



Article

Blackberry Growth Monitoring and Feature Quantification with Unmanned Aerial Vehicle (UAV) Remote Sensing

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Abstract: Efficiently managing agricultural systems necessitates accurate data collection from crops to examine phenotypic characteristics and improve productivity. Traditional data collection processes for specialty horticultural crops are often subjective, labor-intensive, and may not provide accurate information for precise management decisions in phenotypic studies and crop production. Reliable and standardized techniques to record and evaluate crop features using agricultural technology are essential for improving agricultural systems. The objective of the research was to develop a methodology for accurate measurement of blackberry flowers and vegetation coverage using UAV remote sensing and image analysis. The UAV captured 20,812 images in the visible spectrum, and ImageJ software (version 1.54k) was used for segmenting floral and vegetative coverage to calculate variety-specific flower coverage. A moderately strong positive correlation ($r = 0.71$) was found between flower-to-vegetation ratio (FVR) and visually estimated flower area, validating UAV-derived flower coverage as a reliable method for estimating flower density in blackberries. The regression model explained 51% of the variance in flower estimates ($R^2 = 0.51$), with a root mean square error (RMSE) of 2.79 flower/cm². Additionally, distinct temporal flowering patterns were observed between primocane- and floricanes fruiting blackberries. Vegetative growth also exhibited stability, with strong correlations between consecutive weeks. The temporal analysis provided insight into growth phases and flowering peaks critical for time-sensitive management practices. UAV computer vision for quantifying blackberry phenotypic features is an effective tool and a unique methodology that speeds up the data collection process at high accuracy for breeding research and farm data management.

Keywords: blackberry; flower distribution; image analysis; unmanned aerial vehicle (UAV); vegetation coverage



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1. Introduction

The effective management of agricultural systems depends on the timely collection and precise interpretation of data to ensure that decision-making is both accurate and unambiguous. The advancement of technology and remote sensing with unmanned aerial vehicles (UAVs) has enhanced the precision and efficiency of plant phenotyping [1] and orchard management [2], allowing for the successful management of variability. The utilization of these systems in agriculture provides accurate, timely collection and interpretation of data due to the developmental stages of crops characterized by temporal changes that

encompass variations in vegetative growth, flowering, and fruiting [3]. Integrating historical data with real-time data enhances the foundation for informed decision-making. For horticultural farmers, obtaining information on crop conditions leads to efficient distribution of resources and enhances managerial supervision [4]. Due to the temporal variation of specialty horticultural crops, the advancement of technology provides decision support for individual crops.

Blackberry (*Rubus* subgenus *Rubus* Watson) is a commercially important specialty fruit crop grown worldwide, valued at \$31.1 million as of 2017 in the United States of America [5,6]. The crop is valuable for its distinctive taste and has garnered attention in recent years because of growing consumer demand and its correlated health advantages [7,8]. Flowering in blackberry cultivars can vary greatly in terms of timing, duration, and intensity, which has a direct effect on the success of pollination and fruit production [9]. The timing and quantity of these flowers are important markers of the plant's productivity, as it is during this stage that fertilized flowers transform into fruit. Blackberry flowering is influenced by multiple environmental factors, primarily winter and spring temperatures, as well as day length. These variables not only affect floral initiation but also regulate shoot growth and leaf production rates [10,11]. Monitoring the timing of flower blooming and periods of peak floral abundance is critical for optimizing production management. These phenological events significantly impact overall crop yield and quality, making their accurate tracking essential for efficient blackberry cultivation and harvest planning. For breeding purposes, key attributes include fruit quality and size, production, plant resilience to climate conditions, absence of thorns, optimal shoot structure, fruiting on current-year canes, and resistance to diseases and pests [12]. Researchers evaluate flowering times and intensity in breeding efforts to improve the production and resilience of blackberry cultivars [13]. As a result, quantification of blooms in blackberry plants is crucial for improving phenotypic research; however, conventional flower counting techniques are characterized by their high labor requirements, lengthy time consumption, and susceptibility to human mistakes, resulting in data collection inconsistencies [14].

Blackberries predominantly yield fruit on biennial canes, known as floricanes, which justifies their designation as floricanes fruiting varieties. Conversely, contemporary cultivars have been engineered to produce fruit on first-year canes, termed primocanes, allowing for the possibility of two harvests in a single growing season. These are designated as primocane fruiting varieties [13]. The application of high-throughput phenotyping methods to evaluate flowering intensity in both floricanes and primocanes is crucial for accurate assessments in genetic research, breeding strategies, and yield predictions.

Precision agriculture relies on accurate measurement and analysis to enhance crop management techniques. The latest developments in remote sensing technology, specifically the utilization of unmanned aerial vehicles (UAVs) outfitted with specialized sensors such as cameras, have demonstrated their worth in collecting detailed attribute data of crops [15]. Optical sensors encompass a broad range of capabilities, including multispectral, hyperspectral, thermal, and visual (red, green, blue—RGB). These sensors capture images of objects for study [16] and are used to address specific agricultural needs [17]. The utilization of sensors for data acquisition in agriculture has resulted in an enhancement of the previously employed visual observations, leading to time and resource savings and improved data quality. Remote sensing data enables the systematic collection of information across vast geographical areas, rather than relying on individual point observations. This results in the accumulation of extensive datasets in agricultural output over time, which are necessary for achieving automation in the agri-food industry [18].

Red, Green, Blue (RGB) imaging has emerged as a crucial instrument in agricultural research for monitoring crop growth and evaluating phenotypic features vital for crop management, breeding, and yield estimation. RGB imaging, a color model that captures visual information in the visible spectral bands, facilitates the precise acquisition of morphological and chromatic characteristics essential for phenotyping [19–21]. RGB photography in phenotyping studies has enabled researchers to record essential phenotypic characteristics,

including canopy coverage, leaf color, and flowering, which serve as markers of plant health, growth stage, and yield potential [19,22]. RGB imaging provides a cost-efficient and accessible means of acquiring high-resolution data applicable to research [21].

Research on flower quantification and intensity have predominantly concentrated on obtaining data using RGB sensors and implementing color thresholding techniques [22,23] from vast datasets due to the distinction of lower color features from the background. Methods based on image processing techniques of UAV-acquired data have focused on crop feature quantification such as plant biomass and vegetation coverage [24], leaf surface area [25,26], disease detection and identification [13], nitrogen and carbon uptake [24], and flower intensity and quantity [22,27,28]. Flower detection has been assessed on various plants, such as wheat, corn, rice, soybean, peach, citrus, cotton, apple, and ornamental plants such as roses [28–34], using advanced image processing techniques, which can be quite challenging and technical in nature [1,31,35,36]. For flower detection and quantification, the existence of classification-based methods such as YOLO (You Only Look Once), Deep Convolutional Neural Networks (CNNs), and Mask R-CNN [36–38] has been employed. Nonetheless, thresholding technique provides a baseline for understanding and enhancing intricate flower detection algorithms due to its simplicity and efficiency [28,31,39].

Research on using remote sensing and image processing to identify blossoms for phenotyping and orchard management in blackberries is limited compared to other fruit crops such as apples, strawberries, peaches, and grapes. Traditional visual assessments used to measure flowering are typically performed using scales ranging from 0 to 10 or 0 to 100%, depending on vegetation coverage [40]. Further complicating the process of visual estimation, blackberry canes exhibit a tendency to entangle and create a compact, interconnected structure, often resembling a hedge. This creates difficulty in visually discerning the individual canes within the plant for vegetative coverage analysis.

Imaging techniques have been utilized to enhance the efficiency of flower counts, as flowers frequently exhibit noticeable differences in color and texture in comparison to the surrounding vegetation [19]. The need for reliable and consistent standard procedures to precisely record and calculate horticultural crop characteristics utilizing advanced agricultural technology has been established [41]. Using UAV remote sensing and open-source imaging software, previous research estimated blackberry flower intensity. The research revealed notable disparities in the density of flowers among plots and confirmed the significance of setting an appropriate scale based on ground-sampling distance [42]. It is essential to study remote sensing for blackberry to improve breeding programs and orchard management techniques, as the acquisition of this data is crucial for making well-informed decisions that have the potential to enhance fruit quality, yield estimation, and total farm output. The complex structure of blackberry canes, the limited use of image processing techniques, and the limited research on feature quantification of blackberry in this context present significant challenges worth studying.

The objective of this research was to devise a methodology for accurate estimation of blackberry flowers and vegetation using UAV remote sensing. Additionally, the study aimed to establish the image processing parameters required for an autonomous UAV subsystem.

2. Materials and Methods

2.1. Study Area

The study was conducted at the crop breeding trials on blackberry (*Rubus* subgenus *Rubus* Watson) of the University of Arkansas Fruit Research Station in Clarksville, Arkansas (latitude 35°31'58" N and longitude 93°24'12" W) in the foothills of the Ozark mountains. The site is located in USDA hardiness zone 7b, on Linker fine sandy loam. Data were collected from a section of the blackberry orchard (Figure 1) consisting of 123 terraced plots, established between 2020 and 2022, which was approximately 0.61 hectares. Plots were planted at 6 m long and spaced at 3 m, containing 10 untrellised plants spaced at 0.61 m

apart. Plots with primocane and florican fruiting genotypes were 47 and 75, respectively, with one confidential plot. All primocane fruiting genotypes were double cropped. All plots were maintained with standard cultural inputs such as training/tipping primocanes to a hedgerow training system, annual dormant pruning, drip irrigation, and chemical weed, disease, and pest control.

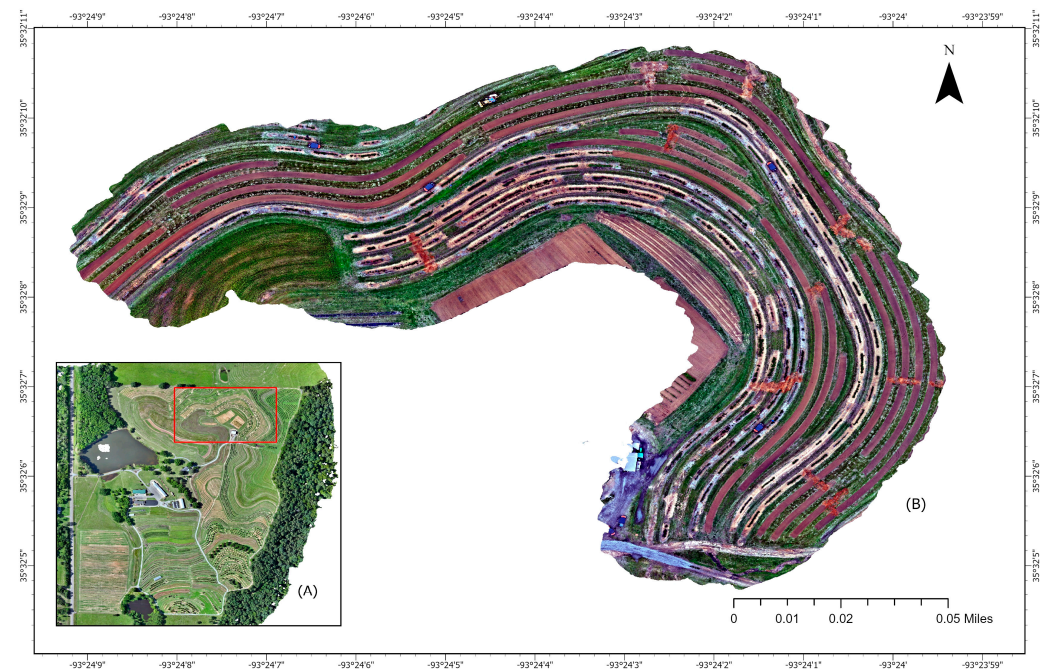


Figure 1. Map of study area: (A) University of Arkansas Fruit Research Station in Clarksville, AR with five sections and a study area labelled in a red box; (B) Orthomosaic of Section 1 depicting blackberry plots.

2.2. Image Acquisition with UAV

Remote sensing of vegetation and flowers were acquired with the Da-Jiang Innovations (DJI) Mavic 3 Enterprise unmanned aerial vehicle (SZ DJI Technology Co., Shenzhen, China). The DJI Mavic 3E (Figure 2) is a quadcopter with 45 mins and 38 mins of maximum flight and hovering times, respectively.



Figure 2. Unmanned aerial vehicle (UAV) and aerial imagery: (A) DJI Mavic 3 Enterprise UAV deployed during field data collection, equipped with 20 MP camera for capturing RGB images used in vegetation and flower coverage analysis; (B) Individual RGB image of blackberry plots captured at 12 m altitude.

The camera utilized in the DJI Mavic 3E is equipped with a 4/3 CMOS sensor, which has a resolution of 20 megapixels. The camera can capture images in visible light: Blue

(450 nm $\pm$ 16 nm), Green (550 nm $\pm$ 16 nm), Red (650 nm $\pm$ 16 nm) [43]. A summary table of materials that were used during data processing is provided in Table 1.

Table 1. Summary table of materials that was used during data processing for blackberry feature quantifications.

Item	Details
Crop	Blackberry
Image acquisition	12 m AGL
Sensors	RGB (Blue (450 nm), Green (550 nm), Red (650 nm))
Image Processing	Thresholding and Binary Segmentation
Features quantified	Flower and vegetation area (cm ²) and percent coverage (%)
Data Analysis	R (Simple Linear Regression and Pearson's Correlation)

The UAV followed an autonomous flight path, collected and saved images on an SD card using a preset navigation control set to normal mode, at a speed of 3 m/s (meters per second) with an 80% frontal and side image overlap. Flight paths were planned with DJI Pilot2 at an altitude of 12 m above ground level (AGL), achieving a 0.32 cm ground sampling distance. Images were collected at weekly intervals from 12 April 2023 to 21 June 2023. Data collection was completed during solar noon between 12:10 p.m. and 2:00 p.m. Data collected was dependent on the existing weather conditions, which had clear skies with little to no wind.

2.3. Image Processing and Feature Identification

From the weekly flights, 20,812 images were obtained. Individual images corresponding to plots in this study were determined using global positioning system coordinates extracted with open-source software ExifTool (Version 13.04, Kingston, ON, Canada). Each image offers multiple perspectives from various angles, resulting in enhanced correlation with ground truth data [44]. Images captured in the RGB band were clipped to obtain only blackberry plots with Microsoft Photos (Windows 10 version, Microsoft Corporation, Redmond, DC, USA).

Image processing and feature quantification involved several offline stages (Figure 3). A binary threshold segmentation was used to differentiate between flowers (white and slightly pink) and vegetation (green). Studies have shown that it is possible to transform high-definition digital photos into other color spaces using the Hue-Saturation-Brightness (HSB) method [45].

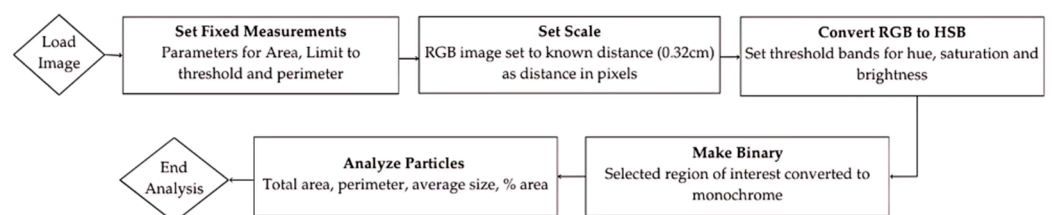


Figure 3. Detailed flow diagram illustrates the step-by-step process of analyzing and interpreting images collected by UAVs to measure the area coverage of flowers and greenery in blackberry plots.

Unprocessed images obtained with the UAV were converted using a hue, saturation, brightness (HSB) filter based on threshold level with open-source Fiji—ImageJ [46] (Wayne Rasband, National Institutes of Health, Bethesda, MD, USA). By employing the specific threshold level, flowers and vegetation in each image were isolated and processed to obtain only binary sections for flowers and vegetation with the scale set at 0.32 cm (Figure 4).

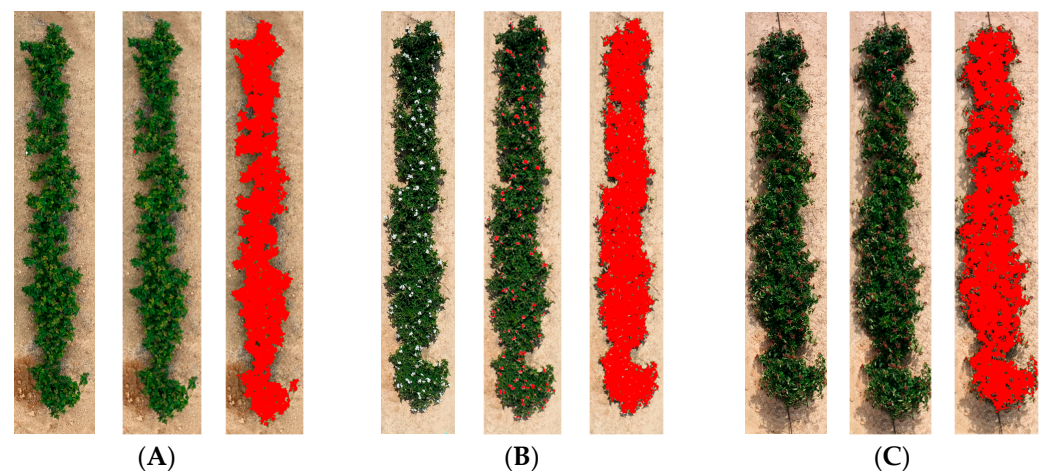


Figure 4. Feature thresholding from UAV image: Clipped and rotated RGB image for plot Z2854 with flower coverage with HSB threshold of Hue 49–255, Saturation 0–40, Brightness 177–255, and vegetation coverage with HSB threshold of Hue 48–255, Saturation 0–255, Brightness 0–255 on (A) 26 April 2023; (B) 31 May 2023; (C) 21 June 2023.

An ImageJ macro programming language, based on the Java language, was completed for the image processing. The paintbrush tool set to a brush width of 50 pixels was used to remove unwanted objects that were within the region of interest. The area coverage for the two regions of interest was extracted with the analyzing particles tool in ImageJ. Microsoft Photos (Windows 10 version, Microsoft Corporation, Redmond, Washington, USA) was employed to manually count the number of flowers per plot, using a paper quadrat with an area of 0.25 cm². To replicate field conditions, images were zoomed in by 36%, and the quadrat was randomly positioned in up to six locations per plot to count the “white flowers” within each quadrat. The total flower count per plot was then calculated and standardized by dividing by the total area sampled (the product of the number of quadrats and the quadrat size), resulting in the number of flowers per cm². This adopted method provides a consistent approach to quantifying flower density, similar to standard visual evaluations commonly used by researchers to phenotype flowering traits [40,47].

To obtain spatial information for the plots, an orthomosaic was created with Agisoft Metashape version 2.1.2 (Agisoft LLC., St. Petersburg, Russia). The high-resolution RGB photos were loaded. The method started with image alignment via the “Align Photos” feature, generating a sparse point cloud to determine the position of each image. This alignment established a robust foundation for producing a dense point cloud, which interpolated Supplementary Data points for a high-resolution model. The “Build Point Cloud” option was utilized with high-quality settings to optimize detail and processing efficiency. A Digital Elevation Model (DEM) was created to incorporate topographic data. The primary orthomosaic was subsequently built with the “Build Orthomosaic” function, georeferenced with GPS data for precise placement. The orthomosaic was ultimately exported as a GeoTIFF, maintaining georeferencing for interoperability with other software.

2.4. Data Analysis and Logic

From the data, it was possible to obtain the area (cm²) and percentage coverage (%) for flowers and vegetation within a plot. A flower-to-vegetation ratio was then calculated for each plot for the 11-week period of data collection. Object-based classification, a direct estimation of flowers, has been employed by researchers to monitor flowering intensity [37,48]. For pixel-based estimation, Aggelopoulou et al. [22] utilize the quantity of pixels associated with flowers, while Wang et al. [49] use a proportion of pixels associated with flowers compared to those associated with leaves or tree canopies for mango orchard flowers. For this study, the quantity of white pixels within the image, which represents flowers, was used to quantify flower area. The vegetation coverage was also determined

based on area coverage by pixels. The flower coverage, also represented as the flower-to-vegetation ratio (FVR), indicates the ratio of the flower covered area (FC) to the overall vegetation covering (VC) [42], expressed as a percentage:

$$\text{FVR} = \text{FC} / \text{VC} \times 100 \quad (1)$$

To evaluate the accuracy of the flower coverage estimation method, the relationship between flower coverage derived from UAV images and visual estimation of flower coverage was evaluated using the coefficient of determination, R^2 . To evaluate the linear relationship of flower area and flower coverage and visual estimates of cane counts to vegetative coverage, the Pearson's Correlation Coefficient, r , was evaluated. To analyze the flower coverage changes of the 11 weeks for each plot, time series analysis was used to visualize trends. Descriptive statistics and visualization were conducted on FVR and vegetation coverage to observe trends for various plots and genotypes. All statistical analysis was performed using R version 4.1.2 [50].

The logic behind using vegetation coverage was to take plant count into account for determining flower density per plot. The standard method for visual estimates takes the number of canes into account to explain flower density. It was impossible to determine either the number of canes or the number of plants from the images. Therefore, percentage vegetation coverage as an indicator of plant count was used to explain blackberry variety-specific flower density. In addition, approximately 5% of the slope in the field could change the Ground Sampling Distance (GSD) images among all plots, causing unreliable flower coverage. To avoid uneven GSD error in flower density estimation, flower coverage measurements were divided by vegetation coverage of the same plot. FVR then resulted in reliable estimation of flower density regardless of elevation difference of plots (Figure 5). The list of abbreviations is provided in the Appendix A in (Table A1).

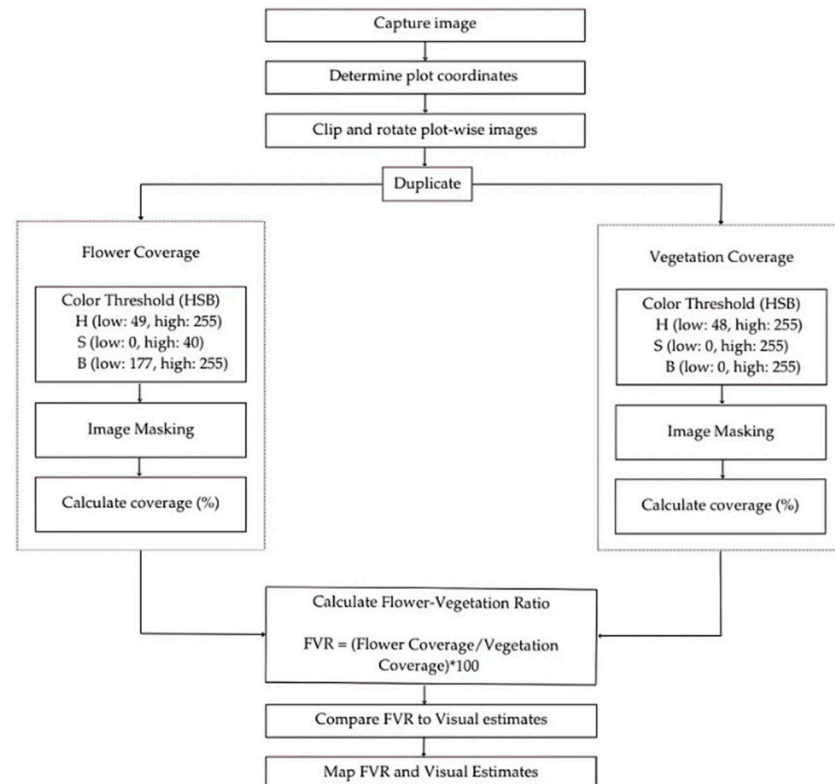


Figure 5. Methodological flowchart and logic for calculating the flower-to-vegetation ratio (FVR) from UAV imagery of blackberry plots.

3. Results

Eleven-week series images of both types of blackberry selections, primocane fruiting (PF) and florican fruiting (FF), were analyzed. PF and FF produce flowers in second-year canes during spring; additionally, PF also produces flowers in first-year canes during summer. We then tested the ability of the proposed methodology to identify flowers and vegetation in both types of blackberry selections. The floral density per plot was determined by estimating the flower coverage in relation to vegetation coverage. Figure 6 displays the binary segmentation results used to identify the Region of Interests (ROI) based on a threshold range of 0 to 255.

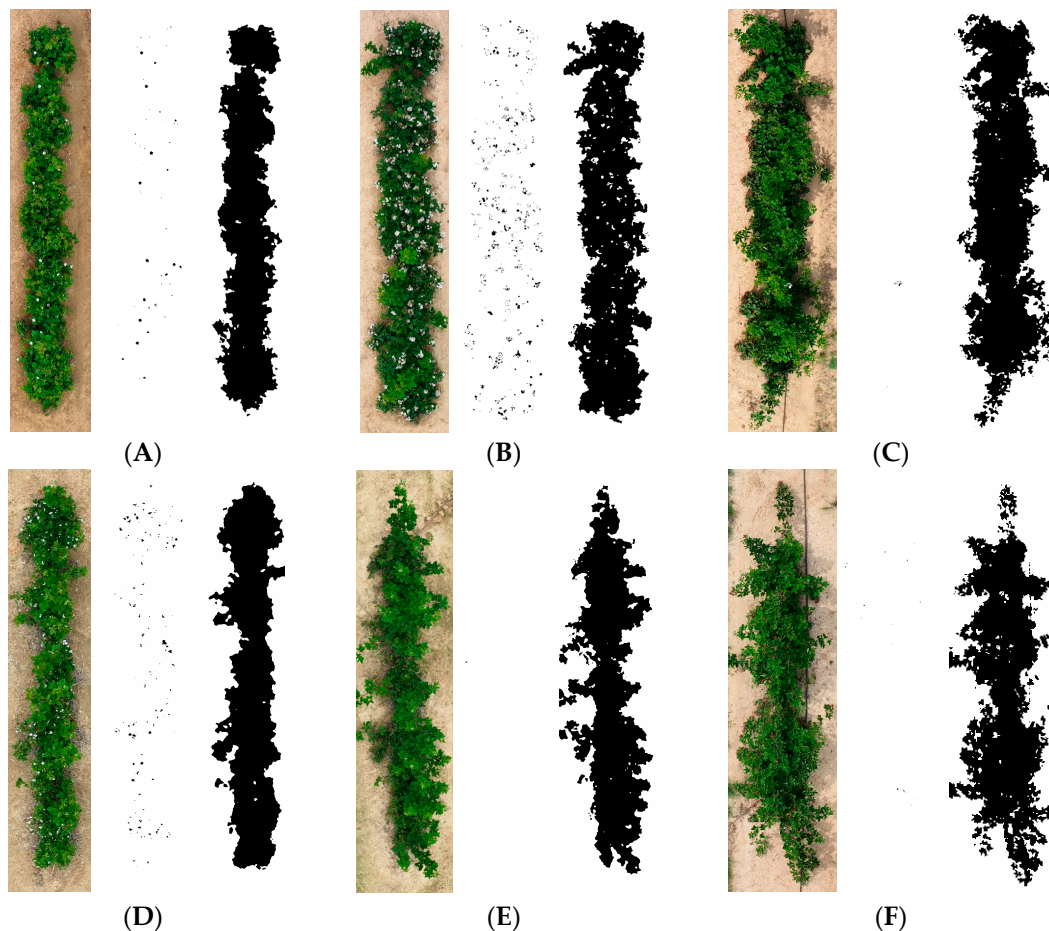


Figure 6. Binary segmentation of flowers and vegetation from RGB images to illustrate segmentation effectiveness for different plot sizes, selections, and times: Clipped RGB image of florican, S340, with binary of flowers and vegetation; (A) FVR = 0.6 (week 3, 26 April 2023); (B) FVR = 3.5 (week 6, 17 May 2023); (C) FVR = 0.0 (week 11, 21 June 2023); Clipped RGB image of primocane, S447 with binary of flowers and vegetation; (D) FVR = 1.5 (week 3, 26 April 2023); (E) FVR = 0.0 (week 6, 17 May 2023); (F) FVR = 0.1 (week 11, 21 June 2023).

The summary of the weekly descriptive analysis of flower-to-vegetation ratio (FVR) and flower estimates is presented in Table 2. The mean FVR varied across the 11 weeks, ranging from 0.15 to 1.47, with a standard deviation that reached its peak in week 3 at 1.96. Similarly, the mean flower counts were between 1.15 and 7.93, with the highest standard deviation of 4.53 observed in week 8. A simple linear regression was conducted to assess the relationship between flower-to-vegetation ratio (%) and flower visual estimates (flower/cm²) per week. The model was statistically significant for all the weeks, with FVR explaining 0.51 to 0.77 of the variances in flower estimates (Table 2). The findings suggest

that FVR accounts for approximately 51% to 77% of the variance in flower counts in the sampled plots over the 11 weeks.

Table 2. Descriptive statistics of flower-to-vegetation ratio (%) and flower count (flower/cm²) over the 11 weeks.

Weeks	Flower-to-Vegetation Ratio (%)			Flower Count (Flower/cm ²)			Regression Coefficient R ²	RMSE	F-statistics
	N	Mean	SD	N	Mean	SD			
1	122	0.18	0.42	122	1.15	1.89	0.77	0.88	424.0
2	122	1.04	1.69	122	4.15	3.35	0.56	2.20	156.2
3	122	1.47	1.96	122	6.66	4.50	0.57	2.91	162.9
4	122	0.95	1.03	122	5.36	3.06	0.57	1.98	164.5
5	122	0.69	0.67	122	6.62	3.45	0.53	2.35	136.2
6	122	0.63	0.69	122	6.17	3.53	0.70	1.91	286.4
7	122	0.38	0.46	122	5.30	3.29	0.51	2.27	129.0
8	122	0.8	0.83	122	7.93	4.53	0.60	2.85	180.6
9	122	0.35	0.49	122	5.34	4.07	0.72	2.13	314.6
10	122	0.22	0.32	122	3.46	3.53	0.67	2.01	246.9
11	122	0.15	0.36	122	3.08	3.50	0.54	2.35	143.0

A simple linear regression was conducted to assess the relationship between flower-to-vegetation ratio (%) and flower visual estimates (flower/cm²). The model was significant ($F(1, 1339) = 1365, p < 0.001$), explaining 51.10% of the variance in flower estimates ($R^2 = 0.51$), adjusted ($R^2 = 0.51$). FVR was a significant predictor of flower estimates ($\beta = 3.46, p < 0.001$), indicating that for every 1% increase in flower coverage, flower estimates increased by 3.46 flower/cm² (Figure 6) with a Pearson correlation coefficient (r) of 0.71, which indicates a moderately strong positive linear relation. The regression equation was:

$$Y = 2.92 + 3.46X \quad (2)$$

where Y represents the predicted flower count (flower/cm²), and X is the flower-to-vegetation ratio (%). A moderately strong positive correlation was observed ($r = 0.71$) with a root mean square error (RMSE) of 2.79 demonstrating the fit of the model (Figure 7).

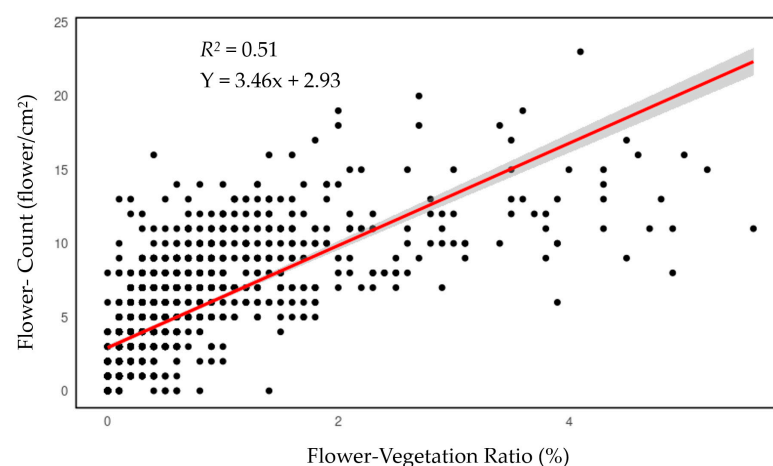


Figure 7. Scatter plot depicting the relationship between the flower-to-vegetation ratio (%) and flower count (flower/cm²).

Using Cook's distance, influential points were eliminated, resulting in the Residual Mean Standard Error (RMSE) decreasing from 2.79 flower/cm² to 2.41 flower/cm², indicating an improved model fit. This reduction suggests the predicted flower estimates differed from actual values by an average of 2.41 flower/cm². The model still explained

54.84% of the variance in flower estimates ($R^2 = 0.5484$; adjusted $R^2 = 0.5481$) and remained statistically significant, $F(1, 1282) = 1557$, $p < 0.001$.

A multiple regression analysis was conducted to predict flower estimates based on flower area and vegetative area. This yielded a substantial model, $F(2, 1350) = 652.4$, $p < 0.001$, $R^2 = 0.492$. The analysis of individual predictors revealed that flower area ($t = 33.88$, $p < 0.001$) and vegetative area ($t = 5.68$, $p < 0.001$) were significant predictors of flower estimates.

$$Y = \beta_0 + \beta_1 \times X_1 + 0.046 \times X_2 + \epsilon \quad (3)$$

where Y is the flower estimates, β_0 is the intercept at 2.165, X_1 is the flower area, 0.046 is the coefficient for vegetative area (X_2), X_2 is the vegetative area, and ϵ is the error term.

Residual analysis (Figure 8) revealed heteroscedasticity, characterized by increasing variance of residuals corresponding to rising expected values. Most residuals congregated around predicted values around 10, while elevated predicted values exhibited increased divergence from the anticipated pattern, indicating possible model constraints at the top estimate range. The quadratic fit model, which included squared variables for both flower area and vegetative area, demonstrated an enhancement in residual distribution. The quadratic model more effectively represented the non-linear connection between the predictors and flower estimates, diminishing heteroscedasticity and enhancing fit for predicted values over 10.

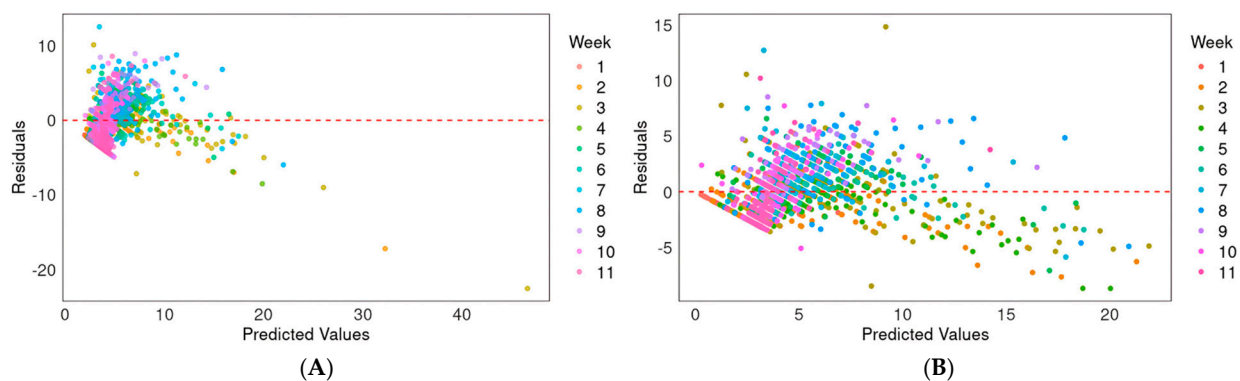


Figure 8. Plots of residuals versus predicted values for the dataset; (A) Multiple linear regression model ($Y = 2.165 + 8.611 \times \text{Flower Area} + 0.046 \times \text{Vegetative Area} + \epsilon$); (B) Quadratic fit model ($Y = \beta_0 + \beta_1 \times \text{Flower Area} + \beta_2 \times \text{Vegetative Area} + \beta_3 \times \text{Flower Area}^2 + \beta_4 \times \text{Vegetative Area}^2$).

An examination of the flower-to-vegetation ratio (FVR) during the 11-week duration yielded valuable observations regarding the growth patterns of primocanes and floricanes in blackberry plants. The violin plots created for weeks exhibited clear temporal patterns and variations in growth behaviors, enabling a more profound comprehension of their unique growth stages (Figure 9).

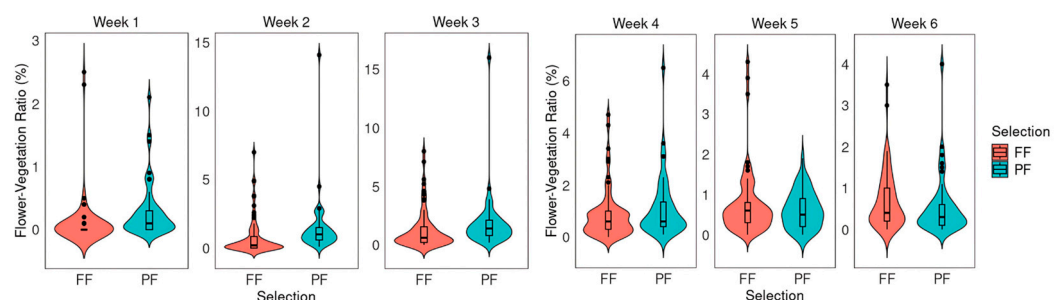


Figure 9. Cont.

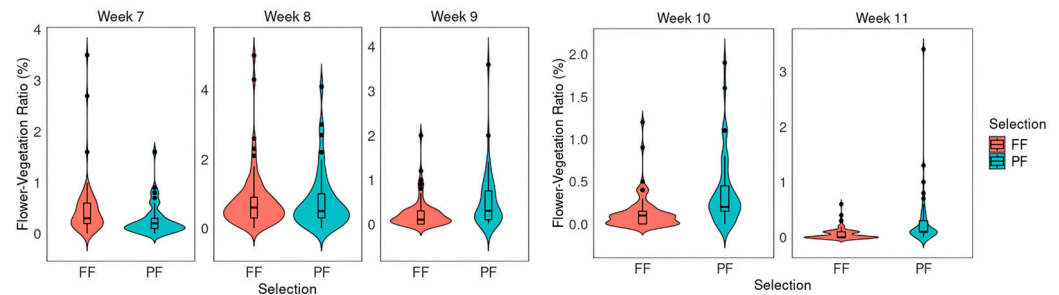


Figure 9. Comparative analysis of FVR dynamics in primocane (PF, $n = 47$) and floricanes (FF, $n = 75$) plots across 11 weeks: The plots illustrate the distribution and variation in flower coverage across 11 weeks, excluding the confidential plot. Boxplots overlaid on the violins indicate the median and interquartile range (IQR), with each week showing distinct patterns for both FF and PF.

Analyzing the flower coverage for the 123 blackberry plots yields useful information about the differences and uniformity of flowering among the different plots. Collectively, the data reveals both uniform flowering patterns in some plots, while others display more variation, as shown by wider interquartile ranges (IQR) and the existence of outliers. In numerous plots, the flower coverage values exhibit quite a low magnitude, with medians concentrated below 1, indicating a consistent flowering pattern across 11 weeks of data collection. The strong correlation between the mean and median values in these plots supports the absence of skewness, suggesting that the flowering activity is dispersed uniformly throughout the 11 weeks of data collection.

Descriptive statistics and trend analysis were used to measure the vegetative and flowering dynamics in floricanes plots over the 11-week period. There was peak flowering between weeks 2 and 4. Notably, Arapaho, Cheyenne, S190, and S194 demonstrated early and intense flowering peaks during this period, reaching FVR values above 6%. Also, flowering, occurring between weeks 5 and 7, was observed in S341, S342, S344, and S346, with FVR values exceeding 3%. Peaks, seen between weeks 7 and 9, were noted in S171, S174, S188, and S187, which exhibited a moderate but sustained flowering trend (Figure 10).

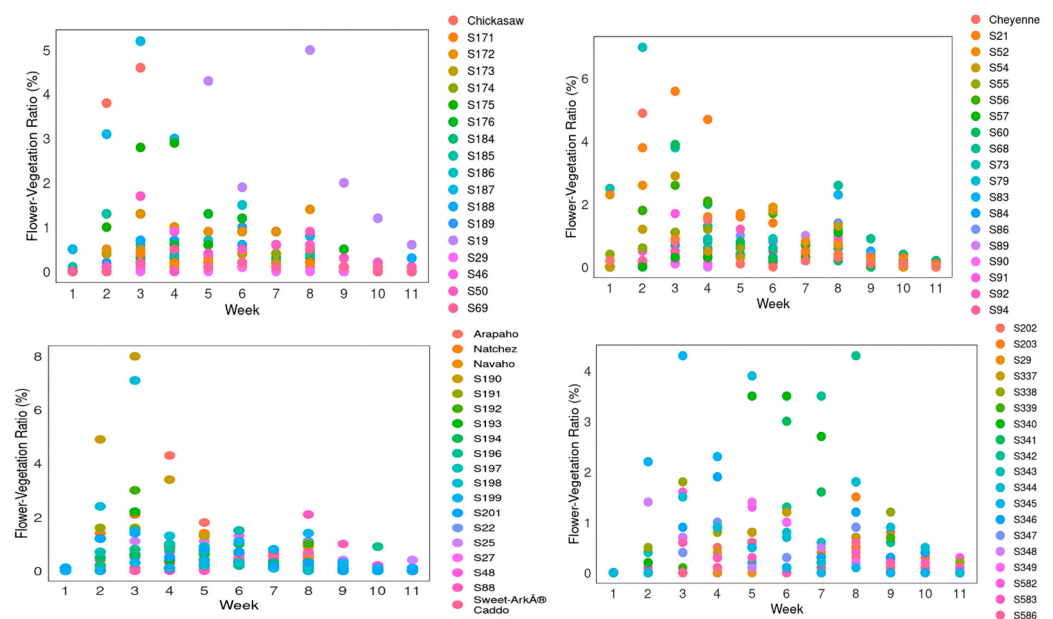


Figure 10. Temporal dynamics of flower-to-vegetation ratio (FVR) across 75 floricanes plots over an 11-week period.

For primocanes, most plots exhibited peak flowering between weeks 2 and 4. Notably, S195 demonstrated an early and intense flowering peak during this period, with FVR

values exceeding 15% (outlier). Other selections, such as S38, S429, and S43, also displayed consistent early flowering patterns with FVR peaks reaching 4%. Flowering, occurring between weeks 5 and 7, was observed in S427, S333, and S311, with FVR values peaking around 4%. Later flowering peaks, observed between weeks 7 and 9, were noted in S308, S437, and S439. Interestingly, selections such as S444, S445, and S450 displayed a bimodal flowering pattern, with distinct flowering peaks observed early in the season (weeks 3 to 4) and secondary peaks occurring in weeks 9 to 11 (Figure 11).

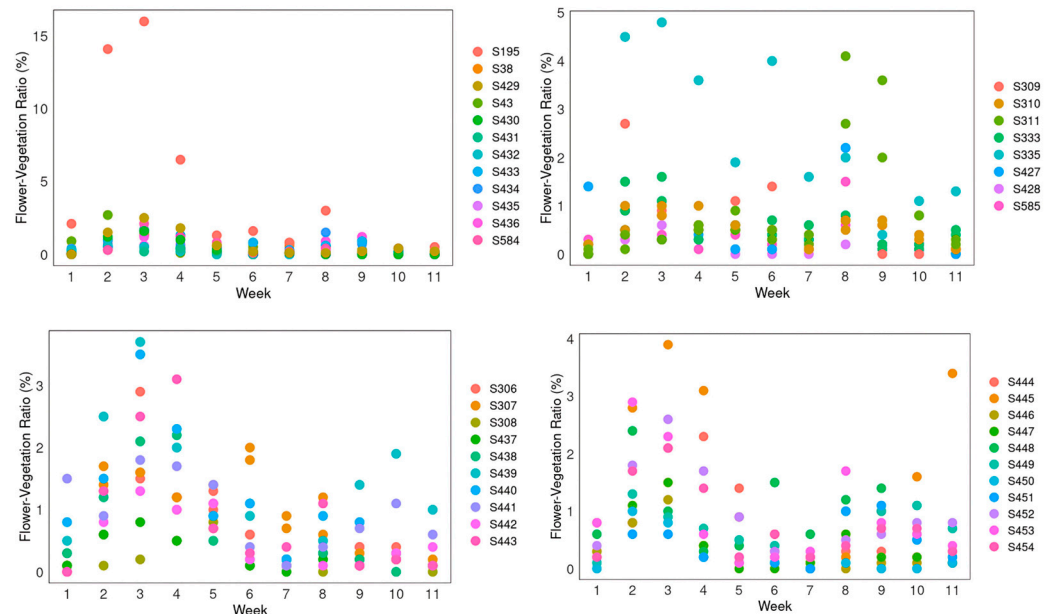


Figure 11. Temporal dynamics of flower-to-vegetation ratio (FVR) across 47 primocane plots over an 11-week period.

Vegetative coverage was assessed over an 11-week period in floricanes fruiting plots to analyze growth dynamics. During the first four weeks, vegetative coverage ranged from 10% to 30% across most plots. Chickasaw, S171, and S69 exhibited strong growth early in the period, reaching approximately 40% by week 4 (Figure 12).

Vegetative coverage in primocane plots was assessed over 11 weeks. Most plots showed steady increases in coverage during the first four weeks, with S195, S38, and S429 reaching 30% to 40% by week 4. By week 6, plots such as S309 and S333 peaked with coverage between 35% and 45%. In the later weeks, plots such as S306 and S307 maintained stable coverage, while others, including S437 and S444, showed slight declines. However, plots such as S444, S445, and S450 sustained coverage above 30% into week 11 (Figure 13), suggesting potential for extended fruit production.

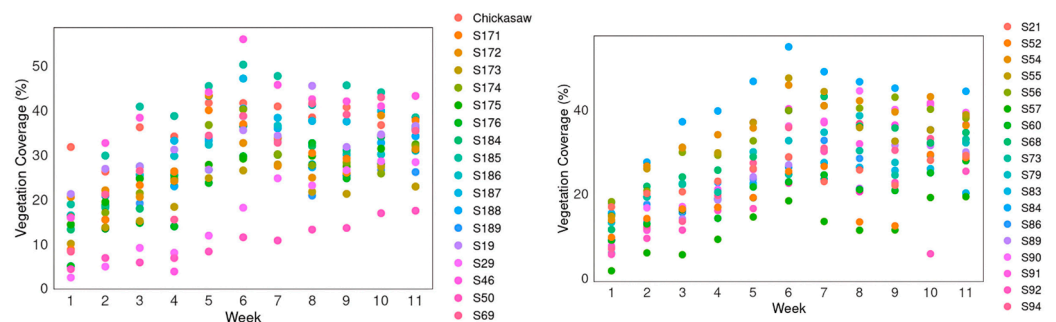


Figure 12. Cont.

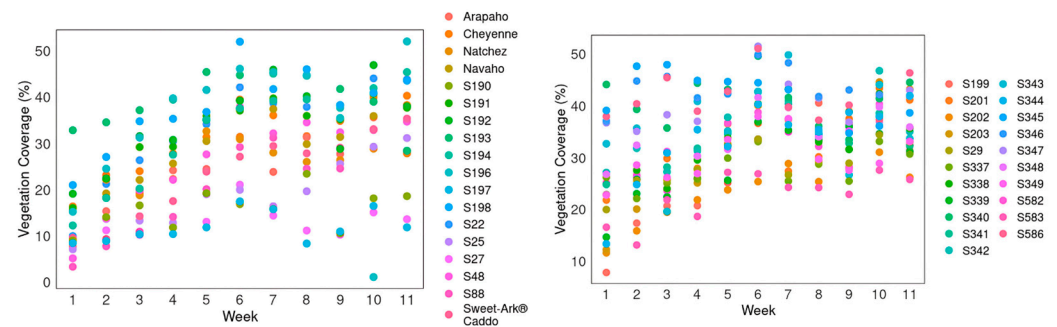


Figure 12. Temporal dynamics of vegetation coverage (%) across 75 florican plots over an 11-week period.

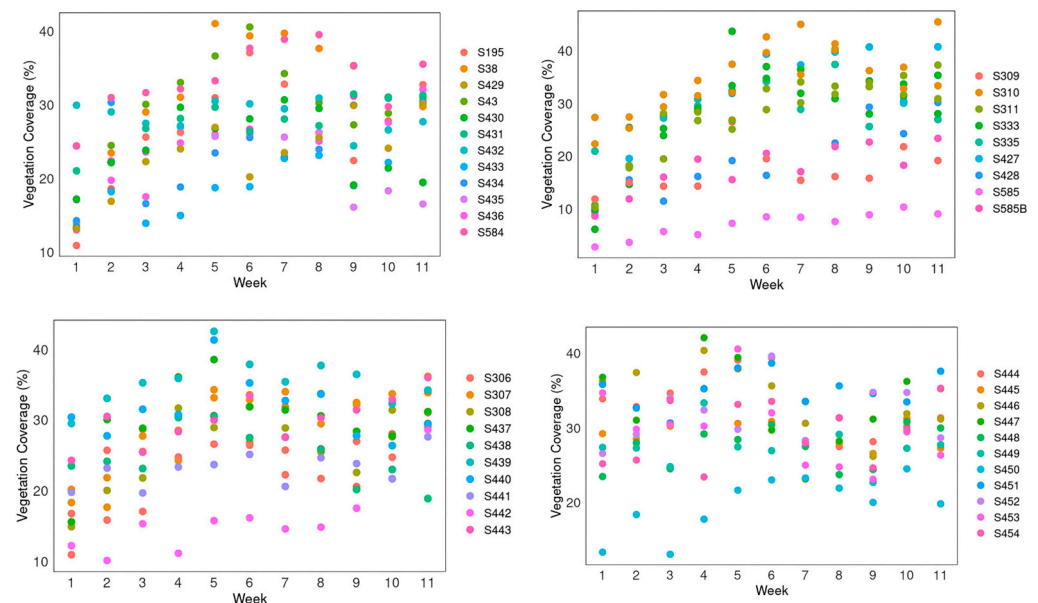


Figure 13. Temporal dynamics of vegetation coverage (%) across 47 primocane plots over an 11-week period.

A correlation matrix was created to analyze the association between plant number per plot and vegetation coverage (%) throughout the 11-week duration. The relationship between the number of plants and vegetation coverage exhibited moderate strength, with the peak correlation recorded in week 8 ($r = 0.38$). In contrast, earlier weeks, such as week 1 ($r = 0.25$), and later weeks, such as week 10 ($r = 0.19$). The correlations between successive weeks were significantly strong, demonstrating a constant pattern of vegetative growth throughout time. The correlation between week 6 and week 7 was $r = 0.90$, and between week 8 and week 9, was $r = 0.85$, indicating that once plants set their growth trajectory, they tended to sustain it as the weeks advanced (Figure 14).

Spatial mapping of flower coverage and visually estimated flower counts per plot across the study area (Figure 15) revealed the fluctuations in flower coverage as revealed by color gradients for data collected on week 3 (26 April 2023).

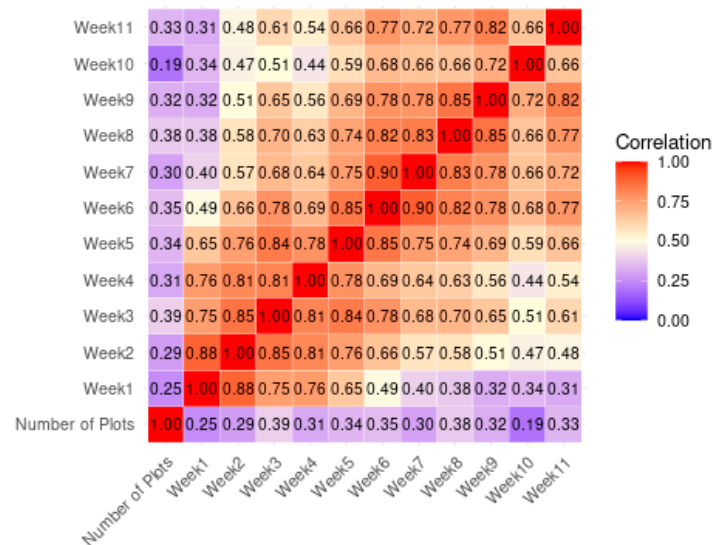


Figure 14. Correlation matrix of number of plants and vegetation coverage (%) over 11 weeks.

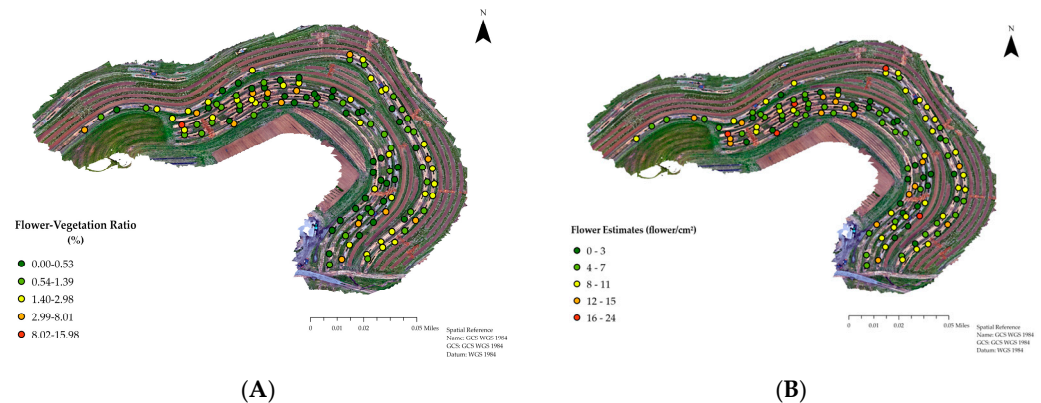


Figure 15. Spatial distribution of flowers (A) flower-to-vegetation ratio (%) (B) visual estimates of flower counts (flower/cm²) for week 3 data collected on 26 April 2023, with a result of each plot created in ArcGIS Pro 10.8.2.

4. Discussion

The utilization of unmanned aerial vehicle (UAV)-based remote sensing in agricultural research has progressively transformed the data collection process, particularly in the field of precision agriculture [37]. The capability of UAVs equipped with RGB sensors, as already used for apples, wheat, and honey trees [20,51,52] proves to be a useful platform. The correlation between the flower-to-vegetation ratio (FVR) and visual estimations of flowers additionally provides a unit of measure from UAV imagery to improve the accuracy of agricultural surveys and plant assessments. FVR is a reliable measure of flowering intensity, which shows a moderately strong correlation with the actual number of flowers obtained using visual estimates. The Pearson correlation value ($r = 0.71$) between FVR and flower visual estimates is relatively strong, explaining approximately 51% of the variance ($r^2 = 0.51$). Studies conducted by Zhang et al. [40] and Khan et al. [53] reported correlation coefficients of 0.84 and 0.75 for flower feature extraction for flowers and crop height, respectively, emphasizing the precision of UAVs in monitoring crop features. Nonetheless, Khan et al. [53] highlights the importance of mobile ground platforms capturing subtle canopy structures. Quantifying flower coverage in terms of vegetative coverage is crucial for evaluating plant productivity over the growth cycle. The use of vegetation coverage acquired satisfactory results, as weekly correlation between FVR and flower estimates ranged from 0.71 to 0.88 (Table 2). Techniques for pixel-based classification of flowers have utilized flower numbers

associated with total area in the image [28] and flower-to-tree canopy or leaf pixels [50]. For RGB images, vegetation coverage affirmed a measure of canopy greenness [54]. Additionally, vegetation area provided important context for understanding the dynamics of flower coverage as a significant predictor ($t = 5.68$, $p < 0.001$). This association underscores a potentially intricate interplay between vegetative development and floral production, which indicates fundamental plant resource allocation mechanisms. Plants frequently equilibrate vegetative growth with reproductive output, and an expanded vegetative area may signify enhanced photosynthetic potential, which could facilitate augmented flowering under optimal conditions [9,13,55].

Progress in image processing techniques has greatly enhanced the ability to extract information from UAV data. The binary methodology effectively separated flower from non-flower areas, improving flower estimate accuracy and simplifying data processing for large datasets (Figure 6), as evidenced by moderately strong model performance ($R^2 = 0.51$). The image processing technique quantified flowers by transforming images from the RGB color system to the HSB (hue, saturation, and brightness) color space, resulting in significant results [20,28,51]. Adamsen et al. [56], Treder et al. [27], Aggelopoulou et al. [22], and Hočevár et al. [28] applied RGB thresholds to map flowers but noted that detection accuracy of flowers was impacted by lighting variations, with the best results obtained from images captured in the late afternoon. Conversely, the brightness channel within the HSB model enabled a more adaptive approach to handling lighting variability, effectively enhancing flower detection and illustrating HSB's robustness in managing environmental lighting conditions. Zhang et al. [40] optimized RGB thresholds specific by comparing spectral reflectance of canopy and flowers from sample images taken at different times, the consistent selection of flowers using the validated HSB figures for flowers (H (low: 49, high: 255); S (low: 0, high: 40); B (low: 177, high: 255)) and vegetation (H (low: 48, high: 255); S (low: 0, high: 255); B (low: 0, high: 255)) (Figure 5) across 11 weeks further confirmed the accuracy of binary segmentation to differentiate flowers from vegetation in line with the wider trend of implementing computer vision in agriculture. Unlike other techniques, such as multi-class and machine learning-based methods, which are computationally intensive and require extensive technical expertise [36,38,57], the binary approach used proved efficient and accessible.

The temporal analysis of flower-to-vegetation ratio (FVR) across the 11-week period demonstrates clear flowering and growth patterns between primocane fruiting and floricanes fruiting plots (Figure 9). Typically, selections with early floral initiation exhibited the highest flowering intensity within the first four weeks, while those with late blooming times peaked in intensity during weeks eight and nine. With minimal skewness and a robust association between mean and median FVRs, indicating balanced flowering distribution and crop uniformity for the two selections. Floricanes fruiting plots demonstrated notable early-season flowering peaks, especially in selections such as Arapaho, Cheyenne, S190, and S194, which recorded FVR values surpassing 6% during weeks 2 to 4 (Figure 10), indicating swift reproductive maturity in these selections [55]. For primocane fruiting selections, we anticipated observing two distinct flowering peaks: one for floricanes in spring and another for primocanes in summer [13]. In contrast, most PF selections displayed only a single peak, predominantly during floricanes flowering in spring. This pattern indicates that spring blooming is generally more intense than primocane blooming in summer. Two factors may contribute to this observation: firstly, the increased vegetation coverage in summer might lead to an underestimation of flowering intensity by the flower-to-vegetation Ratio (FVR) during the final weeks of this study. Secondly, the energy expended by the plant for floricanes flowering and fruitification may result in less intense primocane flowering [10,11]. Nonetheless, early flowering was prominent, although at lower intensities for some primocane fruiting selections (Figure 11), with selections (S444, S445, and S450) exhibiting a bimodal flowering pattern, with peaks in weeks 3 to 4 and again in weeks 9 to 11 as expected [15]. Flowering time has been continuously selected as a trait, both directly and indirectly, as breeders and growers choose materials most suitable

for specific environments [58]. This study suggests that imagery can be utilized to estimate floral initiation and timing, offering valuable insights for planning crosses in breeding programs and potentially forecasting harvest periods for growers.

Morphological assessment is vital in blackberry breeding, as variations in growth form and vegetative reproduction are critical for selecting cultivars with desirable traits suited to various growing conditions and management practices [9]. The assessment of vegetative coverage over an 11-week period in blackberry plots reveals dynamic growth patterns across different genotypes, with distinct stages aligning closely with similar research in other perennial fruit crops. Early in the season, floricanes and primocanes plots displayed a range in vegetative coverage, with certain genotypes such as Chickasaw, S171, and S69 reaching nearly 40% by the fourth week. This early growth advantage suggests that these genotypes may be able to capture resources more efficiently in the initial growth phase and respond to environmental factors. Studies in raspberries and strawberries have underscored the importance of early robust growth for resource capture and root establishment [59–64]. As the season advanced, the vegetative coverage in blackberry plots S306 and S307 exhibited stabilization, whereas S437 and S444 had minor reductions but retained substantial coverage. Genotypes S444 and S450 maintained coverage exceeding 30% until week 11, indicating their resilience features that facilitate prolonged vegetative cover [55]. Strik [55] and Finn and Clark [9] noted that mid-season vegetation stabilization indicates a transition in resource allocation from vegetative to reproductive phases, with canopy maintenance facilitating ongoing photosynthesis and fruit development. For vegetative growth, the methodology differentiated between the two genotypes. Takeda et al. [62] found that alternative primocane management strategies, such as selecting the primocanes that arise early and bending them horizontally, as well as removing leaves to promote budbreak and the formation of flower shoots, can be effective. With the methodology developed by this study, orchard managers can adequately target and perform these management practices aimed at increasing yields.

The challenge of estimating the number of canes a plant produces, which directly correlates with flower production [41], assessing vegetation coverage per plot from UAV imagery provided a valuable metric for determining plant-specific flower density. The relationship between plant count and vegetative coverage further explains these growth dynamics with moderate correlation (Figure 14) peaking at week 8, suggesting that although higher plant density enhances coverage, it is not the sole determinant of growth. Similar correlations have been observed where plant density was moderately influenced by plant height and plot location [63,64]. Additionally, the strong weekly correlations between weeks suggest that growth patterns, once established, are likely to continue. This consistency could have practical applications in predicting late-season growth based on early observations, supporting genotype selection for stable growth traits. Spatial variation in flower coverage (Figure 15) further illustrates the influence of genotype and environmental factors on reproductive development, with variability observed in flower-to-vegetation ratios and visually estimated counts. This may indicate that spatially heterogeneous flowering in vineyard blocks is influenced by genotype, soil fertility, and microclimate [65,66].

Practical Applications

Flower-to-vegetation ratio measurement with UAV presents practical applications that can significantly improve precision agriculture and horticultural management techniques for specialty crop production systems such as blackberry cultivation. The utilization of UAV-based assessment of blooming intensity and vegetative coverage based on spatial differences facilitates accurate resource management, including irrigation, fertilizers, and pesticides, by tailoring their application to the specific requirements of individual plots [67,68]. This methodology enhances resource utilization efficiency, minimizes input waste, and fosters environmental sustainability. For instance, cultivators might modify irrigation and nutrient applications based on precise, current data regarding plant growth, thus reducing resource use and improving crop vitality [69].

The verified flower-to-vegetation ratio (FVR) has the potential to serve as a tool for yield prediction by interpreting flowering patterns. This capacity is essential for predicting harvest quantities, optimizing workforce distribution, and coordinating farm output with market demand, thereby minimizing operating risks and increasing profitability. Furthermore, the ability to track flowering stages accurately enables the timing of pollination activities to coincide with peak flowering periods, which maximizes fruit set and yield potential [22]. The distinctive dual-peak flowering pattern offers insights for growers aiming to implement double cropping strategies with primocane fruiting cultivars.

High-throughput phenotyping methodology in plant breeding significantly aids in the identification and selection of cultivars exhibiting desirable features, including early or prolonged flowering and relevant vegetation features [40]. The UAV-based approach enables breeders to swiftly and objectively assess flowering characteristics across various genotypes, hence promoting data-driven decisions that improve the efficacy of breeding programs [52]. By choosing genotypes with superior flowering traits, breeders can develop high-yield, climate-resilient varieties that are adapted to evolving environmental conditions and market requirements, thereby enhancing crop improvement initiatives [12,13]. Collectively, these applications highlight the significance of UAV-based phenotyping in specialty crops, delivering actionable data that improves yield, decreases input costs, and promotes sustainable, effective resource management across many agricultural contexts.

5. Conclusions

A novel methodology for precise quantification of flower-to-vegetation ratio (FVR) in blackberry (*Rubus* subgenus *Rubus* Watson) crops using unmanned aerial vehicles (UAVs) equipped with RGB sensors was produced. Through the integration of remote sensing technologies and advanced image processing techniques, we were able to assess and monitor the flowering dynamics across different blackberry selections over an 11-week period. The results indicate a strong correlation between the UAV-derived FVR and traditional visual estimates, thereby validating the utility of UAVs for phenotyping and orchard management. Distinct temporal patterns in the FVR of primocane and florican selections were observed, reflecting their unique growth stages and phenological characteristics. By providing a more accurate and scalable approach to monitoring flowering intensity, this research contributes to the enhancement of yield prediction models and the refinement of breeding programs aimed at improving blackberry production.

UAV-based phenotyping for blackberry flowering and vegetative coverage was effective. However, there are limitations that should be considered in interpreting the findings and in guiding future research. Firstly, canopy occlusion posed a challenge in accurately detecting flowers within dense blackberry plots. This occlusion can lead to underestimations of flower density, as the UAV captures only the visible top layer. Another limitation is that environmental conditions such as high wind speeds, gusts, and cold weather can influence UAV flight stability, image quality, and endurance. Changes in sunlight intensity throughout the day can create inconsistent shadows, impacting color-based segmentation. Solar noon UAV flights helped overcome this limitation for image acquisition. Multi-angle imaging could help improve the limitations related to canopy occlusion by obtaining varied perspectives, thereby offering a more comprehensive understanding of canopy structure. Standardizing data collection times and determining favorable weather conditions may enhance data quality by minimizing inconsistencies arising from variable lighting and wind conditions. The implementation of these methods has the potential to improve the accuracy, scalability, and practicality of UAV-based phenotyping methods in specialty crop management in future research.

Vegetation coverage specific blackberry flower quantification with UAV image analysis represents a significant step forward in the application of UAV computer vision in specialty crop management. The developed methodology not only advances the understanding of blackberry phenology but also provides a foundation for the broader application of UAV technology in horticultural research. As the agricultural sector continues to embrace

precision farming techniques, the insights gained from this study will be instrumental in driving innovation and improving the sustainability of fruit production systems. Future research focuses on addressing the limitations identified in this study and exploring the automation of UAV subsystems for blackberry phenotypic feature extraction.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. List of Abbreviations.

Abbreviation	Definition
UAV	Unmanned Aerial Vehicles
RGB	Red, Green, Blue
CNN	Convolutional Neural Networks
USDA	United States Department of Agriculture
DJI	Da-Jiang Innovations
CMOS	Complementary Metal Oxide Semiconductor
AGL	Above Ground Level
HSB	Hue, Saturation, Brightness
FVR	Flower-to-Vegetation Ratio
GSD	Ground Sampling Distance
PF	Primocane fruiting
FF	Florican fruiting
ROI	Region of Interest
RMSE	Root Mean Squared Error
IQR	Interquartile Range

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