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Assessing the precision and consistency of agroview in orchard management: A multi-temporal analysis

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ABSTRACT

Remote sensing technologies and predictive models have seen significant advancements, yet issues related to data quality, consistency, and accuracy persist. While many studies emphasize model accuracy, the precision and consistency of these technologies are often overlooked. This study addresses that gap by conducting a comprehensive evaluation of Agroview, a cloud-based AI-driven application, assessing its performance in analyzing plant-level data, such as inventory, canopy height, area, and leaf density, across two citrus blocks over four distinct data collection dates. Agroview demonstrated consistent reliability, with low coefficients of variation (CV) across key metrics. For example, tree inventory showed variations of <3 %, with CVs of 2.63 % for Block A and 1.56 % for Block B. Canopy height measurements exhibited CVs below 9 % for most trees, with a slightly higher CV of 12 % for trees over 12 ft in Block B. This analysis highlights the software's precision and identifies areas for potential refinement. The findings of this study highlight the importance of precision in remote sensing, providing valuable insights for users and stakeholders while promoting confidence in the broader adoption of advanced technologies in agriculture.

Introduction

Remote sensing (RS) has emerged as an essential tool in modern agriculture, offering efficient, rapid, and often straightforward methods for collecting and interpreting data over time. It plays a critical role in various applications, from agricultural monitoring to environmental management, by providing standardized measurements on both local and global scales [1–3]. Remote sensing includes capturing digital representations of energy responses emitted by targets using sensors positioned at a distance [4]. Since the 1960s, advancements in RS technology, including improvements in sensor quality and the evolution of platforms like unmanned aerial vehicles (UAVs), satellites, airplanes, and robots, have significantly enhanced data collection capabilities. However, despite these advancements, RS data is still susceptible to errors that can affect data quality, consistency, and precision over time. These errors may occur even under consistent data collection conditions due to factors such as specific timing, weather conditions, brightness, and variations in the sensors or their platforms [5,6].

To assess the impact of these errors, recurrent and closely spaced analyses are crucial. Yet, many studies that utilize temporal and consistency analysis tend to focus on long-term patterns, such as those spanning multiple years, rather than closely spaced data comparisons [7]. This approach is particularly common in studies analyzing trends in vegetation dynamics, land cover, and land use [8–10]. While long-term analysis provides valuable insights, it often overlooks the need for understanding precision and consistency in short-term intervals, which are essential for real-time decision-making in agriculture.

In recent years, artificial intelligence (AI) based predictive models have been developed to enhance precision agriculture by offering innovative solutions for crop monitoring [11,12], yield prediction [13–15][13,14], and pest [16,17] and disease [18–20] detection. These models leverage large datasets and advanced algorithms to optimize farming practices and improve decision-making. However, most studies evaluating AI models in precision agriculture primarily focus on their accuracy in single or limited experiments or under specific conditions. This narrow focus limits the understanding of how these models perform across different scenarios and timeframes, raising concerns about their reliability in real-world applications. Addressing this gap is crucial for ensuring that these technologies can be effectively integrated into agricultural practices.

Agroview, a cloud-based application designed to process, analyze, and visualize data collected by UAVs using AI techniques, represents a

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significant advancement in remote sensing technology for agriculture [21]. Developed in 2018 to enhance citrus orchard management [22], Agroview provides growers with rapid tools to create tree inventories, assess tree canopy volume, height, and leaf density, and generate fertility maps [23]. Since its launch, Agroview's algorithms and models have undergone continuous updates and improvements. However, despite several studies assessing the software's accuracy [24,25], there is no research validating its precision and consistency over time.

Given the challenges in remote sensing and AI-enabled predictive model development, such as the potential for data collection errors and the limited focus on precision and consistency, understanding the performance of software like Agroview is essential. Reliable and consistent results are crucial for building user confidence, identifying areas for further refinement, and supporting the broader adoption of advanced technologies in agriculture. By integrating precision and consistency into data analysis, these advancements can foster greater confidence among users and encourage wider implementation across the industry.

To address these critical gaps, this study aims to assess the precision and consistency of Agroview in providing detailed plant-level information, including plant inventory, canopy height and area, and leaf density, within a citrus orchard over four closed data collection dates. This evaluation is vital for improving accuracy, enhancing user confidence, and supporting the broader adoption of advanced remote sensing technologies in agriculture.

Material and methods

Data acquisition

Data were collected from two Valencia citrus (*Citrus sinensis*) orchards located in Hendry County, Florida (26°39′04.2″N, 81°17′14.7″W and 26°39′12.6″N, 81°17′17.2″W) (Fig. 1a and 1b). Block A covered 50.8 acres, while Block B covered 73.7 acres. Both fields had variations in tree and row spacing due to differences in tree age. For the mature trees, the original spacing of ~8 m between rows and ~3.7 m within rows was maintained. However, for the intermediate and reset trees, the spacing was ~1.8 m within rows.

The data were collected between October 23 and November 13, 2023, on four closely spaced dates to minimize field variability and ensure consistent environmental conditions throughout the sampling period.

A UAV, DJI Matrice 300 RTK (Shenzhen, China), equipped with a DJI Zenmuse H20T (Shenzhen, China) RGB camera, was used to collect data on the four closely spaced dates (Table 1). Flights were strategically conducted around solar noon (zenith angle = 0°) to mitigate shadow interference between trees. The UAV operated at a constant altitude of 122 m (400 ft) above ground level and traveled at a consistent speed of 16 km/h (10 mph), achieving a ground sampling distance (GSD) of 4.2 cm per pixel. Each flight lasted approximately 30 min.

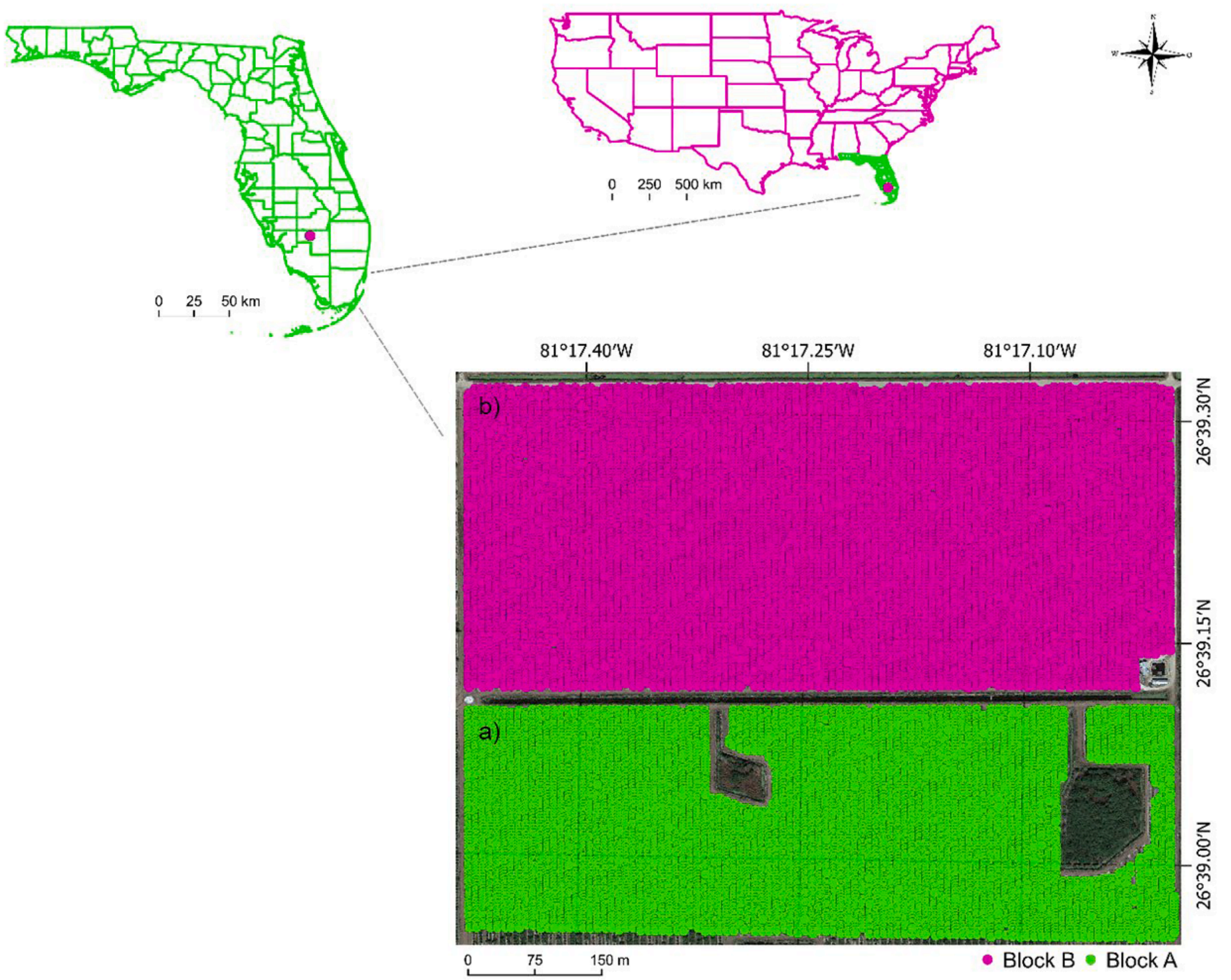

Fig. 1. Data collection over four dates for citrus (a) block A and (b) block B.

Table 1
Specifications of the RGB sensor used for data collection.

Sensor size	1/2.3″ CMOS (6.17 × 4.56 mm)
Effective pixels	12 M
Focal length	4.5 mm (equivalent: 24 mm)
Photo Size	4056 × 3040

Data processing

The collected images were uploaded to the Agroview software for processing and analysis. The workflow involved several key steps: creating an orthomosaic map, cropping the area of interest, initiating the generation process, and finally generating the results (Fig. 2).

Upon completion of this process, the software provided downloadable data on tree inventory (including tree counts), age, height, canopy area, health, and leaf density. Detailed information on the criteria and measurements used, along with an overview of how each variable is defined and scored, is presented in Table 2. Agroview is capable of categorizing trees into two to seven groups based on their height, canopy size, health, and leaf density. In this study, three categories were chosen for analysis. Additionally, the imperial system was employed for the analysis and graph development, as Agroview uses this system for its data processing and visualization.

Statistical analysis

The results for the variables provided by Agroview (inventory, age, health, canopy area, height, and leaf density) were analyzed using descriptive statistics, including standard deviation, mean, and coefficient of variation (CV). In addition, Agroview's results from the four collection dates were used to construct graphs showing trends and changes over the collection dates.

Results and discussions

In Ampatzidis et al. [21], Agroview demonstrated its capability to detect and count trees with a mean absolute percentage error (MAPE) of 2.3 %. This accuracy was achieved in a large commercial citrus orchard spanning 1871 acres and containing 175,977 trees, which were organized into 39 blocks with varying normal and high-density spacings. Additionally, Agroview accurately estimated tree height with a MAPE of 4.5 % for normal spacing and 12.93 % for high-density spacing. It also assessed canopy size with a MAPE of 12.9 % for normal spacing and 34.6 % for high-density spacing. This study evaluated Agroview's accuracy but did not assess its precision, which refers to how consistent the results would be if data were collected and analyzed multiple times, such as four separate instances instead of just one. This current study aims to explore this aspect of Agroview, focusing on its precision by examining how consistent the results are when data is collected and analyzed multiple times.

Table 2
Variables produced and extracted by Agroview.

Inventory	Presents the number of trees and the number of missing trees (Gaps) inside the field.
Age	Categorizes trees based on their age, including resets, intermediate, and mature trees.
Health	Presents the health status of the trees and divides them into dead, at-risk, and healthy trees.
Height	Provides the height for each tree; it can be divided into two to seven categories.
Canopy	Estimates the size of the tree canopy; it can be divided into two to seven categories.
Leaf density	Characterizes the number of leaves in the canopy, and it is measured as a one-sided green leaf area per unit of ground area. It can be divided into two to seven categories.

The results of the extracted values for inventory, age, height, health, canopy area, and leaf density analyzed over the four specified collection dates are summarized in Table 3 and Fig. 3. This comprehensive analysis offers a detailed view of Agroview's performance over time, enabling users and researchers to evaluate the consistency and precision of the software in monitoring orchard conditions. For example, the tree count results from the analysis provide significant insights into Agroview's performance as a high-throughput phenotyping system. For Block A, Agroview recorded an average of 7039 trees with a standard deviation of 185, resulting in a CV of 2.63 %. For Block B, the average count was 10,492 trees with a standard deviation of 163 and a CV of 1.56 %. The relatively low CVs for both blocks, 2.63 % for Block A and 1.56 % for Block B, demonstrate that Agroview's tree count measurements are both accurate and precise. The CV indicates the extent of variation relative to the mean, and lower values suggest that the measurements are consistently close to the average count. This consistency is particularly important in high-throughput systems where large datasets are processed. The data collected over the four collection dates show that Agroview maintains a reliable performance across different times (no changes were expected in these four data collection dates). This temporal stability is essential for monitoring changes in orchard conditions and making informed decisions based on precise, long-term data. Given that Agroview employs UAV data for its assessments, the ability to maintain low variability and provide consistent counts across large areas highlights its effectiveness as a high-throughput phenotyping tool. This capability is crucial for managing extensive orchards efficiently, where manual counting would be impractical.

Similar low CVs are observed in other variables as well, such as tree canopy height and size, and leaf density (Table 3). These low CV values across multiple parameters further highlight Agroview's robust performance. By demonstrating low variability in these additional variables, Agroview reinforces its capability to deliver precise and dependable information, enhancing the overall reliability of the data collected. This is particularly valuable for tasks that require accurate assessments of tree health and development over time.

Higher standard deviations and CVs were recorded for variables with

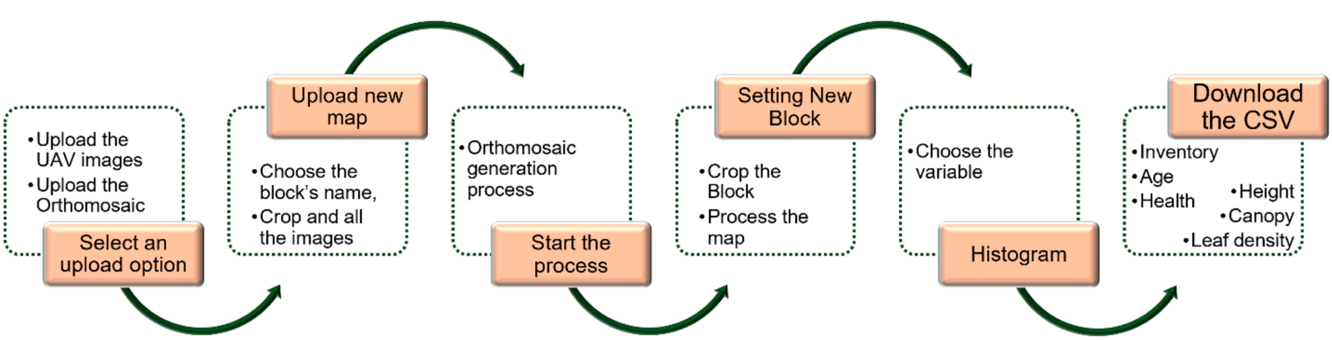

Fig. 2. Workflow from uploading UAV images to generating the final results on Agroview.

Table 3
Average, standard deviation, and coefficient of variation (%) for the Agroview variables (inventory, age, health, canopy, height, and leaf density) collected over four dates for blocks A and B.

		Average		Standard Deviation		Coefficient of variation	
		Block A	Block B	Block A	Block B	Block A	Block B
Inventory	Tree	7039	10,492	185	163	2.63	1.56
	Gap	251	254	57	91	22.92	35.74
Age	Reset	688	3269	43	250	6.3	7.6
	Intermediate	3444	4509	278	366	8.1	8.1
	Mature	2908	2714	142	372	4.9	13.7
Height (ft)	< 7	806	5181	66	310	8.2	6.0
	7 - 12.00	3784	4403	279	130	7.4	2.9
	12+	2449	909	165	109	6.8	12.0
Health	Dead	23	4	20	4	88.1	91.3
	At Risk	337	171	109	25	32.3	14.8
	Healthy	6680	10,318	160	178	2.4	1.7
Canopy (ft^2)	< 87	3016	5297	251	233	8.3	4.4
	87 - 133	1574	1982	95	206	6.0	10.4
	133+	2449	3214	165	284	6.8	8.8
Leaf density	<0.73	688	451	182	66	26.4	14.6
	0.73 - 0.87	3729	4969	426	328	11.4	6.6
	0.87+	2622	5073	429	348	16.4	6.9

smaller sample sizes, such as the detection of tree gaps and dead trees (Table 3). For example, only around 250 gaps were identified in both fields, and the average number of dead trees was 22 for Block A and 4 for Block B. The number of at-risk trees was also relatively low, with 336 for Block A and 170 for Block B. Due to the limited amount of data for these variables, greater variability and differences between the four data collection and analysis dates were anticipated. This is because smaller sample sizes are more susceptible to fluctuations and inconsistencies, which can lead to higher standard deviations and CVs. Thus, the observed higher variability in these metrics is expected and reflects the challenges associated with analyzing data from smaller sample sizes.

Additionally, the selection of block areas in Agroview during the four data collection dates may influence the detection of gaps. If the boundaries of the blocks are not precisely delineated, some gaps may be located near the field edges and might not be accurately detected or recorded. This potential discrepancy could contribute to the observed variability in the data, as gaps near the boundaries may be missed or inconsistently identified, affecting the overall results.

In general, the categorical variables, such as inventory and age, present less variation over data collection dates than the numerical variables, such as height, canopy area, and leaf density (Fig. 3). Categorical data refers to variables that can be measured on a scale consisting of distinct groups or categories that represent qualitative characteristics of the target, for example, variables such as different crops or varieties, flower color, and others fall into this category [26]. In contrast, numerical variables refer to quantitative data collected from the target, such as yield and weight. Although age is a categorical variable, it is determined by numerical factors such as tree height and canopy area [22]. As a result, it exhibits more variation in the data being evaluated than other categorical variables.

Block B, being larger in size, contains a greater number of trees and a higher proportion of reset trees (recently transplanted trees) compared to Block A. As a result, it contains a greater number of trees in the 7 to 12 ft height category. In addition, canopy area and leaf density are typically lower for smaller trees [27] compared to medium and mature trees (Fig. 3c, 3e, and 3f). The number of dead trees is low because farmers typically remove trees that are dead or nearly leafless and no longer productive and replace them with new trees in a process known as resetting. This practice also minimizes the number of gaps, as observed in both Block A and Block B (Fig. 3a).

The variation observed in each variable across dates may be due to data collection or software errors or the inherent range of each variable. For example, in the analysis of canopy height (Fig. 3c), trees are categorized into three groups: <7 ft, 7–12 ft, and >12 ft. Trees near these category thresholds contribute to data variability. Small differences in measurements, such as a canopy height of 12.1 ft or 7.1 ft (Fig. 4), can shift trees between categories, leading to inconsistencies in the number of trees classified into each group on different dates. This variability is not unique to canopy height but is also observed in other variables like canopy area and leaf density. Sensor and data collection inconsistencies can amplify these variations, especially when measurements are close to category boundaries, impacting the overall consistency of the data across collection dates.

Similarly, when each tree is evaluated individually, differences between collection dates become apparent (Fig. 5). For example, one tree's height was estimated at 9.7 ft, 12.4 ft, 10.9 ft, and 11.5 ft during the first, second, third, and fourth data collections, respectively (Fig. 5a, b, c, and d). Although these height estimates appear to vary significantly, the CV in this case is approximately 10 %. This relatively low CV is notable, particularly given that the data was captured using an RGB camera on a UAV flying at an altitude of 120 m. The low CV indicates that despite the apparent variations, the measurements are reasonably consistent and reliable, reflecting the effectiveness of the high-throughput system in maintaining accuracy under challenging conditions.

When the same variable, height, is measured over the entire block instead of individual trees, the CV drops to <9 % (Table 3). The exception is Block B, where trees taller than 12 ft height exhibit a CV of 12 %. This drop in CV when analyzing block-wide data suggests greater overall consistency in measurements compared to individual assessments. The descriptive analysis further reveals that both blocks had a high frequency of trees with intermediate heights, ranging from 7 to 12 ft. Additionally, most trees in both blocks had canopies either smaller than 87 ft^2 or larger than 133 ft^2. Interestingly, the highest mean leaf density observed was 0.73 or greater, indicating that even trees with smaller canopies can maintain high leaf density values (Table 3). These findings highlight the overall reliability and robustness of the measurements, particularly when analyzed on a broader scale.

Another key observation is that the inventory, which represents the total number of trees (with averages of 7039 for Block A and 10,492 for Block B), shows a variation of fewer than 200 trees, as indicated by the standard deviation. This variation, <3 %, is relatively minor and not considered significant. Furthermore, the manual methods used by farmers for counting trees and measuring other characteristics, such as height and canopy area/volume, are inherently prone to errors. These methods typically involve measuring poles, tapes, and manual counting techniques, which are more susceptible to human error and can result in greater variability and inaccuracies compared to sensor-based data collection. Previous studies, such as Ganz et al. [28], have shown that

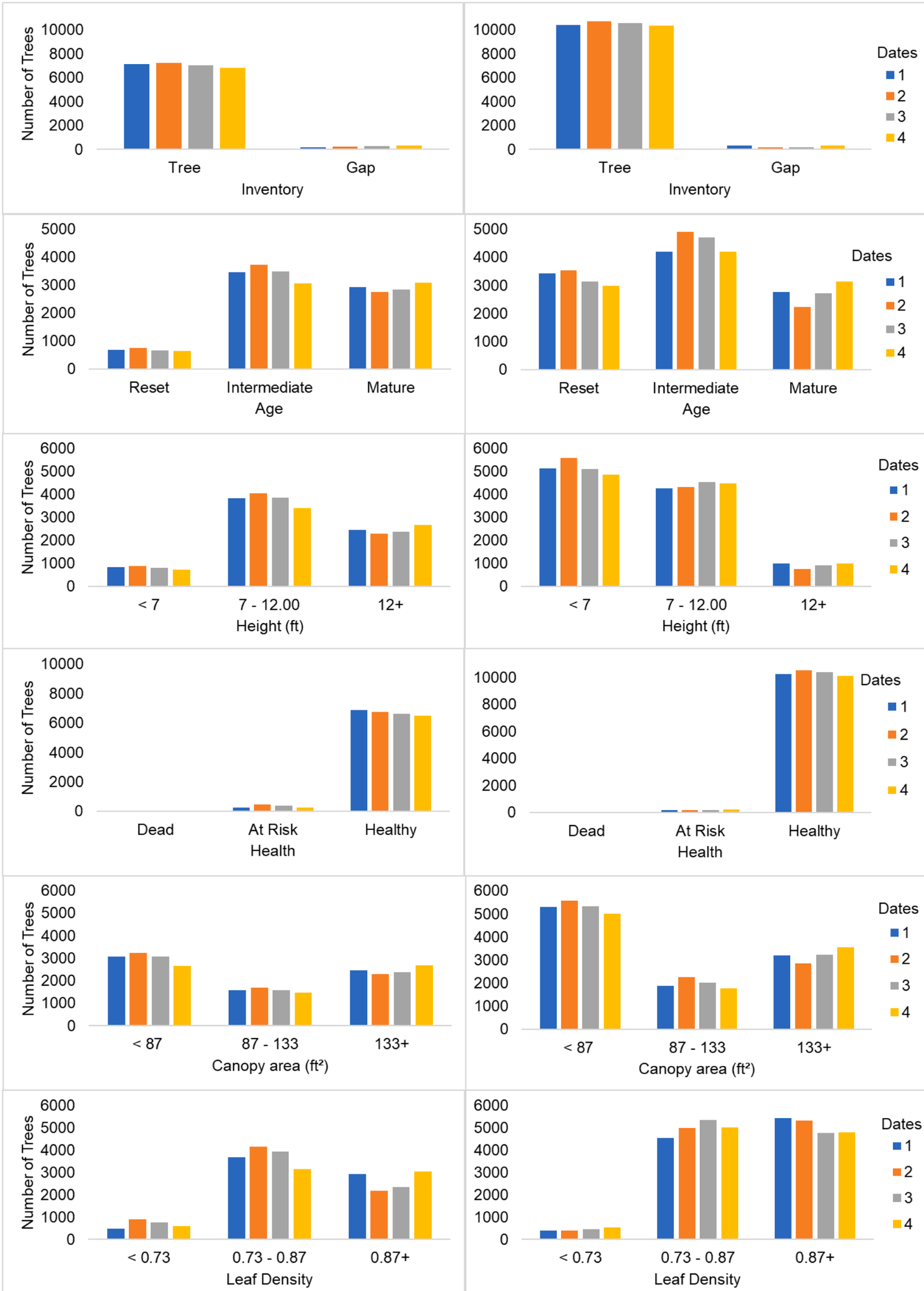

Fig. 3. Agroview's results and temporal analysis of (a) tree inventory, (b) age, (c) health, (d) canopy area (ft²), (e) height (ft), and (f) and leaf density over four dates (1,2,3 and 4) for Blocks A and B.

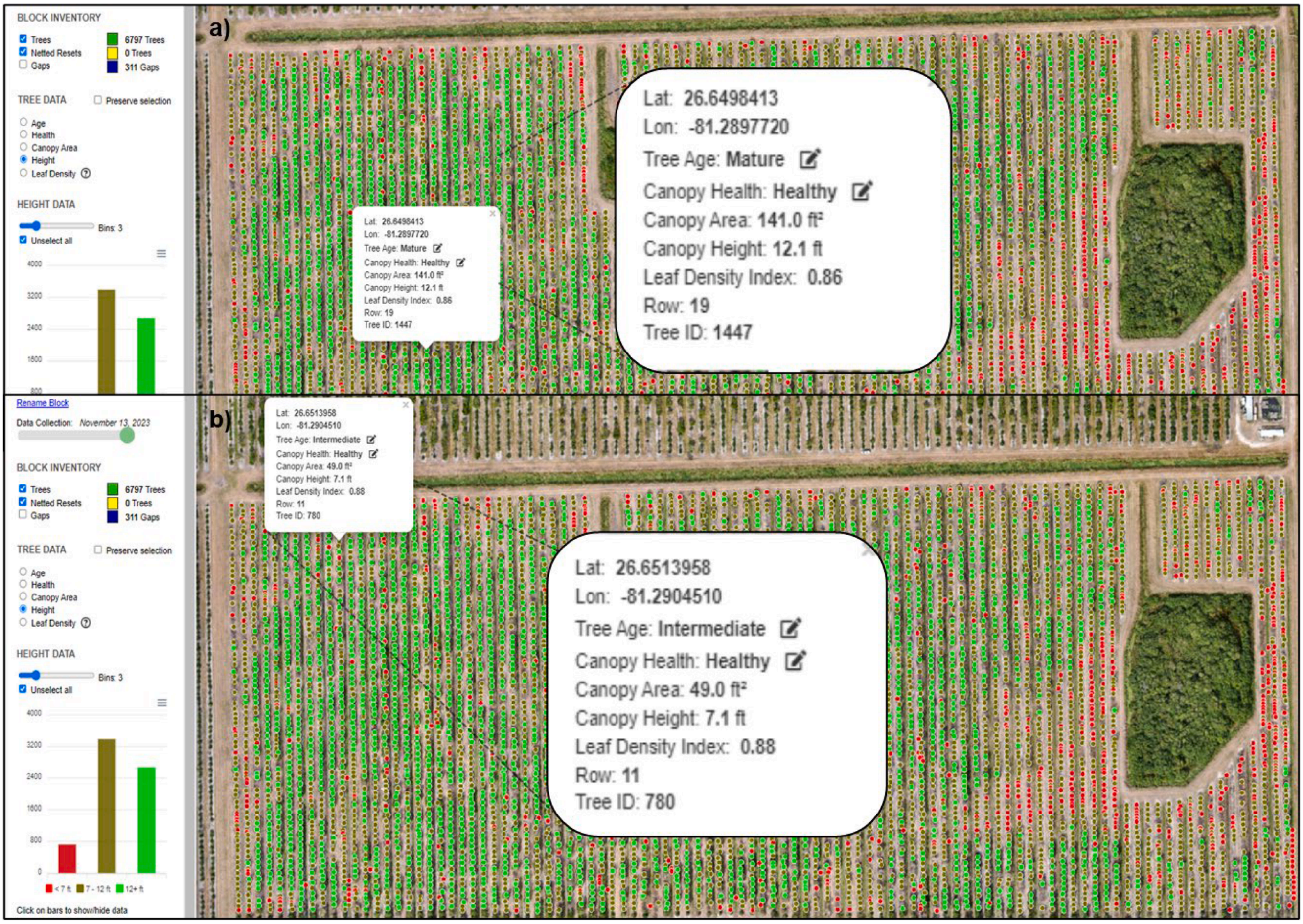

Fig. 4. Examples of tree canopy heights (a and b) near maximum and minimum categories.

manual data collection often leads to higher error rates than data collected with sensors. In contrast, sensor-based data collection tends to be more precise and consistent, reducing the likelihood of such errors. This comparison reinforces the value of Agroview as an effective tool for generating precise and reliable data in citrus fields.

To minimize errors in tree inventory, Agroview provides users with advanced tools designed to improve measurement precision and streamline orchard management. One key feature is the ability to manually edit blocks, enabling users to add or remove trees as needed (Fig. 6). This functionality is crucial for maintaining precise and current records. By allowing users to adjust the digital representation of their orchards to better reflect actual conditions, this feature helps to reduce counting errors and improves the overall efficiency of orchard operations. Improved data precision supports better decision-making and more effective management practices, ultimately leading to optimized orchard management and increased productivity.

While this study primarily focused on evaluating the precision of the Agroview software in analyzing orchard data, it is important to recognize that the sensors used in data collection can also introduce errors. Although sensor-related errors were not directly addressed in this study, their potential impact on the data quality should be considered. Sensors can introduce variability into the data they collect, and precisely measuring these errors poses significant challenges due to the lack of standardized methodologies. This complexity highlights the need for further research to isolate and quantify the sensor's contribution to overall data inaccuracies. Addressing these factors can increase the robustness of future analyses and improve the reliability of both sensor-based and software-based assessments.

Nevertheless, gaps in the literature regarding post-launch verification of software and sensors for accuracy and precision pose significant challenges for meaningful comparison and discussion. Additionally, the methodology for analyzing errors and consistency in such data remains relatively underdeveloped. Addressing these gaps is crucial for both researchers and industry professionals, as it establishes a framework for evaluating the effectiveness of software and applications in delivering precise results to users. This study provides valuable insights that can guide developers in refining their products, leading to more reliable and user-friendly software solutions. Closing these gaps will not only enhance the robustness of future analyses but also support the creation of more precise and effective tools in the industry.

One of the key challenges in this type of study is to obtain high quality data that can effectively isolate the effects of external factors such as weather, lighting conditions, and other potential sources of interference, which may bias the results. In addition, the innovative nature of this research means that there are no similar studies to guide the development of a robust methodology, highlighting the need for careful design and validation of the data collection process.

Conclusion

This study has provided a comprehensive evaluation of the precision of Agroview software in analyzing orchard data, emphasizing its effectiveness as a high-throughput phenotyping tool. The results indicate that Agroview delivers accurate and reliable measurements, with low CVs observed in tree count, canopy height, canopy area, and leaf density. These findings highlight Agroview's capacity to provide consistent data, which is crucial for effective orchard management and research. The analysis also revealed that while variability in measurements is

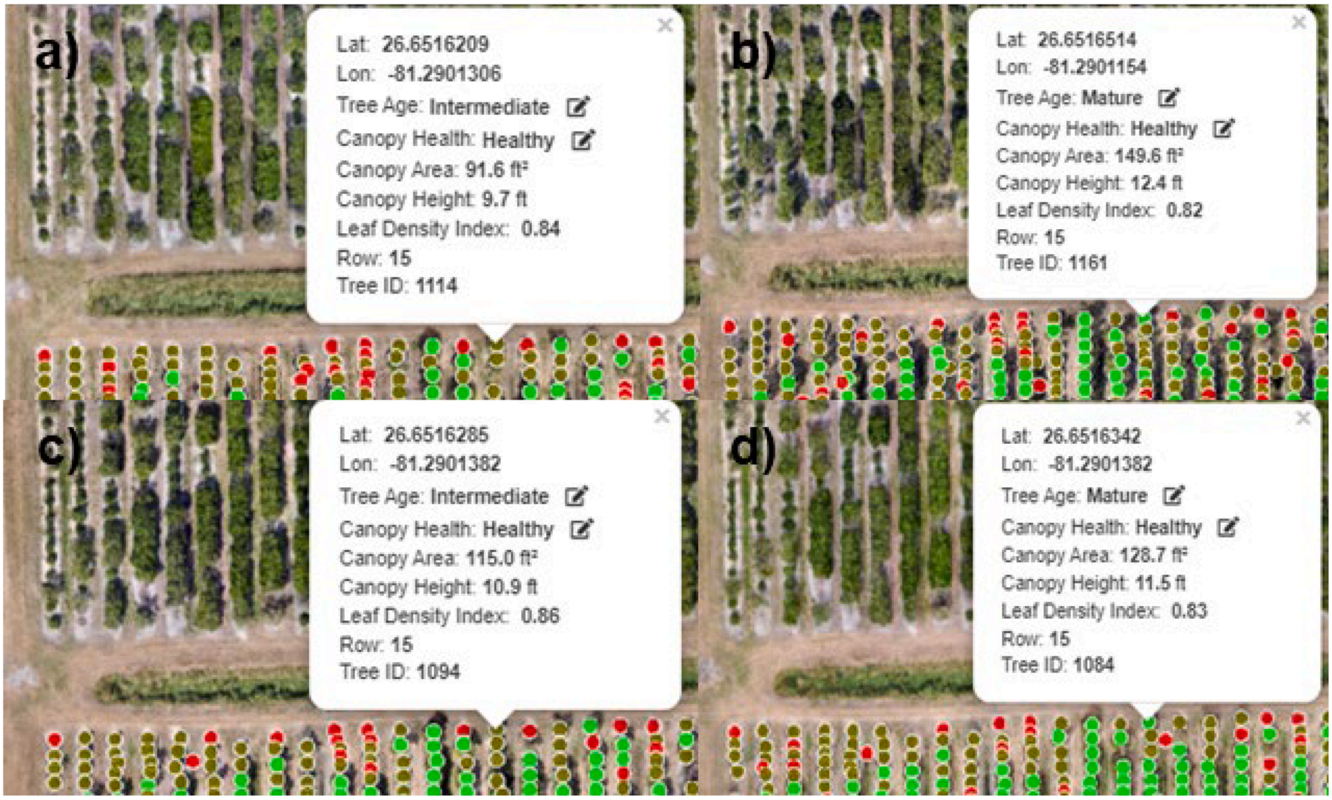

Fig. 5. Variations in tree height categories across different dates (a–d).

Fig. 6. Manual editing tool of tree detection in Agroview.

generally low, certain factors, such as the limited sample size for variables like tree gaps and at-risk trees, contribute to higher CVs. Additionally, the potential impact of sensor-related errors, though not directly addressed in this study, underscores the need for further research to isolate and quantify these effects.

In addition to its precision, Agroview offers significant cost efficiency and speed benefits. The software significantly reduces the time and effort required for data collection, which is typically more costly and subject to greater variability when performed manually. By streamlining the data collection process, Agroview not only enhances measurement accuracy but also supports more cost-effective and efficient orchard management. By establishing a framework for evaluating the effectiveness of software and applications, this research provides valuable insights for developers and users. It suggests that while Agroview is a robust tool for generating precise information, continued efforts to refine data collection and analysis methodologies will further enhance the reliability and utility of such systems. Ultimately, filling these gaps will contribute to the development of more accurate and user-friendly tools, supporting improved orchard management and productivity. Future studies could focus on developing automated error-detection algorithms within Agroview to proactively identify and mitigate sensor-related inaccuracies, thereby enhancing the software's precision, reliability, and overall performance.

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Ethical statement

The authors declare that this study does not involve human or animal subjects.

CRediT authorship contribution statement

Carolina Trentin: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yiannis Ampatzidis:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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