface area and daily transpiration rate.
Change in plants' growth over time, presented by A) change of total surface area (stem + canopy). B) Change in plants' daily transpiration rates over time.

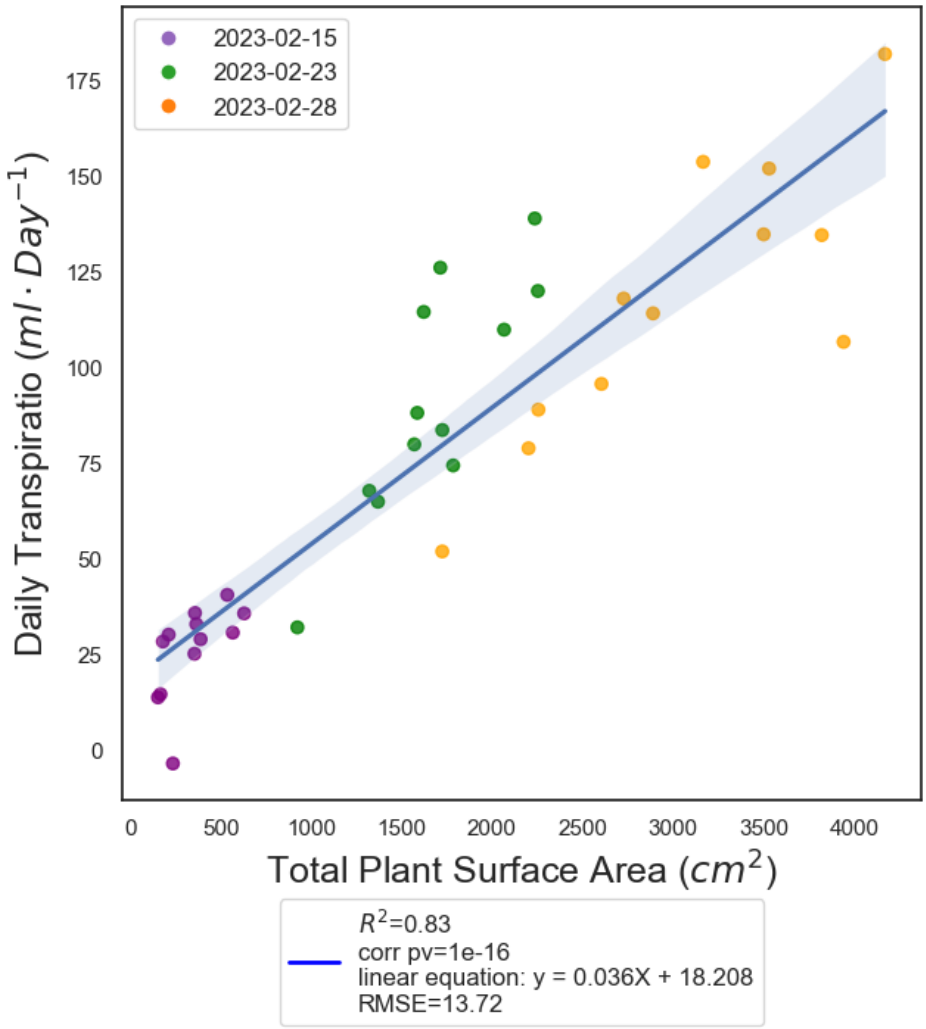


Figure 12 – Plants' daily transpiration rate vs. total surface area.

Data for over the period of three weeks, each date is colored separately.
Date ‘2023-02-28’ represents 3D scan from the ‘2023-02-28’ and transpiration data collected from ‘2023-02-28’.

Point cloud density

To investigate the potential impact of point cloud density on the %error of surface area estimations, we conducted a comparison between point cloud density and number of frames against the mean %error of each manually labeled point cloud (n=14, Materials Table 3). The mean %error was determined as the average %error between the calculated and measured surface areas for each leaf within a plant. Frames are the 2D frames that were utilized by the Polycam app during the scanning process for point cloud construction through superposition. Point cloud density was calculated as the ratio between the number of points and the volume of the point cloud in the Euclidean space, calculated as (max(x) – min(x)) * (max(y) – min(y)) * (max(z) – min(z)).

To explore the relationship between these measurements, linear regression was employed. However, all three analyses resulted in low R^2 values and non-significant p-values (Fig. 13). These findings suggest that variations in the number of frames per file or the point density do not significantly impact the deviation in leaf area calculations. Therefore, it appears that altering the point cloud density within the tested range does not substantially affect the accuracy of surface area calculations for the leaves.

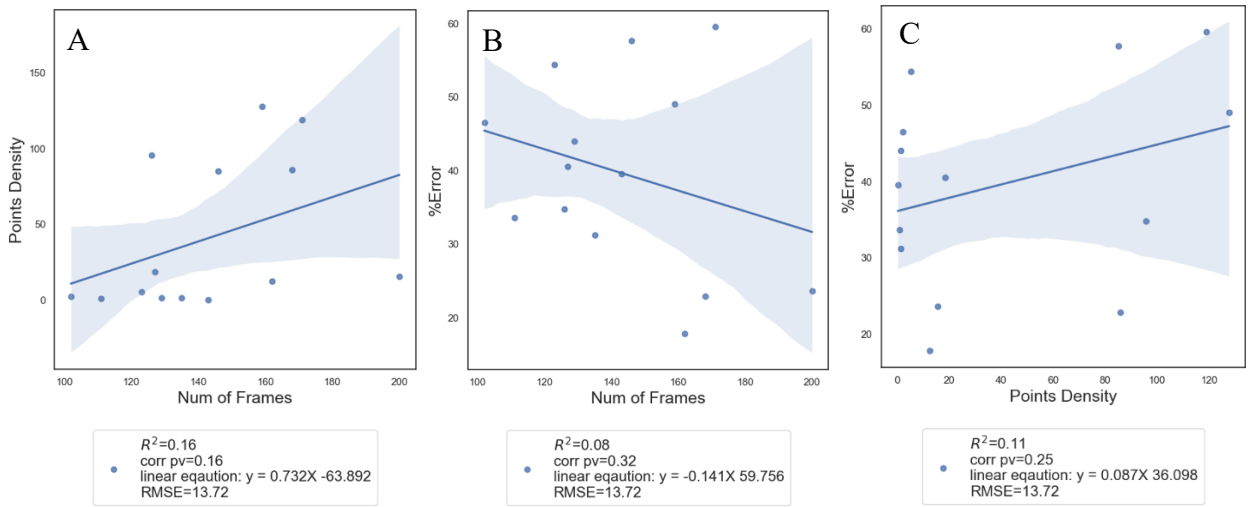


Figure 13 – Non significant comparisons of leaf area %error and point cloud density. Number of frames per point cloud vs. points density generated by the Polycam app point cloud creation. B) Negative linear relationship between %error vs. number of frames. C) Positive linear relationship between %error and points density.

4. Discussion

In this study, we investigated various aspects of plant phenotyping using 3D point cloud data generated using iPhone 13 Pro. Our findings shed light on the potential of this approach for tracking plant growth and whole canopy surface area computations, while using an accurate and more affordable and an easy to use measuring tool than those used in previous works [10, 11, 12, 13].

The iPhone's factory calibration has been proven to be very accurate (Fig. 4, Fig. 5A), saving the user a tedious calibration process, which serves as a significant advantage in general and in particular to scientific goal, as a measuring tool for object sizes.

The accuracy of surface area computations derived from point cloud data revealed that individual maize leaf trait extraction using manually labeled point clouds resulted with a high R^2 value of 0.88, when compared with reference measured area (Fig. 5A), similar to the results showed in [10, 11] when tested more advanced segmentations methods.

Next, we proposed a way for computing the whole canopy surface area by constructing a stem-total area ratio to avoid stem and canopy segmentation prior to comparison. Comparing the computed canopy area to the reference area resulted in R^2 value of 0.895.

We demonstrated that the computed whole canopy surface area of maize plants using CNN-based segmentation approach exhibited strong correlations ($R^2 \geq 95$) with the measured surface area (Fig. 8), though only 27% maize point clouds were segmented successfully, compared to [10], where 100% of stem instances were successfully extracted. Unsuccessful stem extraction in the second part of the model could arise from various stem angles in the maize plants, as the model assumes that stem grows vertically, hence the angle between the stem and z-axis should be less than 10 degrees.

Another significant scientific advantage of the iPhone scanning approach is that this manually-operated tool effectively generates a comprehensive 3D structure of the absolute plant canopy area. Contrasting with high-end machines that traverse over plants to produce only the top canopy's 3D projected area, the iPhone not only demonstrates a robust correlation but also a highly accurate approximation between Y and X (Y=1.036 X, Fig. 5). Meanwhile, top canopy scanners, although establish a decent correlation between their 3D scans of the top canopy and the observed scans, in reality introduce an error margin of ~ 70% in absolute values (Y=0.22X), as detailed in Vincent Vadez [22]. Hence, it is advisable to exercise caution when interpreting biological and agronomic traits related to actual leaf area, such as transpiration, especially when relying on measurements from above-canopy machines. Our, approach revealed that the whole

canopy area values computed using the different methods were highly corelated to the whole plant transpiration. Moreover, we found no significant difference between our different analyzing methods (Fig. 10), suggesting that using the whole plant surface area could be used for transpiration prediction in maize grown under well-irrigated condition.

Then we investigated the relationship between daily transpiration rate and the plant total surface area. Remarkably, we observed a significant correlation (p-value < 0.01) and a high R^2 value of 0.83, implying that transpiration is closely linked to plant surface area (Fig. 12). This finding aligns with existing knowledge, as transpiration is a fundamental process in plants, regulating water uptake and nutrient transport and is directly affected by canopy area [14].

Our findings suggests that the 3D point cloud data, acquired through the iPhone, can be effectively utilized to estimate the surface area of maize leaves. The high R2 and P values, indicate the reliability of the employed methods and highlight the potential for these techniques to be adopted in plant phenotyping studies. We also demonstrated that separating stem area for surface are calculation may not be relevant at this stage of the plant's growth, as the ratio of the stem to the rest of the plant is 11.6% (Fig. 6A) and leaves covering the stem surface are also transpiring (Fig. 9B).

Lastly, we explored the effect of point cloud density on surface area calculations. Surprisingly, we found that altering the number of frames per file or the point density did not significantly impact the deviation in leaf area calculations (Fig. 13), as opposed to [13] that showed that with decreasing resolution the error is increasing. This suggests that within the tested range, variations in point cloud densities have minimal effect on the accuracy of surface area calculations. Therefore, researchers can potentially adopt different point cloud densities based on their specific experimental needs without compromising the reliability of the results, thus saving more time while performing scans and reduce storage usage.

Our study also demonstrated the feasibility of using smartphone-based technologies for plant phenotyping. The iPhone 13 Pro's advanced features, such as three high-quality cameras, facilitated the creation of accurate 3D models of maize plants. This approach offered a more affordable and accessible alternative to dedicated devices available on the market, making it a viable option for plant researchers. Additionally, the successful utilization of smartphone-based technology highlights the potential for wider adoption of similar approaches in plant sciences, opening new avenues for understanding plant physiology and enhancing crop productivity. Considering the iPhone's price, accuracy, ease of use, and self-calibration, it presents a stark contrast to the costly, high-maintenance, and infrastructure-intensive commercial "over canopy" scanners. These more expensive systems are often feasible only in large, well-funded

greenhouses. The accessibility and practicality of the iPhone scanner make it an ideal tool for any research student, scientist, or field practitioner seeking reliable and efficient data collection methods.

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Supplementary Materials

Table 1 – Maize point clouds data for establishing stem-total area relationship, consisting on the canopy area, stem area and total aera (canopy+stem).

plant_num	canopy_area (cm^2)	stem_area (cm^2)	total_area (cm^2)
1	1231.693	127.679	1359.372
2	1633.31	197.917	1831.227
3	2249.073	312.06	2561.133
6	2724.709	338.519	3063.228
7	1709.142	225.541	1934.683
8	2062.331	218.019	2280.35
9	2766.653	332.848	3099.501
10	2062.331	218.019	2280.35
11	541.852	85.17	627.022
13	3233.65	454.37	3688.02
14	2433.586	363.048	2796.634
15	325.171	70.996	396.167
16	2479.284	341.62	2820.904
17	2265.225	250.311	2515.536
18	1891.095	180.178	2071.273

Table 2 - CNN model output and reference canopy area (measured_canopy_area) for each plant and radius parameter used. If stem segmentation was successful (model_log =

'succeeded') then canopy and stem area were estimated (under calculated_area). If stem segmentation did not succeed (model_log = 'failed') then only canopy area was estimated.

plant_num	organ_type	calculated_area (cm^2)	Radius (cm)	measured_canopy_area (cm)	model_log
18	leaf	2718.277	0.01	1891.095	succeeded
18	stem	116.43	0.01	1891.095	succeeded
18	leaf	2692.914	0.02	1891.095	succeeded
18	stem	294.056	0.02	1891.095	succeeded
18	leaf	2571.251	0.03	1891.095	succeeded
18	stem	413.831	0.03	1891.095	succeeded
9	leaf	3521.663	0.01	2766.653	failed
9	leaf	3521.663	0.02	2766.653	failed
9	leaf	3521.663	0.03	2766.653	failed
11	leaf	1256.367	0.01	541.852	failed
11	leaf	1256.367	0.02	541.852	failed
11	leaf	1256.367	0.03	541.852	failed
7	leaf	2201.025	0.01	1709.142	failed
7	leaf	2201.025	0.02	1709.142	failed
7	leaf	2201.025	0.03	1709.142	failed
16	leaf	3529.927	0.01	2479.284	failed
16	leaf	3529.927	0.02	2479.284	failed
16	leaf	3529.927	0.03	2479.284	failed
6	leaf	3820.954	0.01	2724.709	failed
6	leaf	3820.954	0.02	2724.709	failed
6	leaf	3820.954	0.03	2724.709	failed
17	leaf	3163.741	0.01	2265.225	succeeded
17	stem	65.975	0.01	2265.225	succeeded
17	leaf	3149.995	0.02	2265.225	succeeded
17	stem	240.616	0.02	2265.225	succeeded
17	leaf	3064.108	0.03	2265.225	succeeded
17	stem	385.617	0.03	2265.225	succeeded
1	leaf	1724.155	0.01	1231.693	failed
1	leaf	1724.155	0.02	1231.693	failed

1	leaf	1724.155	0.03	1231.693	failed
8	leaf	2603.65	0.01	2062.331	failed
8	leaf	2603.65	0.02	2062.331	failed
8	leaf	2603.65	0.03	2062.331	failed
3	leaf	2888.46	0.01	2249.073	failed
3	leaf	2888.46	0.02	2249.073	failed
3	leaf	2888.46	0.03	2249.073	failed
2	leaf	2255.337	0.01	1633.31	failed
2	leaf	2255.337	0.02	1633.31	failed
2	leaf	2255.337	0.03	1633.31	failed
13	leaf	4169.738	0.01	3233.65	succeeded
13	stem	156.984	0.01	3233.65	succeeded
13	leaf	4076.57	0.02	3233.65	succeeded
13	stem	460.058	0.02	3233.65	succeeded
13	leaf	3868.557	0.03	3233.65	succeeded
13	stem	648.728	0.03	3233.65	succeeded
14	leaf	3484.345	0.01	2433.586	succeeded
14	stem	167.026	0.01	2433.586	succeeded
14	leaf	3426.635	0.02	2433.586	succeeded
14	stem	337.275	0.02	2433.586	succeeded
14	leaf	3365.779	0.03	2433.586	succeeded
14	stem	476.797	0.03	2433.586	succeeded

Table 3 - Point cloud densities including mean %error of leaves area for each plant, number of points and the volume of each point cloud, number of 2D frames used to generate the point cloud via Polycam app and point density.

plant_num	**Mean %error**	**Points**	**Volume** (cm^2)	**Number of Frames**	**Density** $(\frac{points}{cm^2})$
1	54.41275	6090	1175.491969	123	5.18081
2	31.210449	5556	4015.14021	135	1.383762
3	40.506812	7666	416.720474	127	18.396024
6	17.816426	9033	733.992182	162	12.306671
7	39.563886	3480	27649.48908	143	0.125861
8	59.537011	31309	263.141791	171	118.981481

9	22.843798	13116	152.482577	168	86.016385
10	49.042219	28666	224.424118	159	127.731369
11	33.593168	2116	2440.762141	111	0.866942
13	127.389048	15332	37.065625	193	413.644722
14	23.621749	16623	1069.308397	200	15.545562
15	46.49834	2070	967.819881	102	2.138828
16	57.677295	13535	159.2238	146	85.006136
17	43.982029	7496	5331.128993	129	1.406081
18	34.735685	9162	95.719893	126	95.716781

References

1) Kah, M., Tufenkji, N., & White, J.C. (2019). Nano-enabled strategies to enhance crop nutrition and protection. *Nature Nanotechnology*, 14(6), 532-540.
2) Zhang, Q., Ying, Y., & Ping, J. (2022). Recent advances in plant nanoscience. *Advanced Science*, 9(2), 2103414.
3) Rosenzweig, C., Iglesias, A., Yang, X., et al. (2001). Climate Change and Extreme Weather Events; Implications for Food Production, Plant Diseases, and Pests. *Global Change & Human Health*, 2, 90-104. doi: 10.1023/A:1015086831467
4) Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., ... Fang, J. (2010). The impacts of climate change on water resources and agriculture in China. *Nature*, 467(7311), 43-51. doi: 10.1038/nature09364
5) Dall'erba, S., & Domínguez, F. (2016). The Impact of Climate Change on Agriculture in the Southwestern United States: The Ricardian Approach Revisited. *Spatial Economic Analysis*, 11(1), 46-66. doi: 10.1080/17421772.2015.1076574
6) Giraldo, J.P., Wu, H., Newkirk, G.M., & Kruss, S. (2019). Nanobiotechnology approaches for engineering smart plant sensors. *Nature Nanotechnology*, 14(6), 541-553. doi: 10.1038/s41565-019-0470-6
7) Cheng, Z., Kong, J., Wu, D., Guan, Z., Ding, B., & Chen, F. (2023). Wearable Sensor: An Emerging Data Collection Tool for Plant Phenotyping. *Plant Phenomics*, 5 (0051). doi:10.34133/plantphenomics.0051
8) Rungyaem, K., Sukvichai, K., & Phatrapornnant, T. (2021). The 3-dimensional Plant Organs Point Clouds Classification for the Phenotyping Application based on CNNs. In *The 12th International Conference on Advances in Information Technology (IAIT2021)* (pp. 1–7). Association for Computing Machinery. https://doi.org/10.1145/3468784.3469949
9) Miao, T., Wen, W., Li, Y., Wu, S., Zhu, C., & Guo, X. (2021). Label3DMaize: toolkit for 3D point cloud data annotation of maize shoots. *GigaScience*, 10(5). https://doi.org/10.1093/gigascience/giab031
10) Ao, Z., Wu, F., Hu, S., Sun, Y., Su, Y., Guo, Q., & Xin, Q. (2022). Automatic segmentation of stem and leaf components and individual maize plants in field terrestrial LiDAR data using convolutional neural networks. *The Crop Journal*, 10. https://doi.org/10.1016/j.cj.2021.10.010
11) S. Jin et al., "Stem–Leaf Segmentation and Phenotypic Trait Extraction of Individual Maize Using Terrestrial LiDAR Data," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 3, pp. 1336-1346, March 2019, doi: 10.1109/TGRS.2018.2866056.
12) Forero, M.G.; Murcia, H.F.; Méndez, D.; Betancourt-Lozano, J. LiDAR Platform for Acquisition of 3D Plant Phenotyping Database. *Plants* 2022, 11, 2199. https://doi.org/10.3390/plants11172199
13) Paulus, S. Measuring crops in 3D: using geometry for plant phenotyping. *Plant Methods* 2019, 15, 103. https://doi.org/10.1186/s13007-019-0490-0
14) Alam, M.S.; Lamb, D.W.; Warwick, N.W.M. A Canopy Transpiration Model Based on Scaling Up Stomatal Conductance and Radiation Interception as Affected by Leaf Area Index. *Water* 2021, *13*, 252. https://doi.org/10.3390/w13030252
15) Van Rossum, Guido. "Python Programming Language." *USENIX annual technical conference*. Vol. 41. No. 1. 2007.
16) Randles, Bernadette M., et al. "Using the Jupyter notebook as a tool for open science: An empirical study." 2017 ACM/IEEE Joint Conference on Digital Libraries (JCDL). IEEE, 2017.
17) Hackeling, Gavin. Mastering Machine Learning with scikit-learn. *Packt Publishing Ltd*, 2017.
18) Blanco-Silva, Francisco J. Learning SciPy for numerical and scientific computing. *Packt Pub*., 2013.

19) McKinney, Wes. "pandas: a foundational Python library for data analysis and statistics." *Python for high performance and scientific computing* 14.9 (2011): 1-9.
20) Harris, Charles R., et al. "Array programming with NumPy." *Nature* 585.7825 (2020): 357-362.
21) Bisong, E. (2019). Matplotlib and Seaborn. In: Building Machine Learning and Deep Learning Models on Google Cloud Platform. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4842-4470-8_12
22) Alam, M.S.; Lamb, D.W.; Warwick, N.W.M. "A Canopy Transpiration Model Based on Scaling Up Stomatal Conductance and Radiation Interception as Affected by Leaf Area Index." *Water*, 13, 252 (2021). DOI: 10.3390/w13030252.