



Gibberellin treatments enhance foliar coverage, fruitlet retention, and next-season yield in young ‘Hass’ avocado trees: field measurements and UAV-based remote sensing

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Abstract

In evergreen avocado (*Persea americana* Mill.), flowering occurs in parallel with shedding of the previous season’s mature leaves, leaving partially leafless trees highly exposed to heat-induced damage in the spring. Foliar application of gibberellins (GAs) is known to increase vegetative growth while reducing flowering in various fruit trees. Here, we examined the effects of autumn GA₃ treatment on different growth parameters of young ‘Hass’ avocado trees over two years. Our results showed that 200 ppm GA₃ treatment applied in the fall slightly reduced flowering levels. In addition, both 100 and 200 ppm GA₃ treatments significantly increased foliar coverage and the indeterminate-to-determinate floral shoot ratio, changes that were associated with elevated expression of the floral repressor *PaTFL1*. Furthermore, GA₃ treatment also increased leaf area and chlorophyll content, enhanced fruitlet retention, and increased yield in subsequent seasons. In conjunction with field measurements, we acquired high-resolution unmanned aerial vehicle (UAV) imagery, including multispectral imagery and 3D point cloud data, at distinct time intervals after applying the GA₃ treatment. UAV imagery and random forest machine learning models were used to estimate flowering intensity, leaf area density, canopy volume, and chlorophyll content across orchards. The 3D point cloud data revealed significantly more developed canopies in GA₃-treated trees. Furthermore, UAV-derived estimates of flowering, canopy leaf area, and chlorophyll content closely matched field data measurements. Together, our results suggest that GA₃ treatment applied during the fall to young ‘Hass’ trees contributes to protection against heat damage in the spring, thereby increasing yield in the next season.

Keywords Gibberellin (GA₃) · Avocado · Flowering regulation · Heat stress · UAV imaging · Fruitlet retention · Alternate bearing · Vegetative growth

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Abbreviations

AB	Alternate bearing
EBI	Enhanced blooming index
GA ₃	Gibberellic acid
GAs	Gibberellins
GCPs	Ground control points
GNDVI	Green normalized difference vegetation index
LA	Leaf area
LAD	Leaf area density
LiDAR	Light detection and ranging
RF model	Random forest model
RMSE	Root mean squared error
SfM	Structure-from-motion photogrammetry
UAV	Unmanned aerial vehicle
VI	Vegetation indices

Introduction

Over the last decade, ongoing global warming has led to various changes, including a constant increase in ambient temperature, changes in the amount of rainfall, and an increase in the frequency of extreme cold, heat, and drought events (Luber and McGehee 2008; Zandalinas et al. 2021). Subtropical and tropical perennial fruit tree species are especially vulnerable to such changes (Roussos 2024). Specifically, heat stress conditions can affect various physiological processes in fruit trees, reduce photosynthesis, and negatively impact fruit set and development (Roussos 2024). An increase in ambient temperature may also encourage the growth of pests, thereby damaging fruit quality (William Haokip et al. 2020).

Avocado (*Persea americana* Mill.) is a subtropical evergreen fruit tree belonging to the *Lauraceae* family (Davenport 1986). According to FAOSTAT (2023), global avocado production totaled 10.46 million metric tons, led by Mexico and Colombia, with California and Israel also serving as important production regions. (<https://www.fao.org/faostat/en/#data/QCL/visualize>). The ‘Hass’ cultivar, which originated from a natural selection discovered in 1926 in California by Rudolph Hass, now dominates the global avocado industry (Davenport 1986). However, this popular variety is prone to alternate bearing (AB), a phenomenon characterized by a cyclical pattern of high yield in one year (an ‘on’ year), followed by floral repression and low yield in the next (‘off’ year) (Samach and Smith 2013; Goldschmidt and Sadka 2021). Mitigation of AB in avocado may include fruit thinning during an ‘on’ year, girdling or pruning strategies to ensure stable resource availability, and chemical or plant growth regulator treatments to induce flowering, during an ‘on’ year (Samach and Smith 2013; Goldschmidt and Sadka 2021). Despite the AB limitation, consumer demand for ‘Hass’ continues to grow. In fact, high global demand for ‘Hass’ avocado has led to a sharp increase in the number of new plantations, resulting in the massive planting of young ‘Hass’ trees worldwide (Migliore et al. 2017).

‘Hass’ avocado orchards are typically established with grafted seedlings, combining mature scions with rootstocks that enhance resistance to soil stress and pathogens (Ben-Ya’acov and Michelson 1995). After planting, trees cycle through several periods of vegetative growth (i.e., in summer, winter, and occasionally fall) and flower in the spring, with new flushes developing mainly at the periphery, thereby expanding the foliage cover (Davenport 1986). Floral induction of ‘Hass’ avocado occurs upon a decrease in ambient temperature in late autumn (Ziv et al. 2014; Ahsan et al. 2023). Typically, the apical and upper buds of new vegetative flushes undergo floral transition and develop into either determinate or indeterminate inflorescences,

while axillary buds generally remain dormant (Salazar-Garcia and Lovatt 1998; Ziv et al. 2014). The indeterminate inflorescences have a primary axis that continues to grow vegetatively after producing flowers, whereas the determinate inflorescences have a primary axis that terminates in a flower (Davenport 1986). Furthermore, in parallel to the floral shoot’s appearance, the previous season’s leaves, which gradually lose their photosynthetic capacity, start to senesce and abscise. At the same time, new vegetative flushes produce young leaves (Liu et al. 1999). In young trees, flowering that coincides with leaf senescence often leaves them “semi-naked” at full bloom. Under such conditions, spring heat waves may lead to enhanced fruitlet drop, severe leaf damage, or even the death of young trees (Bitá and Gerats 2013). Indeed, a study on young potted ‘Hass’ trees exposed to heat stress (43–53 °C) showed that such conditions cause leaf damage and reduce photosystem II efficiency (Fv/Fm) to varying degrees (Shapira et al. 2021).

Gibberellins (GAs) are a group of plant hormones involved in regulating various developmental processes, including seed germination, shoot elongation, flowering, fruit set, and the delay of organ senescence (Castro-Camba et al. 2022; Ritonga et al. 2023). In certain fruit trees, including avocado, exogenous GAs inhibit flowering and promote vegetative growth (see reviewed by Shah et al. 2023). As such, it has been reported that foliar application of gibberellic acid (GA₃) to mango and citrus prior to the floral induction period promotes vegetative growth, delays flowering, and reduces the number of flowers (Nakagawa et al. 2012; Muñoz-Fambuena et al. 2012; Goldberg-Moeller et al. 2013; Goldschmidt et al. 1998). These effects are associated with suppressed expression of *FLOWERING LOCUS T* (*FT*), known to act as the “florigen” signal that moves from leaves to buds to induce flowering (Pin and Nilsson 2012; Putterill and Varkonyi-Gasic 2016). Similarly, exogenous application of GAs reduces flowering in different apple cultivars (Haberman et al. 2016; Zhang et al. 2019). In this context, it has been suggested that the flowering-suppressing effect of GAs may be mediated through the induction of apple orthologues of the Arabidopsis *TERMINAL FLOWER 1* (*TFL1*) gene, which acts as a repressor of flowering and helps maintain the indeterminate identity of the shoot apical meristem (Ratcliffe et al. 1998; Moraes et al. 2019; Périlleux et al. 2019). Foliar application of GAs also negatively affects the transition to flowering in avocado. Accordingly, application of GA₃ in September to mature ‘Hass’ trees in California carrying either ‘on’ or ‘off’ crops reduces inflorescence production and increases vegetative shoot formation (Salazar-Garcia and Lovatt 1998). Moreover, GA₃ treatment also alters floral shoot morphology, leading to increased formation of indeterminate inflorescences with longer secondary axes at the expense of determinate inflorescences

(Salazar-Garcia and Lovatt 1998). Still, the understanding of the possible molecular mechanisms by which GAs affect avocado flowering and vegetative growth remains lacking.

Exogenous application of GA₃ is expected to influence key structural parameters, such as flowering intensity, canopy volume, leaf area and, in some cases, leaf chlorophyll content (Muñoz-Fambuena et al. 2012; Nakagawa et al. 2012; Goldberg-Moeller et al. 2013). Measuring these physiological parameters at the orchard scale is traditionally complex and time-consuming, and requires significant labor and financial resources. Unmanned aerial vehicles (UAVs) have lately found critical applications in precision agriculture, enabling efficient, cost-effective, and high-throughput monitoring of crop conditions (Tsouros et al. 2019). Sensor fusion, combining multispectral and light detection and ranging (LiDAR) data, enhances the accuracy and depth of analysis, allowing for a more comprehensive assessment of trees' physiological and structural traits (Berger et al. 2022). Optical sensors, such as multispectral capture devices, measure reflectance properties related to leaf chlorophyll content, photosynthetic activity, and flower intensity. Meanwhile, 3D images based on LiDAR or structure-from-motion (SfM) photogrammetry enable precise modeling of tree structure and biomass distribution (Jafarbiglu and Pourreza 2022). These advanced remote sensing-based approaches enable continuous and scalable evaluation of GA₃-mediated effects on tree development at the orchard level.

With anticipated further global warming, severe spring heatwaves are expected to cause damage to young avocado trees, negatively impacting their growth and health. As indicated above, previous studies investigating foliar GA₃ treatments to regulate flowering and vegetative growth have primarily focused on mature 'Hass' avocado trees (Salazar-García and Lovatt 2002). We hypothesized that foliar GA₃ application could similarly influence flowering and promote vegetative growth in young 'Hass' trees that have not yet entered an AB cycle. On the other hand, young trees might as well respond differently to GA₃ treatments because the effects of previous crop loads do not yet constrain their carbohydrate reserves. In this study, we therefore examined the impact of foliar GA₃ application in young 'Hass' plantations as a means to enhance foliar coverage during the transition to flowering and thereby reduce susceptibility to heat stress damage. We also employed an extensive field- and UAV-based remote sensing approach and assessed its effectiveness in monitoring changes in different physiological and structural plant traits over time.

Materials and methods

Plant material and gibberellin treatments

Two-year-old 'Hass' avocado trees grafted on 'Degania 117' rootstocks were used in this study. The trees were planted in the orchards of Kibbutz Ma'abarot (32°22'14.7"N 34°54'23.7"E) and the Beit Dagan experimental station (31°58'41.3"N 34°50'04.4"E), located in the center of Israel, during the 2021/2022 and 2022/2023 seasons, respectively. The two orchards included 'Hass' as the main cultivar and 'Ettinger' as the pollinizer, planted in a 9:1 ratio (i.e., each third row of 'Hass' had an 'Ettinger' tree for every two 'Hass' trees). The experiment at Ma'abarot included treatments with 100 ppm GA₃, 200 ppm GA₃, and a control. Each treatment included three replicates or blocks, comprising two rows of approximately 34 trees each (see Fig. 1a). GA₃ treatments were applied using the commercial product 'Giberlon' (Liad Agro, Israel), combined with 0.1% (v/v) Tivolin surfactant (Liad Agro). The 100 ppm GA₃ treatments were applied in three successive rounds before the expected period of floral induction on October 3, October 25, and November 16, 2021, while the 200 ppm GA₃ treatments were applied in two successive rounds on October 3 and October 25, 2021. Control trees were treated with Tivolin alone. (Supplementary Information (Fig. SI)). Foliar spraying (800 L/ha) was performed at each time point using a mechanized blower sprayer equipped with a hollow-cone nozzle, producing droplets in the 150–300 µm range and an optimal airspeed of 1.3–3.3 m/s. The experiment at Beit Dagan included only a control (trees treated with Tivolin alone) and 200 ppm GA₃ treatments, applied on October 23 and November 27, 2022, as described above (Supplementary Information (Fig. SII)). Each treatment at Beit Dagan included three replicates or blocks, comprising two rows of approximately 22 trees per row (Fig. 1b). In each plot, selected trees were designated as measurement trees for field surveys and measurements (see below). These trees were also used to validate UAV-based remote sensing models. Temperature dynamics during the experimental period, including the timing of GA₃ application relative to UAV flights following seasonal heatwaves, are presented in Supplementary Information Figs SI and SII for both the Ma'abarot and Beit Dagan sites.

Tissue collection, foliar coverage, flowering, and yield records

For each treatment, nine or six trees of uniform appearance were selected and tagged in each block at Ma'abarot and Beit Dagan, respectively, at the beginning of the experiments in September 2021 and September 2022. This resulted in 81

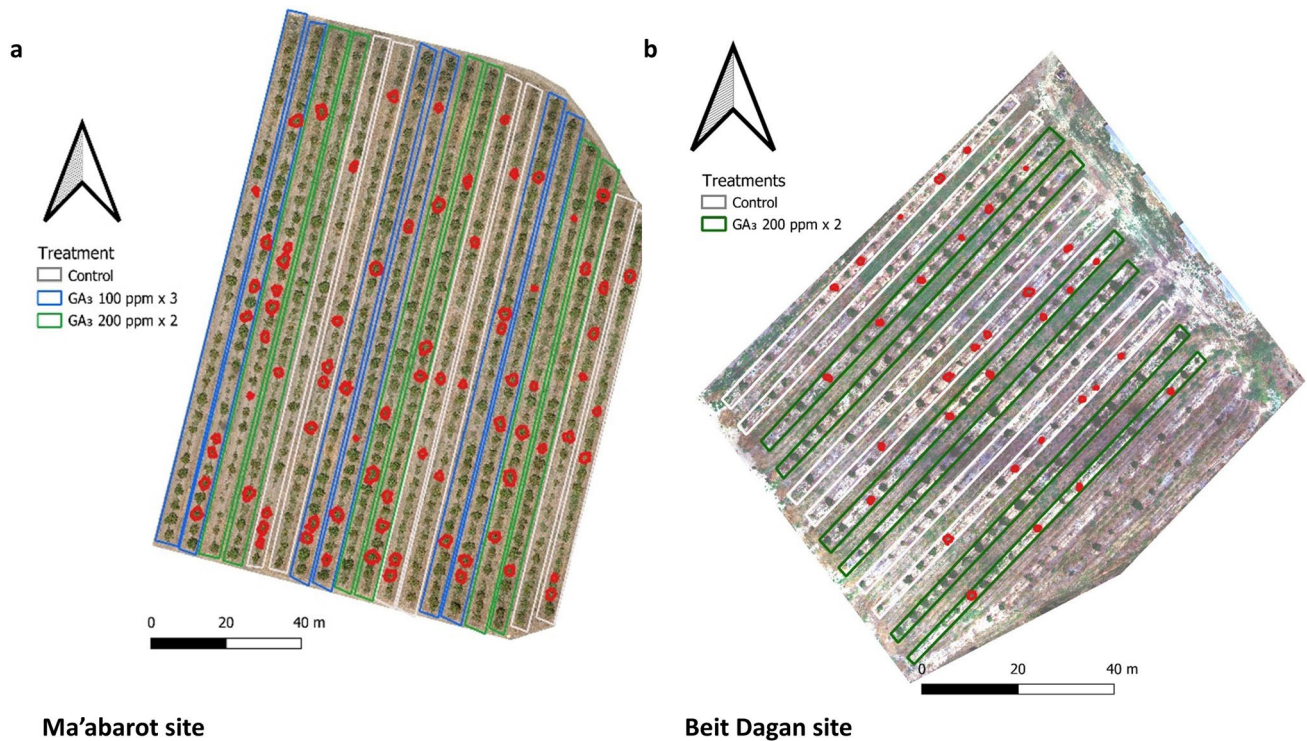


Fig. 1 Young ‘Hass’ experimental plots at Ma’abarot and Beit Dagan. At Ma’abarot, the experiment included treatments with GA₃ (100 ppm × 3, marked with blue rectangles, or 200 ppm × 2, marked with green rectangles), and a control treatment (marked with white rectangles). Each treatment consisted of three blocks, each comprising two rows of trees. At Beit Dagan, the experiment included a GA₃ treatment at

200 ppm for 2 days (indicated by green rectangles) and a control treatment (indicated by grey rectangles). Each treatment consisted of three blocks, each comprising two rows of trees. Red polygons mark trees designated as measurement trees for flowering and foliar coverage surveys within each block

and 36 tagged trees at Ma’abarot and Beit Dagan, respectively. After selection, five to ten newly grown shoots were tagged on each selected tree. These trees were used for tissue collection and recording of tree growth parameters, and for training machine learning models. Tissue sampling was carried out from the Ma’abarot orchard on November 22, 2021 (6 and 28 days after the third and second rounds of the 100 ppm and 200 ppm GA₃ treatments, respectively). Two to three vegetative east-facing shoots were collected from the trees at each interval for uniformity purposes. Upon collection, leaves, apical buds, and upper adjacent axillary buds from the sampled shoots were dissected in the orchard, as described previously (Ziv et al. 2014), and pooled to form three biological replicates for each treatment. The samples were then frozen in liquid nitrogen, transported to the laboratory, and stored at −80 °C for further analysis.

At the beginning of May 2022 and the end of April 2023, at Ma’abarot and Beit Dagan, respectively, the foliar coverage of each tagged tree was estimated using a single-blind test in which three surveyors independently scored each of the trees from 0 (null or very low foliage cover) to 3 (very high foliage cover). At the same time, the intensity of flowering was evaluated as described above, using a scale ranging

from 0 (no flowering) to 4 (very high flowering intensity). Additionally, the fate of the apical buds of the tagged shoots in each tree was assigned as (i) a bud that formed a determinate floral shoot, (ii) a bud that formed an indeterminate floral shoot, or (iii) a bud that developed into a vegetative shoot. Furthermore, the effects of GA₃ treatment on fruitlet number were quantified by counting the fruitlets within each tagged inflorescence shoot by mid-May and mid-June 2023, in the Beit Dagan orchard. Lastly, during the commercial harvest seasons, in February 2023 (Ma’abarot) and December 2023 (Beit Dagan), the yield of all ‘Hass’ trees in each block and treatment group was harvested and weighed separately. For each orchard, the results were processed to present the mean yields as kg/ha.

RNA isolation, cDNA synthesis, and real-time quantitative (q)PCR analyses

Total RNA was extracted from leaves and buds using a Plant/Fungi Total RNA Isolation Kit (Norgen Biotek, Thorold, Canada) according to the manufacturer’s instructions. RNA was quantified using a NanoDrop ND-100 spectrophotometer (NanoDrop Technologies, Rockland, Canada).

RNA (400 ng μL^{-1}) from the total isolated RNA was used as a template for first-strand cDNA synthesis. cDNA synthesis was performed using a qPCR BIO cDNA Synthesis Kit (PCR Biosystems, Wayne, PA), according to the manufacturer's instructions. The annotated sequences of *PaFTI*(KM023154.1) and *PaTFLI*(KY933634.1) were utilized in this study. For each selected transcript, gene-specific primers were designed using the Integrated DNA Technologies PrimerQuest program (<https://www.idtdna.com/pages/tools/primerquest>), with product sizes ranging from 100 to 200 bp (Supplementary Information (Table SI)). Gene expression analysis was performed using a Step-One Plus Real-Time PCR System (Thermo Fisher Scientific) with Absolute QPCR SYBR Green ROX Mix (ABgene, Epsom, UK), as described previously (Pochamreddy et al. 2024). Expression levels of *PaFT* and *PaTFLI* were normalized to the geometric mean of two internal reference genes, namely, *PaACTIN* and *PaGAPDH*, in the same samples.

Leaf area and chlorophyll measurements

For the experiment conducted at Ma'abarot at the beginning of June 2022, new leaves that had formed on vegetative flushes during the spring of 2022 were sampled, collecting three leaves per tree from nine trees per control or GA₃-treated block. The leaves were sampled from the middle parts of newly emerged, south-facing shoots to maintain uniformity.

A similar procedure was undertaken for the experiment at the Beit Dagan orchard. However, in this case, we sampled both mature leaves that had nearly completed their development (2 to 3 months after the last round of treatment) and new developing leaves that emerged from new vegetative shoots during the spring of 2024. Accordingly, leaf sampling was conducted at this site in February, May, and June 2024, in parallel with the UAV flight campaign (see below).

Before sampling, a SPAD-502 chlorophyll meter was used to determine the chlorophyll content of each sampled leaf. Measurements were performed from 8:30 to 10:30 AM to ensure leaf freshness. The sampled leaves were then placed in plastic bags and transported to the laboratory in ice containers. In the laboratory, the leaves were scanned with ImageJ (64-bit, Java 1.8.0_1722; National Institutes of Health, Bethesda, MD, USA) to estimate leaf area (LA). Chlorophyll concentration and LA measurements were used to develop UAV-based remote sensing models, as detailed below.

UAV flights

In the first year of the study at the Ma'abarot site, we conducted a UAV flight on June 1, 2022, using a Phantom 4

multispectral sensor equipped with four spectral bands, i.e., blue (450 nm), green (560 nm), red (650 nm), and red edge (730 nm). In the second year, we expanded our data collection at Beit Dagan by employing a more advanced Matrice 300 RTK UAV system featuring thermal (Zenmuse H20T), multispectral (MicaSense), and LiDAR (Zenmuse L2) sensors. Flights at Beit Dagan were scheduled on the same day as, or close to, field measurements to maintain data consistency. Accordingly, UAV flights were conducted on February 23, May 9, and July 5, 2023.

A multispectral RedEdge sensor (MicaSense Inc., Seattle, WA, USA), covering the visible-to-near-infrared (VIS-NIR) spectral range of 400–980 nm, was used to detect changes in tree vitality indicators, including chlorophyll concentration and flowering density. Concurrently, thermal imaging was performed using a DJI Zenmuse H20T camera (DJI, Shenzhen, China), capturing thermal radiation in the 8–14 μm spectral range. The thermal sensor also included built-in emissivity calibration and atmospheric correction functionalities, enhancing data accuracy. A DJI L1 LiDAR scanner (DJI, Shenzhen, China) was also used in conjunction with a high-resolution RGB camera. LiDAR flights were conducted at an altitude of 50 m, enabling accurate three-dimensional mapping of tree structure, including foliage density, canopy growth patterns, and structural characteristics, at centimeter-level precision. LiDAR-derived data facilitated a precise assessment of tree vitality by detecting subtle variations in tree structure, canopy volume, and growth patterns. Multispectral and thermal data were acquired at midday, between 12:00 and 13:00 local time, at an altitude of 50 m, under clear-sky conditions to ensure optimal illumination. LiDAR surveys were similarly conducted under favorable weather conditions. All flights maintained consistent data-collection protocols, including an overlap of approximately 80% between consecutive images, to ensure comprehensive and accurate spatial coverage.

Canopy structure and volume were assessed using 3D point clouds derived from structure-from-motion (SfM) in Ma'abarot and LiDAR scans in Beit Dagan. Flowering patterns were analyzed using a multispectral-enhanced blooming index (EBI) model (Chen et al. 2019), and correlated with average flowering estimation values derived from field surveys conducted in Beit Dagan. Additionally, leaf chlorophyll concentration was estimated from multispectral imagery by analyzing various vegetation indices (VIs). The most representative index was identified and validated using chlorophyll levels estimated from SPAD meter readings at both sites.

Pre-processing of UAV optical images

Multispectral imagery pre-processing included two steps. Radiance values were first converted to reflectance values to account for atmospheric and illumination conditions. Radiometric calibration of raw radiance values captured by the sensor was converted into reflectance using a widely used relative method known as the empirical line calibration (ELC) technique (Smith and Milton 1999; Pompilio et al. 2018). Subsequently, image georectification was performed, combining individual images into a continuous mosaic using ground control points (GCPs) and camera positions derived from overlapping image regions. All multispectral images were georeferenced using approximately 5 GCPs common to all images. Georeferencing was performed in QGIS using polynomial transformation equations, spatially aligning all images and enabling consistent analysis across datasets.

Pre-processing 3D point cloud data

In the first experiment conducted at Ma'abarot, SfM photogrammetry was used to generate 3D point clouds for tree modeling (Mlambo et al. 2017; Piermattei et al. 2019). In the second year, the study at Beit Dagan utilized LiDAR sensors for this purpose. Processing 3D point cloud data involves several steps to ensure accurate extraction of structural parameters for analysis. The raw point cloud data were initially classified into a digital terrain model (DTM) and a digital surface model (DSM), effectively separating ground and vegetation components. Following classification, ground-filtered point clouds were normalized to vegetation height using the `classify_ground` and `normalize_height` functions of the `lidR` package in R. This normalization enables accurate estimation of canopy height. Subsequently, a canopy height model (CHM) was generated by subtracting the DTM from the DSM. The resulting CHM provides a detailed representation of vegetation height and serves as the foundation for subsequent structural analyses.

Once both spectral imagery and point cloud data were processed, the segmentation phase was initiated to enable the extraction of spectral indices and structural parameters at the individual tree level. This process involves partitioning the canopy data into distinct tree crowns. Initially, a selected sampling of trees was manually delineated to ensure high accuracy and support the calibration and validation of subsequent automated procedures. Then, automatic segmentation was applied across the entire orchard to facilitate large-scale analysis. This was accomplished using the `classify_ground` and `csf` algorithms of the `lidR` package in R. The combination of manual and automatic segmentation enables reliable extrapolation of structural and spectral features from sampled trees to the full orchard.

While manual segmentation provides high-precision reference data for model development, automated segmentation offers a scalable, efficient approach to orchard-wide structural and physiological assessments. Finally, the calculation of canopy volume, leaf density, and leaf area distribution was performed based on the normalized point cloud data using voxel-based methods and height stratification techniques (Caras et al. 2024). These structural metrics were then used to assess canopy architecture and its relationship with physiological and agronomic parameters at the tree level (Jiménez-Brenes et al. 2017).

Vegetation spectral indexes

Using the tree-segmentation model, we extracted the mean values of selected VIs for each tree. These included chlorophyll-related indices and the EBI, which was used to detect flowers (Chen et al. 2019). All chlorophyll- and flowering-related indices were averaged across the canopy and directly correlated with field flowering measurements; no thresholding was applied. Details of all VIs used in this study are provided in the Supplementary Information (Table SII).

Modeling

We used random forest (RF) models to estimate spatial information for all trees in the orchard, rather than measuring trees alone (Segal 2004). RF is a machine-learning algorithm that predicts continuous outcomes by building multiple decision trees and is especially suitable for predicting chlorophyll content and yield, given its ability to handle nonlinear relationships, high-dimensional datasets, and variable interactions. RF employs bootstrap aggregation, in which each decision tree is constructed from randomly selected subsets of predictors to determine the optimal splits at each node (Breiman 2001; Iverson et al. 2004). The method is robust against overfitting and requires only two predefined parameters, the number of decision trees and the number of variables randomly selected at each node (Breiman 2001; Iverson et al. 2004). Before training RF models, we performed a correlation analysis to assess relationships among predictors and reduce multicollinearity-induced redundancy. Variables exhibiting multicollinearity, defined as a Pearson's correlation coefficient (R) > 0.7, were removed. We employed a quantile-based approach to address outliers, setting lower and upper bounds at the 5th and 95th percentiles, respectively (Taghikhah et al. 2024). Data points outside these bounds were considered outliers and removed from the analysis. The remaining dataset was then randomly split into three subsets, with 56% for training, 24% for validation, and 20% for testing.

The RF models were implemented using the randomForest package in R (Garge et al. 2013). Different model configurations were evaluated, varying the number of trees (50–300) and the number of randomly selected predictors at each node (1–50). Model performance was assessed using 10-fold cross-validation, where each model was trained on 9 subsets and validated on the remaining 1 subset. This procedure was repeated ten times to ensure robust validation and to prevent model overfitting. Model accuracy was evaluated using the coefficient of determination (R^2) and root mean squared error (RMSE). In addition, mean squared error (MSE) and normalized root mean squared error (nRMSE) were calculated to quantify prediction errors. Scatter plots comparing measured and predicted values (with estimated values on the x-axis and predicted values on the y-axis) were created to visually assess model accuracy, with a 1:1 reference line indicating ideal prediction performance. Predictor importance was quantified using the "importance" function within R's randomForest package to identify the most influential variables. After model development and validation, we applied the RF model to predict and map the outcomes for all trees across the orchard. Predictions were generated using the same set of variables employed in the training stage to ensure consistency and accuracy. Careful attention was paid to matching predictor data formats and structures used during model training. Finally, predicted values for each tree in each plot were generated in R using the predict function from the randomForest package.

Statistical analysis

All statistical analyses were conducted using JMP Pro 16.0 (SAS Institute, Cary, NC, USA). For each response variable, the assumptions of one-way ANOVA, independence of observations, normally distributed residuals, and homogeneity of variances, were evaluated before selecting the appropriate statistical test. Residual normality was assessed using the Shapiro-Wilk test, and homogeneity of variances using Levene's test. When both assumptions were met, treatment effects were analyzed using one-way ANOVA, followed by Tukey-Kramer HSD for pairwise comparisons. When either the normality or equal-variance assumptions was violated, the nonparametric Kruskal-Wallis test was applied, followed by Wilcoxon rank-sum pairwise comparisons. Box plots display medians, interquartile ranges (IQR), whiskers extending to $1.5 \times \text{IQR}$, and means (indicated by "X"). Outliers were identified but retained unless attributable to measurement error. Correlations between field measurements and UAV-derived indices were evaluated using Pearson's correlation coefficient for normally distributed variables and Spearman's rank correlation for non-normal variables. Model accuracy for random forest regressions was assessed

using the coefficient of determination (R^2), RMSE, nRMSE, and 10-fold cross-validation. Statistical significance was set at $P \leq 0.05$, and the specific test applied for each figure is indicated in the corresponding figure legend.

Results

Effects of fall GA₃ treatment on flowering in the first year of study

During the first year of the study, foliar applications of 100 and 200 ppm GA₃ were conducted in October and November 2021 (see Supplementary Information (Fig. SI)). Control young trees presented a high degree of flowering, as expected, while especially the 200 ppm GA₃-treated trees displayed a slight reduction in flowering levels (Fig. 2a). When mapping the fate of apical buds, a low percentage of vegetative shoots was noted for both control and treated trees (Fig. 2b). On the other hand, 35% and 64% of indeterminate and determinate floral shoots were recorded on control trees, respectively. A different trend was observed with treated trees. Here, a significantly higher proportion of indeterminate floral shoots was recorded in the GA₃-treated trees (80% and 85% for the 100 ppm and 200 ppm treatments, respectively), with fewer determinate inflorescences.

Following the flowering surveys, *PaFT* and *PaTFLI* expression analyses were performed on leaf and bud tissues collected from control and treated trees (see materials and methods). qRT-PCR analysis of the leaves showed a slight, though not statistically significant, decrease in *PaFT* transcript accumulation toward the end of November, as compared with the control. At this point, *PaFT* levels remained stable and very low in both control and treated bud tissues (Fig. 2c and Fig. 2e). Different trends were observed for *PaTFLI*. Specifically, bud samples from trees treated with 100 ppm GA₃ showed a significant increase in *PaTFLI* accumulation 6 days after treatment, compared with the control. A similar rise in *PaTFLI* levels was observed in buds from trees treated with 200 ppm GA₃ 28 days earlier. However, this change was not significant (Fig. 2f). Lastly, *PaTFLI* levels in the leaves remained low under both control and treatment conditions (Fig. 2d).

Monitoring the effects of fall GA₃ treatment on tree foliar coverage and volume in the first year of study

The foliar cover survey, conducted alongside the flowering survey, showed that trees treated with 100 or 200 ppm GA₃ had significantly greater foliage cover than controls. These differences were visually reflected in the orchard by the beginning of May (Fig. 3c vs. Fig. 3d and Fig. 3e). The

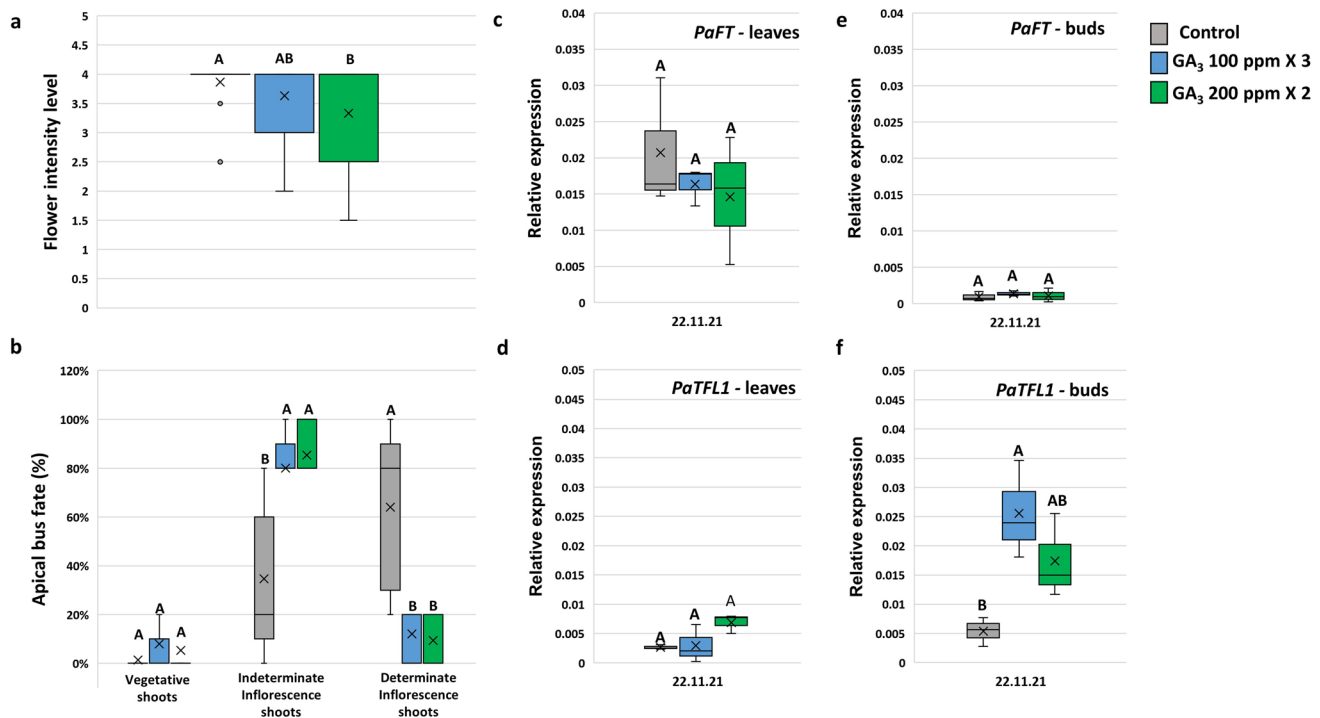


Fig. 2 Effect of GA₃ treatments on young ‘Hass’ trees: (a) flowering intensity, (b) apical bud fate, and (c–f) expression levels of *PaFT* and *PaTFL1* in leaves and buds. The experiment included two GA₃ treatment regimes: 100 ppm applied in three rounds and 200 ppm applied in two rounds. Flowering intensity was assessed in May 2022 using a 0–4 scale (0 = no flowering, 4 = very high flowering). The data represent the mean of three replicates (five trees per block). The reproductive fate of apical buds formed on new summer 2021 shoots was assessed in May 2022 and categorized as vegetative shoots, indeterminate inflorescences, or determinate inflorescences. The proportions of each category were calculated as percentages of the total. The data repre-

sent means of three replicates (five shoots from five trees per block). qRT-PCR was used to analyze *PaFT* and *PaTFL1* expression levels in leaves and buds. GA₃ treatments were applied during the floral induction period, when the summer flushes had fully matured. Tissue sampling was conducted in November 2021, 6 and 28 days after the third and second GA₃ applications of the 100 ppm and 200 ppm treatments, respectively. In panels (a) and (b), different letters indicate statistically significant differences as determined by pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$). In panels (c–f), different letters indicate statistically significant differences as determined by Tukey–Kramer multiple comparison tests ($P \leq 0.05$).

enhanced foliar coverage could be attributed both to the high proportion of indeterminate floral shoots bearing newly emerged leaves, observed following GA₃ spraying (see Fig. 3f vs. Fig. 3g and Fig. 3h), and to a delay in the senescence and abscission of mature leaves (data not shown). Additionally, analysis of the remote sensing data indicated a pronounced increase in tree volume with higher GA₃ treatment levels, with significantly lower volumes in the control group than in the 200 ppm GA₃ treatment (Fig. 3b).

Monitoring GA₃ treatment effects on chlorophyll content and leaf area, in the first year of study

Measurements of young leaves that emerged on new vegetative flushes by the beginning of June, 2022 showed that the GA₃ spraying carried out at the previous fall led to a significant increase in both leaf area and leaf chlorophyll content (Fig. 4a and Fig. 4b). Side by side, we developed an RF model to estimate the effect of GA₃ treatment on tree chlorophyll content at the orchard level (see Materials

and Methods). The model, with $R^2 = 0.83$ and RMSE = 15.46, fit well with the 1:1 line in the validation dataset collected in the orchard. The key influencing factors in the RF model were tree height, the blue (B) and green (G) spectral bands, and GA₃ treatment (see Fig. 5). Furthermore, the remote sensing data of the tagged trees correlated with measurements of LA and SPAD leaf values and showed a significant increase in both canopy leaf area (Fig. 4c) and canopy chlorophyll content in response to GA₃ treatments (Fig. 4d and Supplementary Information Fig SIII). Lastly, the extrapolated spatial distribution of canopy chlorophyll content for all orchard trees in June 2022 revealed that GA₃-treated trees had higher chlorophyll levels compared with the control (see Fig. 6a). Table SIII presents the correlations between field-based leaf measurements and UAV-derived spectral indices, showing that chlorophyll content was positively correlated with structural parameters such as: point count and canopy volume, and negatively correlated with blue band reflectance. Similarly, leaf area also showed a

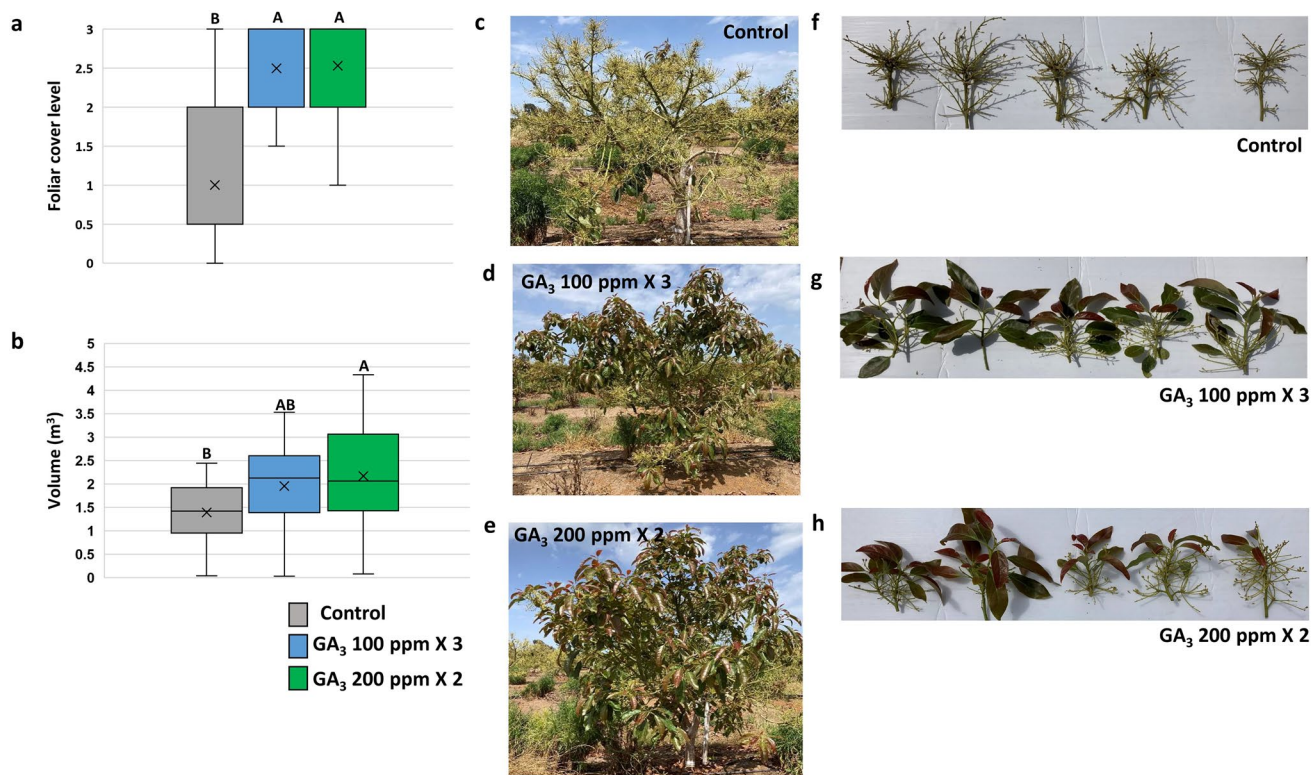


Fig. 3 Effect of GA₃ treatments on young 'Hass' trees: **(a, c–e)**, foliar cover level, **(b)** tree volume, and **(f–h)** inflorescence shoot types. Foliar cover levels were visually ranked in May 2022 using a scale of 0 (no or very low foliage) to 3 (very high foliage). The data represent the means from three replicates or blocks (five trees per block). Tree volume was estimated using SfM 3D modeling. In panel **(a)**, different letters indi-

cate statistically significant differences based on pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$). In panel **(b)**, different letters indicate statistically significant differences based on Tukey–Kramer multiple comparison tests ($P \leq 0.05$). Representative images of control and GA₃-treated trees, along with their inflorescences, were taken in May 2022, following flower abscission

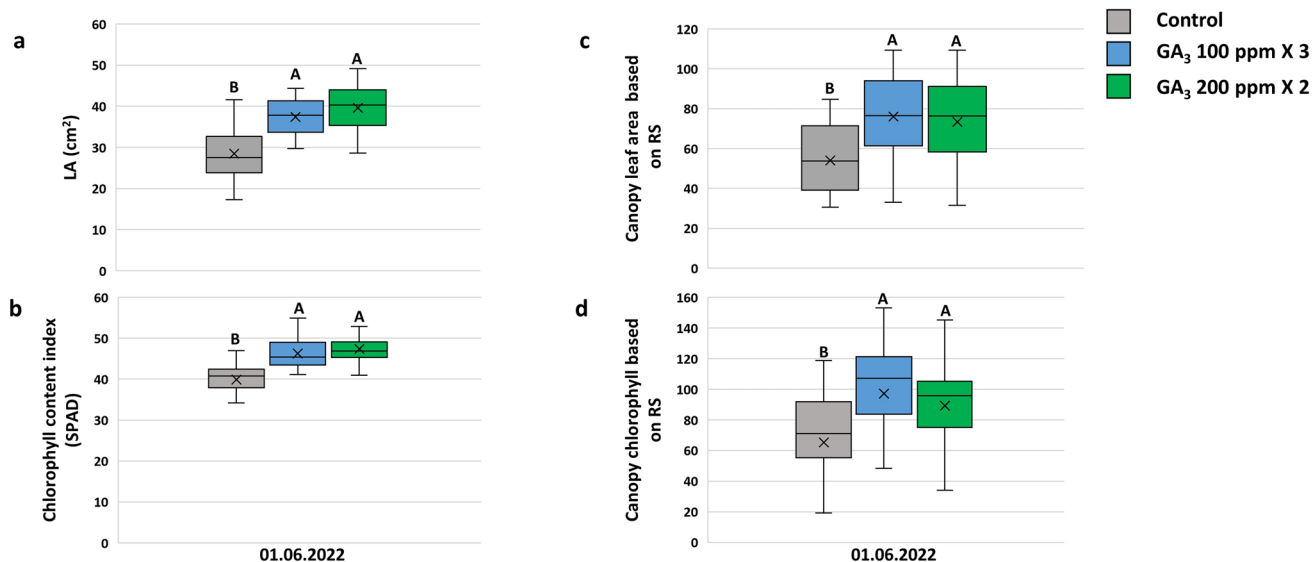


Fig. 4 Effect of GA₃ treatment on young 'Hass' trees: **(a)** leaf area, **(b)** chlorophyll content index, and **(c–d)** canopy leaf area and chlorophyll content estimated from remote sensing data. Leaf area and chlorophyll measurements of new spring-born leaves were performed in control and GA₃-treated trees at the beginning of June, 2022. Canopy and chlorophyll content were estimated based on remote data. The data

reports means of three replicates/blocks (nine trees/block and three leaves/tree). In panels **(a)** and **(b)**, different letters indicate statistically significant differences based on Tukey–Kramer multiple comparison tests ($P \leq 0.05$). In panels **(c)** and **(d)**, different letters indicate statistically significant differences based on pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$)

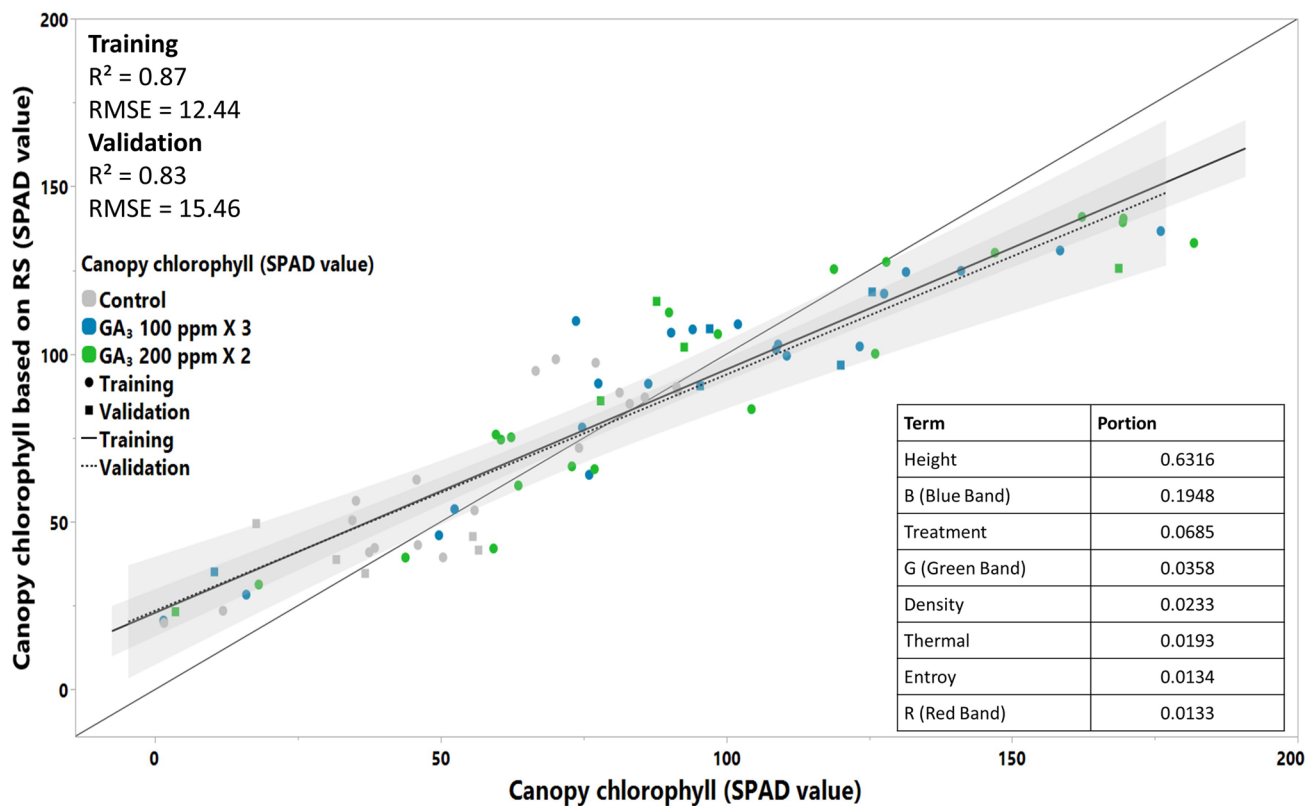


Fig. 5 Random Forest regression results for predicting canopy chlorophyll content using UAV-based remote-sensing data, shown in comparison with field-measured SPAD values from Ma'abarot ($R^2 = 0.83$; RMSE = 15.46). The scatter plot illustrates the relationship between

predicted and observed chlorophyll values. The accompanying variable-importance panel shows the relative contribution (%) of each predictor in the model, with tree height, the blue spectral band, and the GA₃ treatment identified as the most influential variables

consistent positive correlation with structural indicators and a negative correlation with blue band reflectance.

Monitoring GA₃ treatment effects on next-season yield in the first year of study

The obtained results indicated that the GA₃ treatment applied in the fall improved tree growth the following spring. To determine whether this response also influenced yield in the following season, total fruit yield was measured at the time of commercial harvest season (see Materials and Methods). The results indicated that the treated young trees yielded 2500–3000 kg per hectare, whereas the control trees yielded less than 500 kg per hectare (Fig. 6b).

Monitoring the effects of GA₃ treatment on various parameters in the second year of study

In the second year, only 200 ppm GA₃ was applied to two-year-old 'Hass' trees at Beit Dagan orchard (see material and methods). Surveys conducted in the orchard in the spring of 2023 showed that application of GA₃ led to a significant reduction in flowering rates, accompanied by a notable

increase in tree foliar coverage (Fig. 7a and Fig. 7b). In this season, GA₃ treatment significantly increased the number of apical buds that remained vegetative and decreased the proportion of determinate inflorescence shoots, while causing a moderate, non-significant, increase in indeterminate shoots (Fig. 7c).

The EBI-based flowering assessment showed a marked reduction in EBI values, in agreement with the decreased flowering observed in GA₃-treated trees (Fig. 7e). By contrast, LiDAR measurements detected no significant change in canopy volume in May 2023, suggesting that, during this season, early leaf development captured by the foliar cover survey had not yet resulted in measurable changes to overall canopy architecture (Fig. 7d). It is also noteworthy that the EBI model revealed significant differences among the measured trees exclusively in May. On the other hand, no significant differences were detected in the flowering index results from the first (February) and last (July) remote sensing datasets (not shown). These results align with our expectations, as flowering had not yet begun in February but had already ended by July.

Regarding leaf parameters, the LA and chlorophyll levels of the mature leaves, which were measured before their

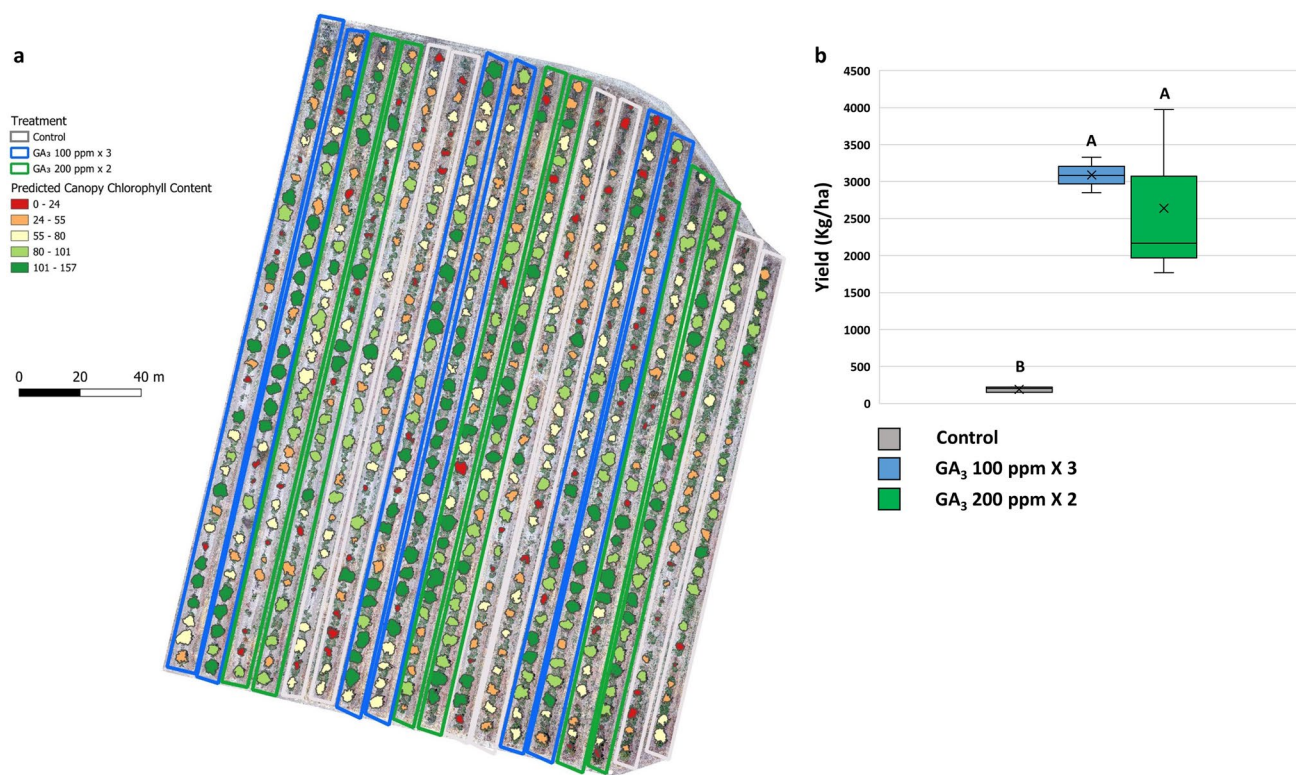


Fig. 6 Effect of GA_3 treatments on young 'Hass' avocado trees: (a) canopy chlorophyll content mapped across the orchard using UAV-based predictions, and (b) total yield in the following season. Yield

data represent three replicate blocks per treatment. Different letters indicate significant differences among treatments based on a Tukey-Kramer multiple comparison test ($P \leq 0.05$)

natural shading, were higher than those of the new leaves that emerged in the spring (Fig. 8a and Fig. 8b). Furthermore, GA_3 treatment induced an increase in LA on the three measured dates and resulted in an increase in leaf chlorophyll levels by July 2023. Table SIV summarizes correlations observed between measurements collected from the orchard and spectral indices derived from remote sensing data from the Beit Dagan experiment. Several canopy structural indices were examined, with leaf area density (LAD) emerging as the most significant indicator of variation across measurement dates. From February to July 2023, LAD values, which reflect changes in leaf area at the canopy level, showed an upward trend (Fig. 8c). Moreover, substantial differences in LAD were observed between treated and control trees in May 2023. However, no significant differences were observed in February and July. Furthermore, significant correlations were identified between the number of determinate inflorescences and spectral indices related to chlorophyll and flowering, as well as between SPAD chlorophyll meter readings and the green normalized difference vegetation index (GNDVI) (see Supplementary Information (Table SIV)).

Next, to estimate the effect of GA_3 treatment on chlorophyll content across all three sampling dates, an RF model was again developed, as in the first year of study. The model

demonstrated strong predictive accuracy, achieving an R^2 of 0.91 and RMSE of 2.4, and showed close alignment with the 1:1 line in the validation dataset (Fig. 9). The most influential features included various chlorophyll-related vegetation indices, particularly Red-Edge Chlorophyll Index (CI_{re}), Chlorophyll Index Green (CI_{gr}) and the Modified Triangular Vegetation index (MTCA). The remote sensing results corresponded well with field measurements, showing a clear increase in canopy chlorophyll content by June 2023 (Fig. 8d). Extrapolated canopy chlorophyll content for all trees in the orchard is presented for the three sampling dates in Fig. SIV.

Monitoring the effects of fall GA_3 treatment on yield in the second year of study

To evaluate the effect of fall GA_3 treatment on yield in the second year of the study, we first examined its impact on fruitlet retention. The results showed that the fruitlet retention capacity, assessed in May and June, 2023, was significantly higher in the GA_3 -treated trees than the controls (Fig. 10a). Total yield data, collected during the commercial harvest season in December, 2023, confirmed this trend, with treated trees producing approximately 2500 kg per hectare, in contrast to about 900 kg per hectare in the control group

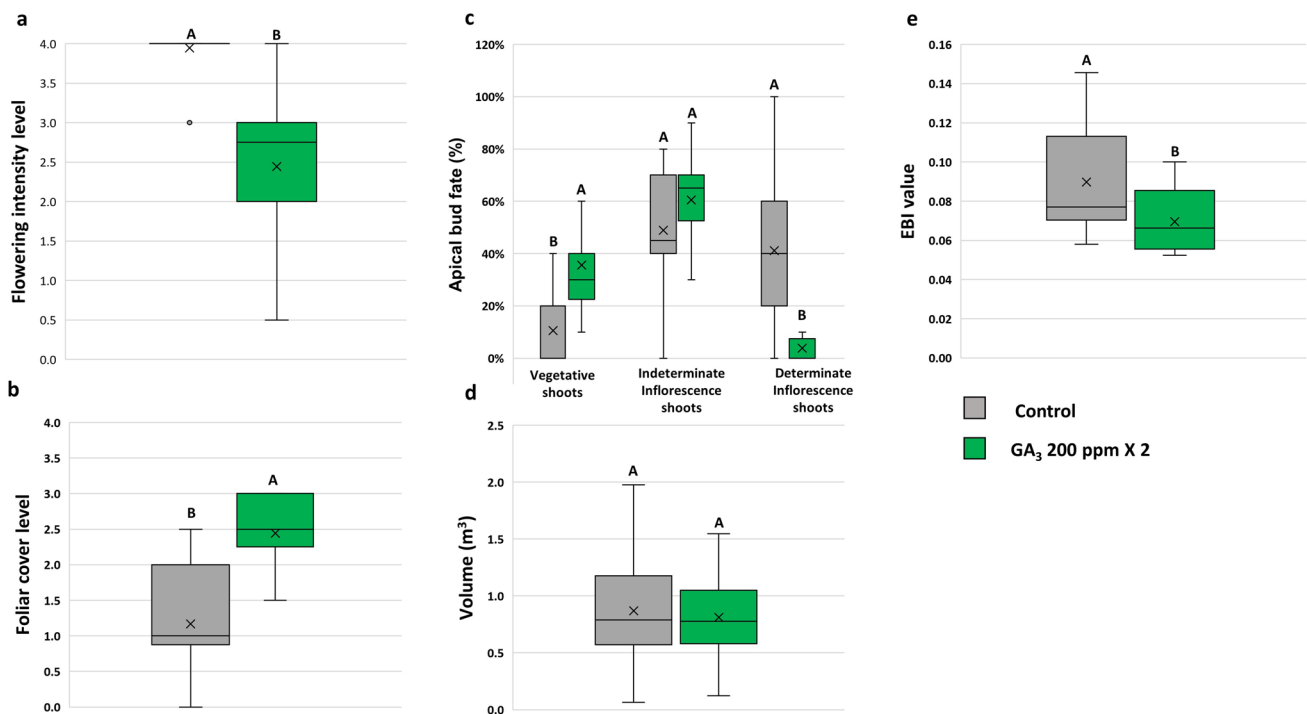


Fig. 7 Effect of GA₃ treatment on young 'Hass' trees: **(a)** flowering intensity, **(b)** foliar cover level, **(c)** apical bud fate, **(d)** EBI derived from remote sensing data, and **(e)** canopy volume derived from LiDAR analysis. The experiment was conducted at Beit Dagan and included two treatments: 200 ppm GA₃ and a control, applied on October 23 and November 27, 2022. Flowering intensity, foliar cover, and apical bud fate were evaluated in early April 2023. Data represent means of three replicates (six trees per block for flowering intensity and foliar

cover, and fifteen shoots from four trees per block for apical bud fate). Remote-sensing-derived flowering estimates were assessed using the EBI index. Canopy volume was estimated using an LiDAR model. In panels **(a)**, **(c)**, and **(d)**, different letters indicate statistically significant differences based on Tukey–Kramer multiple comparison tests ($P \leq 0.05$). In panels **(b)** and **(e)**, different letters indicate statistically significant differences based on pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$).

(Fig. 10b). These differences were visually apparent in the orchard, further reinforcing the positive impact of GA₃ treatment on canopy development and yield (see Fig. 10c).

Discussion

The transition to flowering in avocado is positively controlled by a decrease in the regional ambient temperature during late autumn (Davenport 1986). It has been suggested that an increase in the expression of *PaFT*, which acts as the factor that induces flowering in avocado, is positively controlled by a decrease in the regional ambient temperature during late autumn (Ziv et al. 2014; Ahsan et al. 2023). With this in mind, we assumed that to achieve the desired response of reducing flowering to a certain extent while increasing young tree's foliar coverage, GA treatment should be carried out before the expected period of floral induction. Indeed, we showed that GA₃ applications of 200 ppm to young 'Hass' trees during October and November, namely, before a drop in the regional ambient temperatures below a maximum of 20 °C and a minimum of 10 °C, resulted in a slight reduction in flowering levels,

as compared to the control. Moreover, and consistent with results obtained upon treating mature 'Hass' trees with GA₃ (Salazar-Garcia and Lovatt 1998; Salazar-García and Lovatt 2000), we also showed that the decrease in flowering levels was accompanied by an increased indeterminate vs. determinate floral shoot ratio. Notably, in the present study, this change was associated with an increase in *PaTFL1* transcript levels in the buds shortly after GA₃ treatment. This observation fits with experimental data reported from other species showing that exogenous GA treatment induced enhanced accumulation of *TFL1-like* genes (Randoux et al. 2012; Haberman et al. 2016; Zhang et al. 2019). In addition, these findings could also support data from our recent study showing that during an 'on' year, 'Hass' heavy fruit-load generates auxin (IAA) signaling in buds that in turn induces *PaTFL1*, leading to repression of inflorescence development (Pochamreddy et al. 2024). In that study, we proposed that IAA plays an indirect role in controlling *PaTFL1* by inducing GA content in the buds (Pochamreddy et al. 2024). Moreover, knowing that in *Arabidopsis* *AtTFL1* assumes a dual function, both repressing flowering and controlling the indeterminate status of the buds (Moraes et al. 2019; Périlleux et al. 2019), the results of the present study support

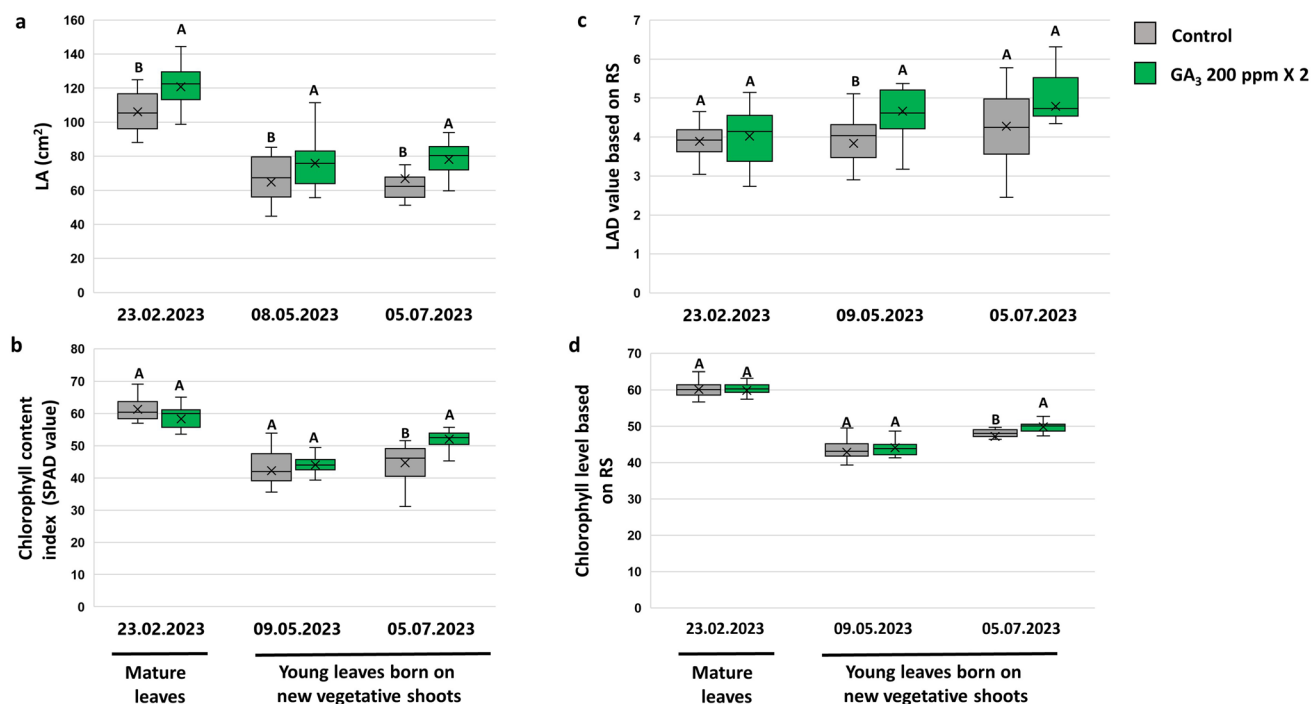


Fig. 8 Effect of GA₃ treatment on young 'Hass' trees: (a) leaf area, (b) chlorophyll content index, and (c–d) leaf area density and chlorophyll content derived from remote sensing data. The data reports means of three replicates/blocks (nine trees/block and three leaves/tree). In panels (a) and (d), different letters indicate statistically significant differences based on pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$). In panels (b) and (c), different letters indicate statistically significant differences based on Tukey-Kramer multiple comparison tests ($P \leq 0.05$)

the notion that *PaTFL1* plays similar roles in avocado. The exact role of *PaTFL1* in avocado, however, remains to be established.

In this context, it is worth noting that earlier fruit tree studies have shown that GA treatment may affect the type of inflorescences that emerge from bud meristems. Such is the case in citrus trees, where the bud meristems can develop either into a leafless inflorescence, a leafy inflorescence (mixed type), or remain vegetative (Agustí et al. 2022). Specifically, in 'Orri' mandarin, mild GA treatment (25 ppm) performed during the winter results in higher levels of mixed-type inflorescences, as compared to leafless ones, and in an increase in the total yield (Haim et al. 2025). Similarly, GA₃ treatment of litchi increases the proportion of leaf-bearing inflorescences. This effect was only observed when treatment was applied ahead of a drop in the ambient temperature below 20 °C, which is the effective temperature of inflorescence induction in 'Yu Her Pau' litchi (Chen et al. 2014). Taken together, these results suggest a common mechanism through which GA₃, in contrast with the winter flowering-inducing effect, not only negatively affects flowering but also impacts inflorescence architecture in certain fruit trees.

Furthermore, in this study, we also examined the effects of GA₃ treatment on several growth parameters. We showed

ences based on pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$). In panels (b) and (c), different letters indicate statistically significant differences based on Tukey-Kramer multiple comparison tests ($P \leq 0.05$)

that fall application of GA₃ significantly enhanced vegetative growth, leaf area, and chlorophyll content. These effects were evident in both mature leaves (i.e., prior to their natural shedding period) and newly emerged leaves in the following spring. Similar improvements in growth and developmental indices in response to GA treatment have been reported in other species (Leite et al. 2003; Noori et al. 2018; Lakshmipathi et al. 2017). An additional benefit of GA treatment may be enhanced nitrogen use efficiency. For example, studies performed on mustard have shown that GA₃ treatment significantly increased plant growth rate, CO₂ exchange rates, and other growth parameters by enhancing nitrogen-use efficiency (Khan et al. 2002). It was suggested that the better utilization of nitrogen induced by GA₃ occurs, among other factors, via an effect on the activity of nitrate reductase, a key enzyme in the nitrogen cycle (Khan et al. 1996). Nitrogen is considered one of the most important nutrients in avocado plantations, and accordingly, avocado growth and yield are greatly affected by soil nitrogen availability (Rebolledo-Roa and Burbano-Diaz 2023; Salvo and Lovatt 2016). Whether a similar phenomenon occurs in avocado following GA₃ application remains to be established.

Next, studies on 'Hass' avocado have shown that higher starch and boron content in styles at anthesis correlate with

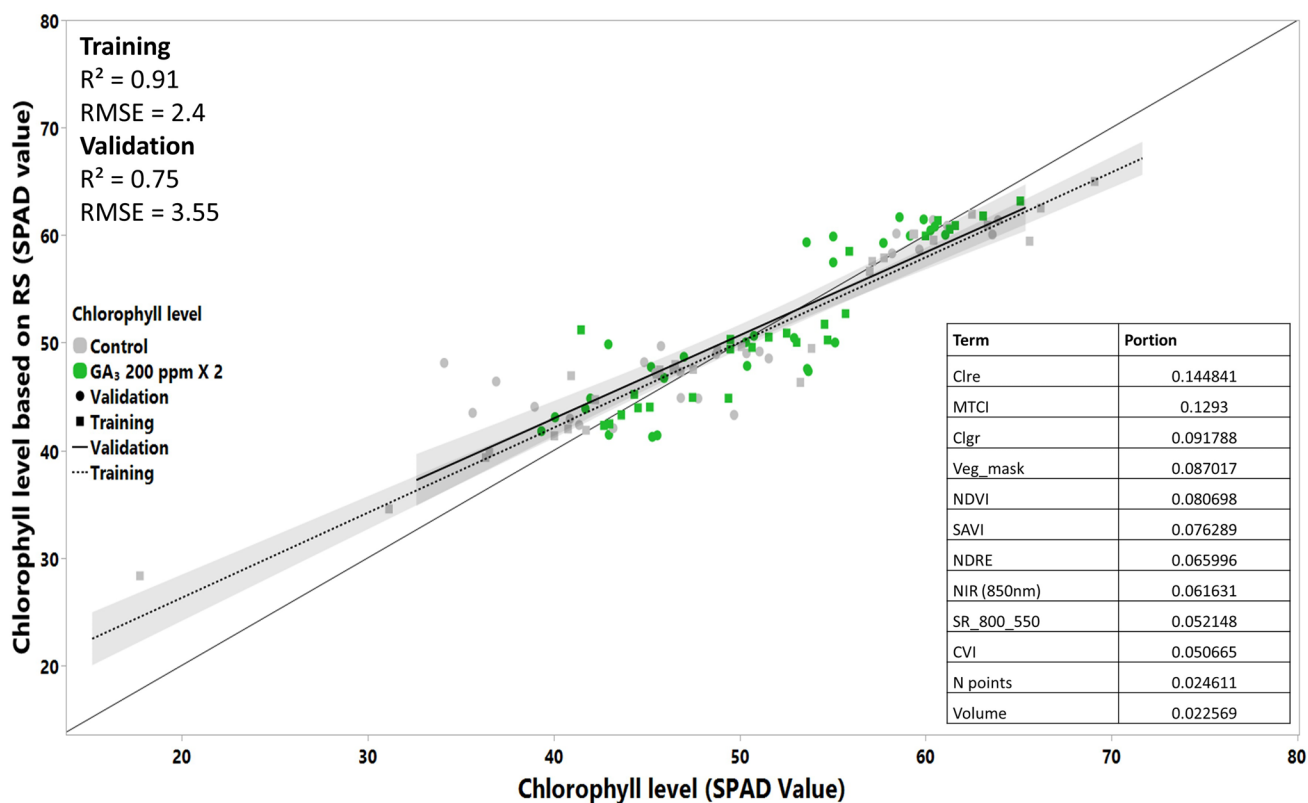


Fig. 9 Random Forest regression results for predicted canopy chlorophyll content using UAV-based remote sensing data compared with field-measured SPAD values from Beit Dagan ($R^2 = 0.91$, $RMSE = 2.4$). The scatter plot demonstrates a strong correlation between predicted and observed chlorophyll values. The accompanying table (see

Supplementary Information Table SII) presents the relative importance (%) of remote sensing features used in the model, highlighting key spectral bands and vegetation indices (e.g., MTCI and CI green) as primary predictors

successful fruit setting. (Alcaraz et al. 2013; Boldingh et al. 2016). Additionally, indeterminate inflorescences have lower fruit-set than determinate inflorescences (Salazar-García et al. 1998). This phenomenon has long been attributed to competition for carbohydrates and nutrients between flowers and newly emerging leaves (Cutting and Bower 1992; Salazar-García et al. 1998). However, a recent study on the ‘Lamb-Hass’ avocado cultivar challenged this concept by showing that fruit set depends not only on carbohydrate competition but also on changes in GA and cytokinin (CK) levels. Accordingly, in the same study, higher GA_1 and trans-zeatin (tZ) contents were detected in the ovaries of flowers of determinate inflorescences than indeterminate ones (D’Asaro et al. 2021). In the case studied here, it can be assumed that the reduction in flowering levels and increased ratio of indeterminate to determinate inflorescences observed following GA_3 treatment will result in fewer fruitlets per inflorescence and decreased total yield. Interestingly, our results showed that GA_3 treatment significantly increased fruitlet retention capacity and total yield. This effect was observed over the two-year study period. A possible scenario is that the fall GA_3 treatment increased

GA content in the ovaries of the treated tree flowers, thereby enhancing spring fruit set. Indeed, exogenous application of GA has been shown to significantly improve fruit set in both tomato and citrus (Serrani et al. 2007; Garmendia et al. 2019). Moreover, in avocado, leaves serve as major carbohydrate reservoirs that support floral development and initial fruit set, while the tree’s adjustment of crop load in response to these resources is thought to play a key role in regulating fruit drop (Blanke and Lovatt 1993; Whiley et al. 1988). Accordingly, it can be speculated that the presence of both mature leaves and newly emerged, larger leaves on indeterminate floral shoots provides a strong carbohydrate supply during the fruitlet development period, reducing fruitlet drop. Further research is therefore needed to elucidate the exact mechanisms through which fall GA treatment affects avocado fruit set and fruitlet retention.

Lastly, in the present study, we utilized a remote sensing application to assess the effects of GA_3 on tree traits. The use of UAV-based remote sensing proved highly effective. Multispectral vegetation indices, particularly EBI, detected significant differences in flowering intensity between treatments, with GA_3 -treated trees consistently exhibiting higher

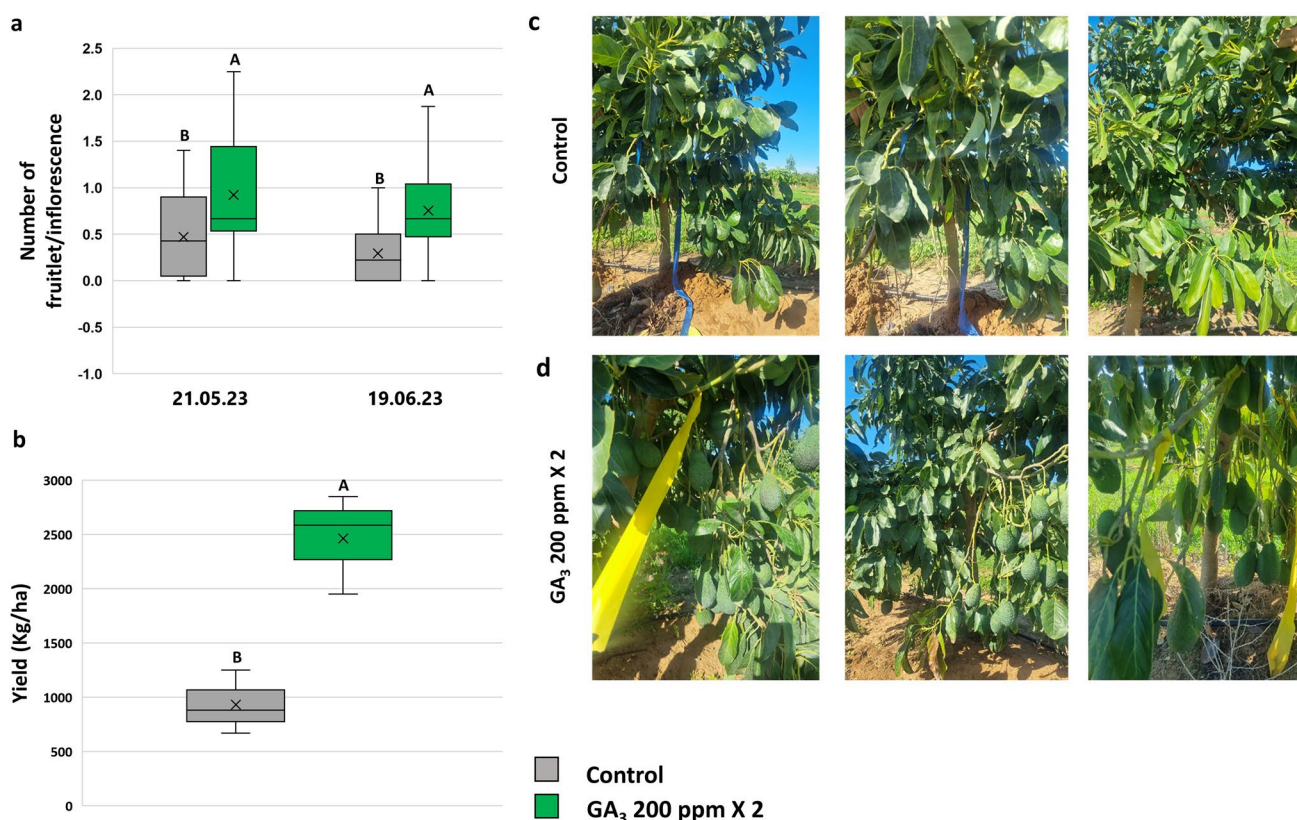


Fig 10 Effect of GA₃ treatment on young 'Hass' trees: (a) number of fruitlets retained per inflorescence and (b–d) total yield. Fruitlets retained per inflorescence were counted at two time points in May and June, 2023. Each value represents the mean of three biological replicates (ten inflorescences per tree, with six trees per block). Total yield was measured at the end of December 2023. Yield data represents the

mean of three blocks. In panel (a), different letters indicate statistically significant differences based on pairwise Wilcoxon rank-sum comparisons ($P \leq 0.05$). In panel (b), different letters indicate statistically significant differences based on Tukey–Kramer multiple comparison tests ($P \leq 0.05$). Representative images of control and GA₃-treated trees were taken in December 2023

index values (mean EBI = 0.76) than controls (mean EBI = 0.42). Additionally, 3D point cloud data enabled accurate estimation of canopy volume, which was substantially higher in the 200 ppm GA₃-treated group (mean volume = 4.6 m³) than in untreated controls (mean volume = 2.3 m³), indicating accelerated vegetative growth. Moreover, the RF models used to predict canopy chlorophyll content achieved strong performance ($R^2 = 0.83$, $R^2 = 0.91$), based on vegetative indices such as GNDVI and EVI, further supporting the ability of spectral data to reflect physiological status. Indeed, these remote sensing tools enabled high-resolution, non-destructive monitoring at the orchard scale, providing a practical, scalable alternative to labor-intensive field surveys. However, limitations were noted. The accuracy of remote sensing-derived structural parameters can be affected by occlusions, inconsistent tree segmentation in dense or overlapping canopies, and weeds on the orchard floor. Moreover, spectral indices are sensitive to soil background effects and canopy geometry, particularly in sparse or young orchards, which may introduce variability (Van Beek et al. 2015; Yang 2022). Despite these constraints,

we demonstrated that integrating UAV multispectral imagery and 3D point clouds provides a powerful approach for evaluating crop responses to bioregulators, such as GA₃. Future studies could incorporate multi-temporal and multi-sensor approaches, including thermal or hyperspectral data, to enhance stress detection and elucidate the relationships between GA₃-induced responses and nitrogen and carbohydrate dynamics (Mei et al. 2015; Li et al. 2018). Such advances will enhance the evaluation of early-season treatments and contribute to precision horticultural management strategies in perennial crop systems.

Conclusions

We demonstrated that foliar application of GA₃ at concentration of 200 ppm, applied prior to the expected period of flower induction (i.e., between October and November in the northern hemisphere), slightly reduced flowering, delayed senescence of mature leaves, and enhanced spring vegetative growth in young 'Hass' avocado trees. Canopy

volume reached higher levels in GA₃-treated trees than control trees, indicating a pronounced stimulatory effect on structural expansion. Furthermore, leaf chlorophyll content was markedly higher in GA₃-treated trees, perhaps reflecting improved photosynthetic capacity and enhanced nitrogen assimilation. Our results also suggest that, especially upon an increment in ambient temperature, which often peaks above a maximum of 30–35°C by the end of May (see supplementary Figs SI–SII), high foliar coverage contributes to enhanced fruitlet retention, thereby positively impacting next-season yield. Finally, this study also demonstrated the effectiveness of UAV-based remote sensing in evaluating the physiological and structural responses of young avocado trees to GA₃ treatment. Future studies should focus on expanding multi-temporal models, integrating thermal and biochemical indicators, and exploring physiological links among GA₃ application, nitrogen dynamics, and carbohydrate availability to further refine decision-support tools for early-season avocado management.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10725-026-01427-6>.

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Author contributions V.I. and T.P.K. conceived the research. T.S., T.I., E.K., L.W., and S.Z. conducted the orchard surveys. T.S., T.I., and E.K. collected the tree measurements and plant material, and performed the molecular analyses. T.S., T.C., and N.L.Z.L. conducted the UAV flights, pre-processed the UAV optical images and 3D point cloud data, and carried out the modeling and analysis of the remote sensing data. VI and TPK designed the experiments, were the supervisors of TS and wrote the manuscript. All authors contributed to the article and approved the submitted version.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval We confirm the originality of our work and compliance with the ethical standards mentioned in the journal guidelines.

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