From Pocket to Pixels: Smartphone-Based Proximal Sensing for Quantitative Monitoring of Peach Canopy Dynamics

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Abstract.

Monitoring peach canopy dynamics is essential for optimizing irrigation scheduling and promoting sustainable water management in intensively managed orchards. In well-watered systems, conventional irrigation practices often overlook spatial and temporal variability in canopy size and leaf area index (LAI), potentially leading to inefficient water use. Canopy size, as reflected by LAI, the ratio of total leaf area to ground area, serves as a key biophysical indicator linked to crop transpiration and water demand. However, conventional LAI measurement methods require specialized equipment and technical expertise, making them impractical for routine commercial implementation. Bridging this operational gap calls for scalable, smartphone-based sensing approaches that can translate visual canopy information into actionable irrigation indicators.

This study presents a smartphone-based proximal sensing framework for quantitative monitoring of peach canopy dynamics in high-density orchards. The objectives were: (1) to compare different methods of canopy segmentation for side-view imagery; (2) to develop a robust image-based workflow for delineating individual tree canopies and estimating visible canopy area; and (3) to evaluate the capacity of this metric to capture seasonal canopy development relative to standard LAI measurements.

The experiment was conducted during the 2025 growing season at the Matityahu Research Farm (Israel) using five lysimeter-grown peach trees (cv. 1952, rootstock 677). Canopy imaging and LAI measurements were performed on 11 sampling dates covering major phenological stages. Six RGB images per tree were acquired at each date using a Samsung A50 smartphone *positioned at standardized height (1.35 m) and distance (2.5 m). LAI was measured using an AccuPAR LP-80 ceptometer based on above- and below-canopy Photosynthetic Active Radiation (PAR) readings.*

A Python-based image processing pipeline was developed to estimate side-view canopy area (SVCA) (m²). Canopy segmentation employed a hybrid method with Segment Anything Model (SAM), followed by refinement using color space transformation and adaptive thresholding. A calibration target enabled pixel-to-metric conversion. Seasonal LAI values ranged from 0.61-4.23 (April-May), 5.52–6.63 (July-September), and 3.55-1.65 (November-January). The smartphone-derived SVCA showed a positive relationship with LAI (R = 0.85; RMSE = 2.9), with tree-specific relationships ranging from R = 0.85 to 0.93

Although estimation errors remain non-negligible, the proposed method successfully captured seasonal canopy trajectories and relative differences among trees. This work demonstrates the potential of consumer-grade smartphone imaging combined with advanced segmentation algorithms as an accessible, scalable proximal sensing tool. By translating pocket-level imagery into quantitative canopy metrics, this framework supports adaptive irrigation strategies and advances accessible precision agriculture in intensively managed orchard systems.

Keywords.
Smartphone imaging; Proximal sensing; Canopy segmentation; Canopy monitoring; Leaf Area Index; Precision irrigation

Introduction

Monitoring canopy dynamics in high-density peach orchards is critical for sustainable water management. High-resolution thermal and visual unmanned aerial vehicle imagery, coupled with statistical and spatial algorithms, has been successfully implemented to delineate tree canopies for assessing water status in stone fruit orchards (Katz et al., 2023). However, these top-down aerial techniques are less effective for modern fruit-wall or hedgerow configurations due to their low canopy-to-ground ratio. This challenge is further exacerbated when commercial orchards are covered by protective netting, which physically and spectrally obstructs the overhead view.

To overcome these structural barriers, ground-based optical methods have traditionally been employed to estimate the Leaf Area Index (LAI), defined as leaf area per unit of ground surface area, a key biophysical indicator linked directly to intercepted radiation, crop size, transpiration and water requirements (Girona et al., 2011; Fereres et al., 2012). Netzer et al. (2009) showed that both the crop coefficient and crop evapotranspiration were highly correlated to the LAI of grapevines, and that the crop coefficient can be estimated for precision irrigation using LAI. Classically, this is achieved through direct, destructive harvesting or indirect optical tools such as hemispherical photography and ceptometers (e.g., AccuPAR LP-80) (Poblete-Echeverría et al., 2015). Yet, these conventional indirect methods present significant operational limitations: they are highly dependent on specific sky conditions (requiring uniform overcast or stable, direct beam angles), demand meticulous above- and below-canopy Photosynthetically Active Radiation (PAR) sampling, and require substantial technical expertise (Rogers et al., 2021). Furthermore, in high-density fruit wall or hedgerow planting systems, standard spatial assumptions of a homogeneous, random canopy distribution fail (Welles & Cohen, 1996).

Consequently, research has shifted toward ground-based, side-view profile data collection as a promising alternative. While active proximal sensing platforms using all-terrain vehicles (Bailey & Mahaffee, 2017) and robotics (Tang et al., 2020) have demonstrated accuracy improvement, their high initial capital costs and computational complexity make them less accessible for small-scale operations or developing agriculture sectors. In contrast, smartphone imagery offers a highly practical, decentralized solution due to its low cost, extreme portability, and worldwide accessibility. However, capturing and processing side-view orchard profile images introduces two primary computer vision challenges: 1) The precise isolation and delineation of a specific target tree from adjacent elements and noisy backgrounds (including overlapping trees, soil, cover crops, protective meshes). 2) The accurate determination of actual canopy area within that target region.

Image segmentation methods applied to proximal orchard imagery range from classical vegetation index thresholds to data-driven deep learning models. Classical color-index approaches operate on pixel-level color spaces to distinguish vegetation (Hamuda et al., 2016). Their main advantage is low computational cost and high speed, making them ideal for instant smartphone applications. However, they are extremely vulnerable to environmental noise and struggle to separate target foliage from weeds, cover crops, or adjacent trees with similar green hues. Conversely, modern deep learning (DL) tools use contextual semantic understanding to isolate structural boundaries (Katal et al., 2022). DL's key advantage is its ability to delineate the global silhouette of a single tree within an interconnected hedgerow (Metuarea et al., 2025). Its disadvantage is the inability to parse exact inner foliage pixels from intra-canopy gaps or shadows directly from standard RGB inputs. Recent advancements have highlighted this transition; for instance, Gong et al. (2025) successfully demonstrated the deployment of edge-computing threshold frameworks for real-time orchard assessments, while Metuarea et al. (2025) leveraged robust DL models to isolate complex visual features under variable field illumination.

Bridging the operational gap in LAI measurement that make it impractical for routine commercial implementation while balancing current image analysis advantages and disadvantages calls for scalable, smartphone-based sensing approaches that can translate visual canopy information into usable canopy development metrics and latter actionable irrigation management indicators. Therefore, this study presents a smartphone-based proximal sensing framework for quantitative monitoring of peach canopy dynamics in high-density orchards. The objectives were:

(1) to compare different methods of canopy segmentation for side-view imagery;
(2) to develop a robust image-based workflow for delineating individual tree canopies and estimating visible side-view canopy area; and
(3) to evaluate the capacity of this metric to capture seasonal canopy development relative to standard measurements.

Methods

Research area and experiment setup

The study was conducted in 2025 at the Matityahu Research Farm in northern Israel (33°3'49''N, 35°27'15''E). Five late-harvest peach trees (cv. 1952, rootstock 677), planted in 2022 at a spacing of 1.2 m, were trained to a fruit wall (FW) architecture (**Fig. 1**). Each tree was grown in an individual lysimeter (500 L) filled with inert perlite.

The lysimeter system enabled continuous estimation of tree water uptake (TWU, *L*) as the difference between irrigation input and drainage output (Mpelasoka et al., 2001), assuming negligible soil evaporation. Irrigation was supplied with seven $4\,L\,h^{-1}$ button drippers per tree (Netafim, Hatzerim, Israel), totaling approximately $42\,L\,day^{-1}$. Drainage was automatically collected and weighed, allowing daily calculation of irrigation input, drainage, and TWU. Fruit was harvested on 12 October 2025.

Fig. 1 The research was conducted at the Matityahu Research Farm in a lysimeter experiment. Five peach trees were trained to fruit wall (FW) architecture. 1 April 2025.

Side-view canopy area (SVCA)

Image campaigns

Image campaigns were conducted on 11 dates between April 2025 and January 2026. During each campaign, images were acquired between 11:00 – 13:00 using a Samsung Galaxy A50 smartphone mounted on a leveled monopod at a height of 1.35 m, positioned 2.5 m from the tree and oriented perpendicular to the canopy plane. Six images were captured per tree. A co-planar reference calibration target of known dimensions was included in each frame to enable image scaling.

Image analysis pipeline

To estimate side-view canopy area (SVCA) (m^2), a hybrid multi-stage image analysis pipeline was developed that integrates structural boundary detection with spectral filtering (**Fig. 2**). SVCA is defined as the projected canopy area derived from side-view imagery. The processing workflow follows a sequential procedure, combining DL–based canopy delineation with color-based pixel segmentation.

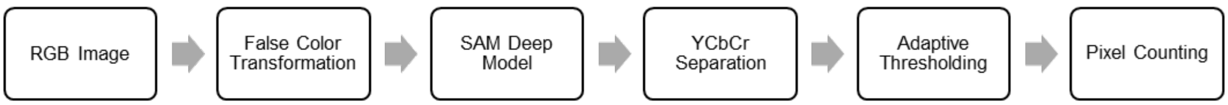


Fig. 2 Side-view canopy area (SVCA) using hybrid segmentation method.

The image processing pipeline integrates structural segmentation and spectral filtering to estimate SVCA. Raw smartphone RGB images were first transformed into a false-color representation to enhance canopy boundary contrast. The Segment Anything Model (SAM) was then applied to delineate the target tree and generate a canopy mask, which was used to isolate the region of interest. To refine within-canopy segmentation, the masked image was converted to the YCbCr color space, and the Cr (Chroma red) channel was selected for its sensitivity to vegetation under variable illumination. An adaptive binary threshold was applied within the mask to classify pixels as leaf area (value = 255) or background (value = 0), thereby reducing the influence of gaps, branches, and non-foliar elements.

The total canopy pixels were counted and converted into the normalized SVCA (m^2) using a co-planar reference calibration target. The total number of active canopy pixels (P_{canopy}) is extracted via an automated count matrix. To convert this abstract digital pixel sum (P_{ref}) into a true physical measurement, a co-planar reference target of known geometric dimensions (A_{ref}) placed within the tree's vertical plane is automatically segmented to determine the local pixel-to-surface scaling factor (SF) (**Eq. 1**)

$$SF = \frac{\mathrm{P_{ref}}}{A_{ref}} \tag{1}$$

The final estimated side-view canopy area (SVCA) (m^2) is calculated in **Eq 2**:

$$SVCA = P_{canopy} \times SF \tag{2}$$

This automated metric serves as a reliable, non-destructive proximal sensing proxy for tracking temporal canopy development and latter evaluating tree-specific water requirements.

Canopy segmentation experiment
Three canopy segmentation methods were evaluated to assess their performance in estimating SVCA.

<u>RGB thresholding using the ExG index (RGB-ExG):</u> This pixel-based method converts RGB images to the Excess Green (ExG) vegetation index (Hamuda et al., 2016), followed by Otsu thresholding (Otsu, 1979) to separate vegetation from background. While computationally efficient and effective under uniform illumination, this approach lacks spatial context and is sensitive to lighting variability, often misclassifying non-target vegetation such as weeds or adjacent canopies (Hamuda et al., 2016).

<u>Segment Anything Model (SAM):</u> A deep learning–based segmentation model, SAM, was implemented with a Python pipeline to delineate tree structure using contextual and geometric features. The model enables robust isolation of individual trees from complex backgrounds; however, it produces binary masks that do not resolve internal canopy structure, leading to inclusion of non-foliar elements (e.g., branches, gaps) and potential overestimation of canopy area (Li et al., 2023).

<u>Hybrid pipeline</u>**:** A multi-stage approach was developed to integrate structural and spectral information (**Fig. 2**). The SAM-derived mask was first used to define the region of interest and exclude background elements. Subsequently, color-space–based thresholding was applied within the mask to extract leaf pixels and suppress non-foliar components. This combined approach enables both accurate tree delineation and improved estimation of effective canopy area.

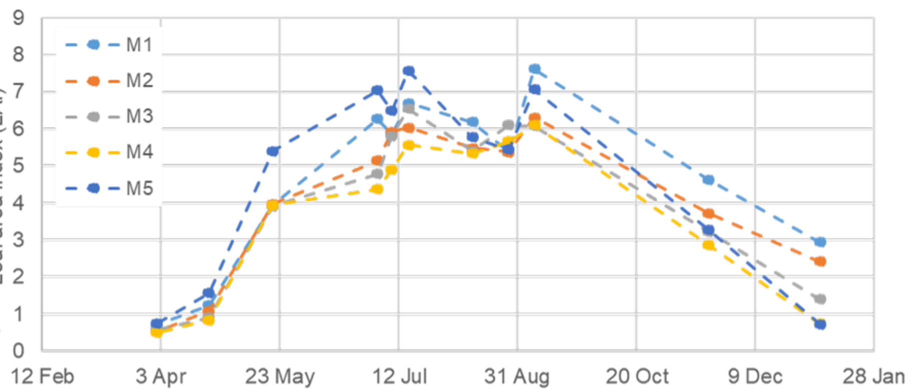
Data collection and analysis
LAI measurement campaigns:
LAI measurements were conducted concurrently with smartphone-based SVCA imaging across 11 sampling dates between April 2025 and January 2026. LAI was measured per tree using an AccuPAR LP-80 ceptometer (Meter Group, Washington, USA) between 11:00 and 13:00 under standard measurement protocols. Following instrument calibration, above-canopy PAR was recorded in an unobstructed clearing (n = 3). Below-canopy PAR measurements were taken on the east and west sides of each tree, approximately 10 cm from the trunk (n = 6 total per tree).

Data Analysis
Descriptive statistics of LAI were calculated for each sampling date. A mixed-effects model with repeated measures was used to evaluate the effects of tree, measurement date, and their interaction on LAI (JMP® Version 19, SAS Institute Inc., USA). Statistical significance was assessed at $p < 0.05$. Relationships between LAI and SVCA for each segmentation method were evaluated using Pearson correlation analysis, and model performance was further assessed using root mean square error (RMSE). Correlation coefficients (R) and RMSE values were computed using JMP.

Results

Seasonal canopy development

A consistent seasonal pattern of canopy development was observed across all trees, with LAI increasing from bud break to full canopy and declining toward dormancy (**Fig. 3**). Mean LAI ranged from 0.61±0.11 on 3 April to a maximum of 6.63±0.68 on 7 September, followed by a decrease to 1.65±1.0 in January. A decline in LAI was observed in August across all trees. No significant differences in LAI were detected between trees throughout the season ($p > 0.05$).



a

b

LAI	1 Apr	23 Apr	20 May	3 Jul	9 Jul	16 Jul	12 Aug	27 Aug	7 Sep	19 Nov	5 Jan
Average	0.61	1.12	4.23	5.52	5.80	6.48	5.64	5.59	6.63	3.55	1.65
Stdev	0.11	0.29	0.65	1.11	0.57	0.76	0.35	0.31	0.68	0.68	1.00
CV	0.18	0.26	0.15	0.20	0.10	0.12	0.06	0.06	0.10	0.19	0.61
Min	0.49	0.83	3.92	4.37	4.91	5.57	5.34	5.37	6.08	2.87	0.73
Max	0.74	1.56	5.4	7.04	6.49	7.58	6.19	6.11	7.62	4.63	2.94

c

Above-PAR	1 Apr	23 Apr	20 May	3 Jul	9 Jul	16 Jul	12 Aug	27 Aug	7 Sep	19 Nov	5 Jan
Average	796	825	2160	2122	2149	2078	1740	2139	1878	1247	1239
StdDev	125	75	94	15	8	8	10	61	22	3	7

Fig. 3 Leaf area index (LAI) trajectory in five peach trees (M1 – M5) in the Matityahu lysimeter experiment during 2025 and winter of 2026 (a). Descriptive statistics of LAI per measurement day (b). Above-canopy photosynthetically active radiation (PAR) (μmol m^{-2} s^{-1}) (c). Measurements performed using the AccuPAR LP-80 ceptometer.

Given the low variability among trees, temporal dynamics were further examined using a representative tree (M4). Three segmentation methods—RGB-ExG, SAM, and a hybrid method—were compared (**Fig. 4**). All methods captured the seasonal trajectory of canopy development. The RGB-ExG method classified all vegetation within the image, while both SAM and the hybrid approach successfully delineated the target tree from surrounding elements. Only the RGB-ExG and hybrid methods resolved within-canopy features (e.g., leaf pixels). A strong correlation was observed between RGB-ExG and hybrid-derived SVCA estimates (R=0.95).

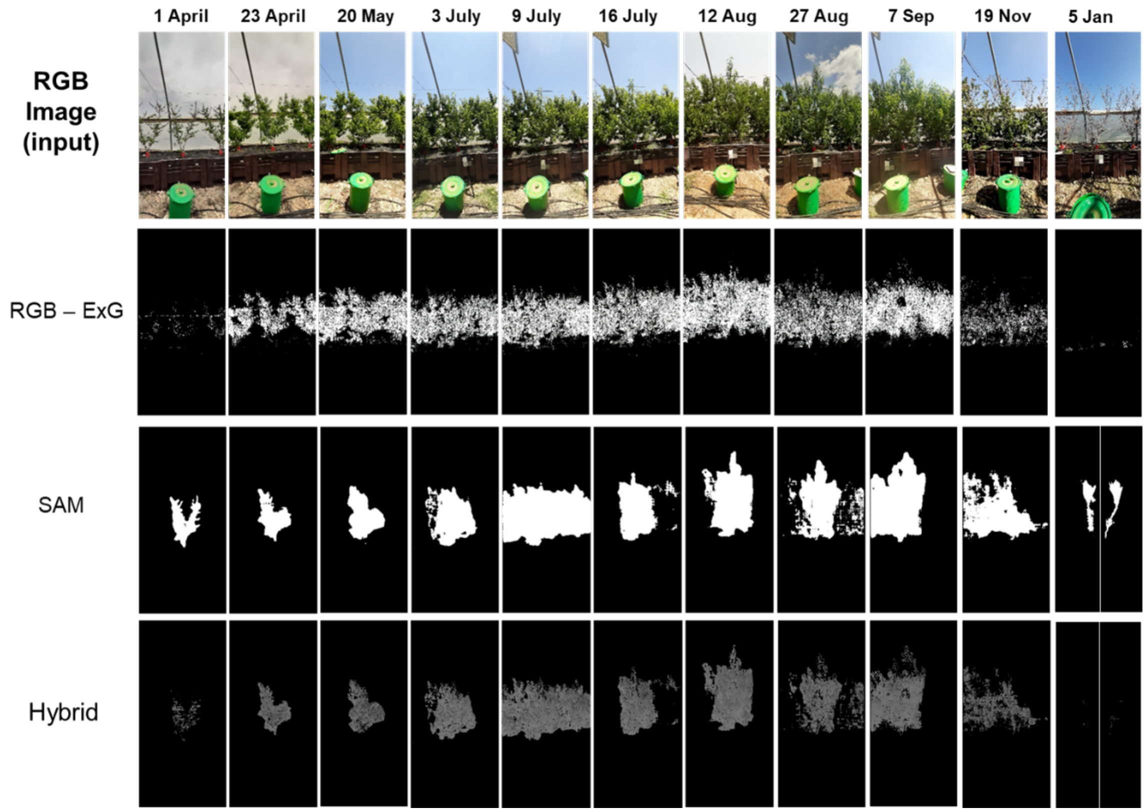


Fig. 4 Side-view canopy area (SVCA) (m^2) of peach tree M4 in the Matityahu lysimeter experiment during 2025 and 2026 with three canopy segmentation methods: RGB statistical thresholding using the ExG index (RGB-ExG), Segment Anything Model (SAM), and the hybrid method. The green bin was removed manually prior to final calculation.

Temporal trends in SVCA for tree M4 were consistent with LAI dynamics (**Fig. 5**), although differences in growth rate were observed between May and July, where LAI increased more rapidly than SVCA. This pattern was consistent across all measured trees.

The relationship between LAI and SVCA varied by segmentation method. When all measurement dates were included, the hybrid method showed the strongest correlation with LAI (R=0.82), followed by RGB-ExG (R=0.79) and SAM (R=0.77). Excluding measurements acquired under low radiation conditions improved correlations for the hybrid (R=0.91) and RGB-ExG (R=0.96) methods, while performance decreased for SAM (R=0.64).

Across all trees (M1–M5), the hybrid SVCA metric was positively correlated with LAI throughout the season (R=0.85, RMSE = 2.9), with individual tree correlations ranging from 0.85 (M4) to 0.93 (M3) (**Fig. 6**).

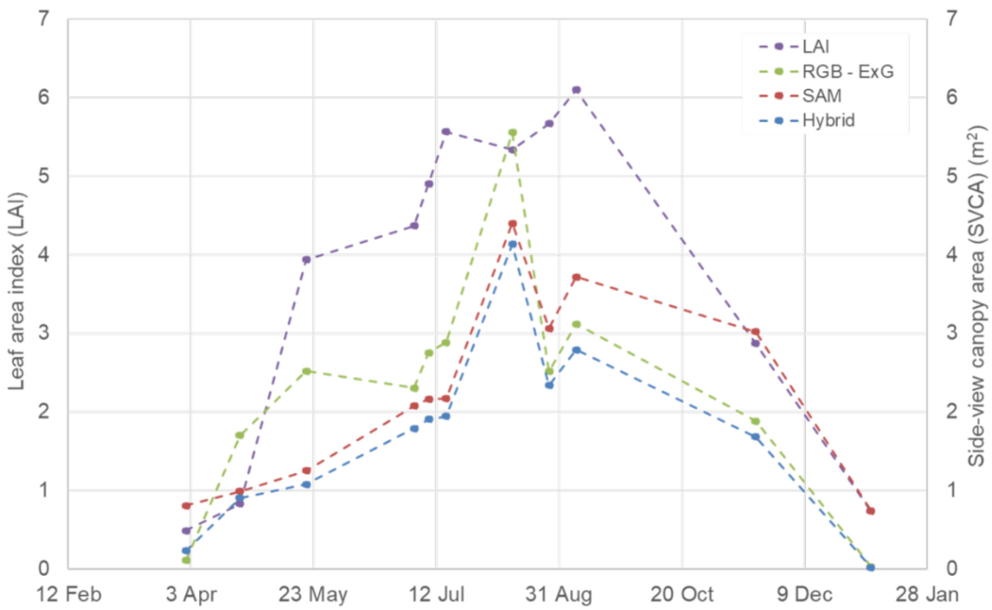
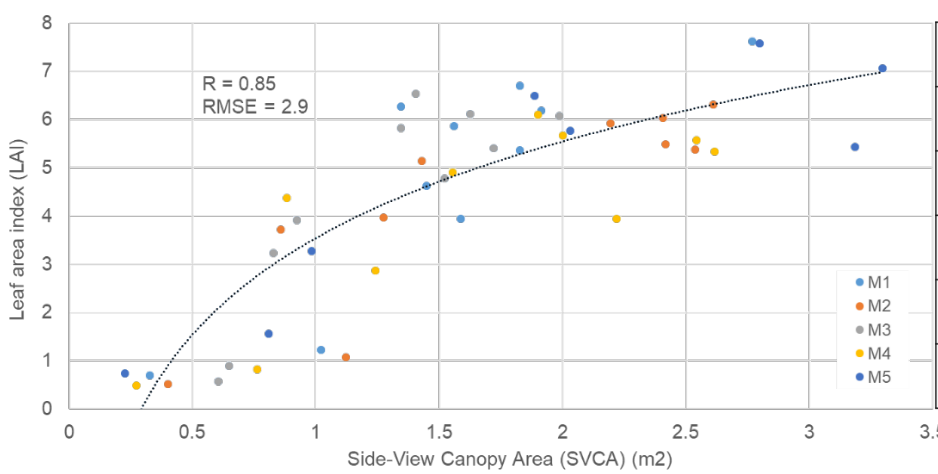


Fig. 5 Seasonal canopy dynamics of tree M4 in the Matityahu lysimeter experiment during 2025 and 2026. Leaf area index (LAI) (*purple points and dashed line*) and side-view canopy area (SVCA) (m^2) using the RGB-ExG (*green points and dashed line*), Segment Anything Model (SAM) (*red points and dashed line*), and hybrid *(blue points and dashed line*) canopy segmentation methods. The SVCA using SAM and hybrid methods on 9 July 2025 was calculated proportional to the trees in the images.



Tree	R
M1	0.85
M2	0.88
M3	0.93
M4	0.85
M5	0.91

Fig. 6 Relationship between leaf area index (LAI) and smartphone-based side-view canopy area (SVCA) (m^2) using the hybrid canopy segmentation method in five peach trees (M1 – M5) in the Matityahu lysimeter experiment during 2025 and 2026. R = 0.85, RMSE = 2.9.

Discussion

The comparison of canopy segmentation approaches highlights a fundamental trade-off between computational simplicity, robustness, and biological relevance in estimating SVCA (**Table 1**). The RGB-ExG method provided a fast and accessible solution and showed strong agreement with LAI under stable illumination conditions; however, its inability to distinguish target trees from surrounding vegetation may limit its applicability in controlled and commercial orchard environments. In contrast, the SAM method improved structural delineation of individual trees within complex scenes, but consistently overestimated canopy area due to its inability to resolve internal canopy porosity. The hybrid method effectively combined these complementary strengths, enabling both accurate tree isolation and improved representation of foliar area. These findings are consistent with previous studies indicating that segmentation performance depends strongly on canopy structure and background complexity (Katal et al., 2022).

Table 1 Comparison of canopy segmentation methods for smartphone-based side-view canopy area (SVCA). ** significant at 0.01 Level

Canopy Segmentation Method	Approach	Computational Power	Ability to Distinguish Between Neighboring Trees	Ability to Identify Within-Tree Objects (e.g. Leaves)	Correlation factor (R) between LAI and SVCA		
					Tree M4 (all days)	Tree M4 (no cloudy days)	Trees M1-M5 (all days)
RGB thresholding with ExG vegetation index (RGB-ExG)	Statistical thresholding	low	low degree	high degree	0.79**	0.96**	-
Segment Anything Model (SAM)	Deep learning foundation model	high	moderate to high degree (development stage dependent)	low degree	0.77**	0.64	-
SAM and YCbCr thresholding (Hybrid)	Deep learning foundation model and color space thresholding	high	moderate to high degree (development stage dependent)	moderate degree	0.82**	0.91**	0.85**

A key limitation of LAI measurements is their dependence on specific illumination conditions and restricted acquisition windows, around midday. This constraint reduces temporal flexibility and introduces variability under non-ideal radiation conditions, as observed in the present study. Reported LAI values in this study (0.6 to 6.63) exceed typical orchard ranges but are consistent with dense, planar fruit wall systems (Tustin et al., 2022). Variability under low radiation conditions further highlights the sensitivity of indirect optical LAI methods to canopy structure and light distribution. In contrast, the developed smartphone-based SVCA approach demonstrated greater operational flexibility, enabling data acquisition across a wider range of environmental conditions without strict illumination constraints.

Differences observed between LAI and SVCA dynamics, particularly during the rapid growth phase (May–July), suggest that side-view canopy metrics may be less sensitive to volumetric canopy expansion. While LAI captures total leaf area development, SVCA represents a two-dimensional projection and may therefore underestimate structural changes occurring within the canopy depth. This distinction highlights an important geometric limitation of side-view approaches, but also suggests that SVCA captures complementary information related to canopy architecture and light interception.

Future research should focus on validating SVCA under commercial orchard conditions, where increased canopy overlap, background heterogeneity, and management variability introduce additional complexity. The sensitivity of SVCA to acquisition geometry, illumination conditions, and seasonal variability should also be systematically evaluated to define robust operational protocols. Furthermore, integrating SVCA with volumetric or multi-view approaches may improve its physiological interpretability and strengthen its relationship with key agronomic variables such as transpiration.

Conclusion

The results demonstrate that smartphone-based proximal sensing, coupled with a hybrid segmentation pipeline, provides a robust and scalable approach for quantifying peach canopy dynamics in high-density fruit-wall systems. The proposed SVCA metric showed strong agreement with LAI across seasonal development, while offering greater flexibility under variable field conditions and reduced dependency on strict illumination constraints. By effectively combining structural delineation and spectral filtering, the hybrid method addressed key limitations of both classical and deep learning approaches. These findings highlight the potential of low-cost, widely accessible imaging tools to support canopy monitoring for precision irrigation, particularly in modern orchard systems where traditional aerial and optical methods are constrained.

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