Vegetation Coverage Specific Flower Density Estimation in Blackberry Using Unmanned Aerial Vehicle (UAV) Remote Sensing

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A paper from the Proceedings of the
16th International Conference on Precision Agriculture
21-24 July 2024
Manhattan, Kansas, United States

Abstract

The effective management of agricultural systems relies on the utilization of accurate data collection techniques to analyze essential crop attributes to enhance productivity and ensure profits. Data collection procedures for specialty horticultural crops are mostly subjective, time consuming and may not be accurate for management decisions in both phenotypic studies and crop production. Reliable and repeatable standard methods are therefore needed to capture and calculate attributes of horticultural crops using agricultural systems technology, as well as develop automated agricultural systems. The objective of this research was to develop a standard method for vegetation coverage specific blackberry flower density estimation with unmanned aerial vehicle (UAV) remote sensing. The study was conducted at the University of Arkansas Fruit Research Station at Clarksville, AR. The UAV captured 1,894 images in the visible spectrum for image processing. In total, 123 pictures were selected from dataset to determine blackberry plots for image analysis. The image processing utilized ImageJ software for segmenting floral and vegetative coverage to calculate Flower-Vegetation Ratio (FVR). Significant variance in flower density across different plots were observed, with an FVR correlation of 19.44% and a p-value 0.047, indicating an increase in flower count with increasing vegetation coverage. With a ground sampling distance of 0.32cm, there was no statistically significant difference between FVR by area (cm^2) and percent coverage (%). A Pearson correlation analysis showed correlation coefficient (r) of 0.675 between FVR and visual estimates. The practical application of UAVs in detailed monitoring of specialty crops demonstrates a significant advancement over conventional methods, offering reliable and applicable data that could refine crop management and breeding strategies.

Keywords.
Precision Agriculture, Flower distribution, UAV, GIS, Blackberry

Introduction

Agricultural systems require timely data collection and interpretation to enable farmers to make management decisions that are accurate and not subject to misinterpretation. Precision Agriculture (PA), a developing field that involves the strategic combination of sensors and data analytics to inform agricultural decision-making aimed at enhancing the efficiency, production, and sustainability of agricultural operations (ISPA, 2018). PA is driven by technologies such as variable rate technology, and robotics (Blackmore, 2016; Ahmad & Mahdi, 2018), remote sensing (Liu, Xiang, Jin, Liu, Yan, & Wang, 2021), Geographic Information Systems (GIS) (Radoglou-Grammatikis, Sarigiannidis, Lagkas, & Moscholios, 2020), Global Positioning Systems (GPS) (Guo et al., 2018) and data analysis which incorporates internet of things, machine learning and artificial intelligence (Akhter & Sofi, 2022). The use of historical data and collection of real-time data with sensors provides a basis for better decision-making. For horticultural farming, it enables farmers to gather and assess data pertaining to site selection, soil quality, meteorological patterns, and information on crop status for pruning and training decisions. This results in enhanced resource allocation and improves agricultural oversight (Sishodia, Ray, & Singh, 2020).

Remote sensors provide information from target objects, being active or passive sensors based on their energy source to illuminate observed objects (Liu et al., 2021). Sensor types used in PA include electromagnetic, airflow, mechanical, electrochemical, dielectric soil moisture sensors, and optical sensors (Singh et al., 2020). Specifically, optical sensors are wide-ranged and include multispectral, hyperspectral, thermal, and visual (red, green, blue - RGB) offering an opportunity to collect images of objects for analysis (Bogue, 2017). Optimal sensors capture a wide range of data from reflectance in the visible light spectrum of red, green, and blue wavelengths, to reflectance across multiple distinct wavelengths that extend beyond the RGB range, including infrared to solve specific farm problems (Deng et al., 2018). Using sensors for data collection in agriculture has provided an upgrade on previously used visual observations, thus saving time, resources and improving the quality of data collected. Remote sensing data can be systematically collected over extensive geographical regions instead of limited to individual point observations and therefore lead to large datasets in agricultural production collected over the years with needed to achieve automation in the agri-food industry (Akhter & Soffi, 2022).

Blackberrys (Rubus subgenus Rubus Watson) as a specialty crop provides distinct challenges that require specific strategies to optimize yield and improve fruit quality (USDA-AMS, 2020). The production of blackberries has had a significant increase due to the introduction of new and enhanced cultivars, as well as the growing interest among consumers in its substantial medicinal and nutritional benefits (Clark & Finn, 2014; Wu et al., 2022). In plant breeding, a combination of fruit firmness, post-harvest storage, and plant architecture of blackberry has been a major focus of research (Worthington & Clark, 2019). Additionally, the impact environmental factors causing flower loss, yield reduction and antioxidant capacity of blackberry has resulted in breeding objectives targeting flower timing and intensity of blackberry canes (Clark, 2008; Lewers, Wang & Vinyard, 2010). To select phenotypes, plant breeders adopt a process of visually observing the number of flowers per vegetation based on a scale. Additionally, blackberry crop growers lack access to standard data collection methodologies needed for site-specific management as compared to growers of large-area crops such as soybean or corn. For blackberry, the available data to support management decisions is mostly restricted to visual assessments made on the ground. However, these methods used for estimating plant characteristics are subjective, time-consuming, and labor-intensive. As a result, data extrapolation is mostly used to encompass vast regions and heavily depends on the expertise of the data collector to get pertinent information that can be used to the entire farm (Teodorescu, Moise & Cosac, 2016).

The advancement of unmanned aerial vehicle (UAV)-based remote sensing systems has significantly enhanced the field of remote sensing and PA. For agricultural surveillance it presents significant opportunities for obtaining field data in a convenient, fast, and economical manner, as compared to conventional techniques of visual observation (Sankaran et al., 2015). The low altitude capability of UAVs enables the capture of ultra-high spatial resolution images of crops, with a level of detail down to a few centimeters. This enhances the efficiency of the monitoring systems and provides data collection opportunities (Sankaran et al., 2015). UAVs equipped with sensors enable breeders to perform High throughput phenotyping, which encompasses the usage of technology to characterize plants ranging from imaging conducted on the ground to aerial phenotyping (Gill et al., 2022). The requirement for high-resolution photographs arises when attempting to acquire spectral information from small objects, such as flowers and flower clusters, to identify them from the surrounding background (Aggelopoulou et al., 2011; Ren, Zhu & Xiao, 2018).

Previous research has primarily focused on extracting flower detection and intensity data using RGB sensors and applying color thresholding techniques (Aggelopoulou et al., 2011; Liakos et al., 2017). Flower detection has been evaluated on several plants including wheat, corn, rice, soybean, peach, citrus, cotton, apple and ornamentals as rose flowers (Hočevar, Širok, Godeša & Stopar, 2014; Kuar & Powell, 2015; Yahata et al., 2017; Gogul & Kumar, 2017; Dias, Tabb & Medieros, 2018; Guo et al., 2018; Tiay, Benyaphaichit & Riyamongkol, 2018; Farjon, Krikeb, Hillel & Alchanatis, 2020) with corresponding image processing techniques which are often highly challenging and technical in nature (Dias et al., 2018; Lin & Chen, 2018; Mu et al., 2023) to estimate agronomic traits and achieve various farm management goals ranging from yield estimation, pollination, thinning and plant breeding.

In these studies, the use of ground and unmanned aerial vehicles (UAVs) has provided access to flowers (Gill et al., 2022), however, no research has involved the detection of blackberry flowers for phenotyping and orchard management purposes. Additionally, the potential of the significant overlap (80%) between the successive photos captured during a UAV flight and the use of newer UAVs provides a multi-view perspective of the plants for precise flower quantification in blackberry orchards. Agricultural automation and the improvement of agricultural systems technology require research with the aim of providing a reliable information database.

The objective of this research therefore was to develop a method to accurately measure blackberry flowers from UAV remote sensing and determine image processing parameters to be used for an automated UAV subsystem.

Materials and methods

Remote Sensing Data Acquisition and Experiment Site

The study used a Da-Jiang Innovations (DJI) Mavic 3 Enterprise Unmanned Aerial Vehicle (Mavic M3E, Da Jiang Innovations Science and Technology Co. Ltd., Shenzhen, China). The DJI Mavic 3E quadcopter was used to obtain photos of blackberry crops using the Red (650nm), Green (550nm), Blue (450nm) color spectrum with a ½ inch CMOS sensor and an image resolution of 12 megapixels. Using a preset navigation control set on normal mode and mission plan developed for the area of study, data was autonomously collected and saved on an SD card in the UAV. To enhance precision, data capture was conducted at a height of 12 meters above ground level (AGL) as allowed by the DJI Mavic 3E flight controller, at 80% cross overlap (DJI, 2024).

The identification of blackberry flowers was defined by segmentation of flower and vegetation. All 123 images captured at the 12m AGL were manually labelled. Microsoft Photos (Microsoft Corporation, Redmond, Washington, USA) was used to manually count the number of flowers per plot using a paper developed quadrat of 0.25cm^2. To ensure images mimicked field data capture, images were zoomed-in 36% with quadrat randomly placed a maximum of six rando locations on the plot to count number of “white flowers” per quadrat. The total number of flowers per plot was determined and divided by the product of number of quadrats and size of quadrat resulting in the number of flowers/cm^2. Visual assessment of flowering characteristics of plants is often used by researchers and plant breeders, using scales of 0-10 or 0-100% depending on the nature of study (Zhang et al., 2020). Furthermore, these visual assessments must account for the number of canes, complicating the evaluation process using UAV images since the number of canes is not detectable from such images. Consequently, the method developed in this study addresses this challenge.

The study involved Blackberry (Rubus subgenus Rubus Watson) crop breeding trails located at the University of Arkansas Fruit Research Station in Clarksville (lat. 35°31′58″N and long. 93°24′12″W). The blackberry orchards at the station have five sections for breeding purposes (Figure 1.1). For this study, data was collected from Section One (1) with 123 plots of blackberry plants with erect growth habits on April 26, 2024.

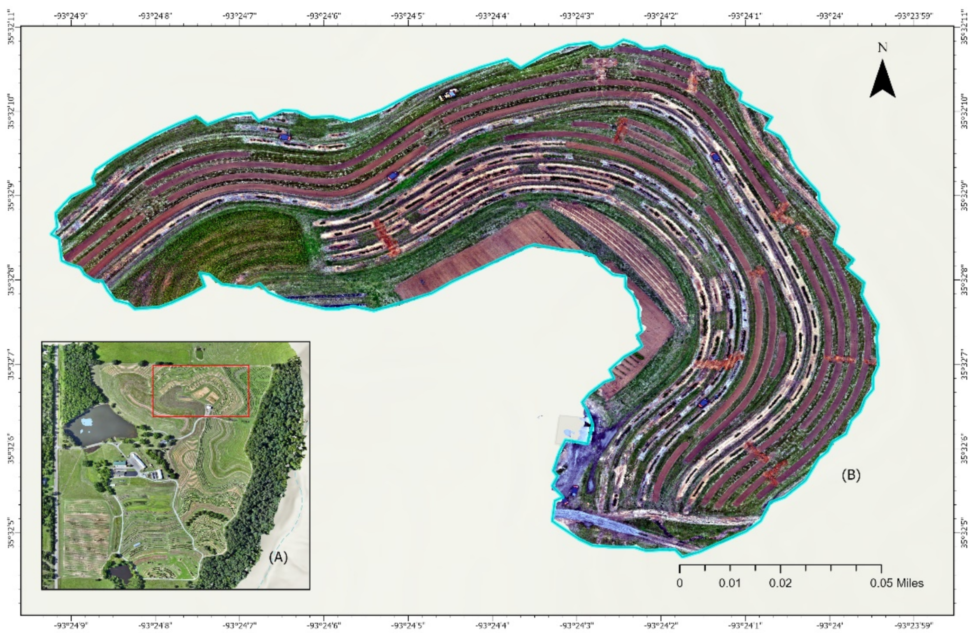


Figure 1.1. Map of the study area. (A) shows the University of Arkansas Fruit Research Station with five sections and section 1 labelled in red box; (B) shows the orthomosaic for section with images captured on 26th April 2023. Figures were generated by ArcGIS Pro Desktop 10.8.2 software (ESRI, Redlands, California, USA).

Image Processing and Analysis

After the UAV flight, the photos were analyzed using the Fiji - ImageJ software suite (Schneider, Rasband & Eliceiri, 2012). This process consisted of multiple stages offline (Figure 1.2). It began with individual plot extraction in Microsoft Photos (Microsoft Corporation, Redmond, Washington, USA). Research has demonstrated that high-definition digital photographs can be converted into other color spaces using Hue-Saturation-Brightness (Tsai & Yeh, 2008). The colors of these visible images captured with the UAV were transformed into HSB color model. Subsequently, a binary threshold segmentation was employed to distinguish between flowers (white) and vegetation (green).

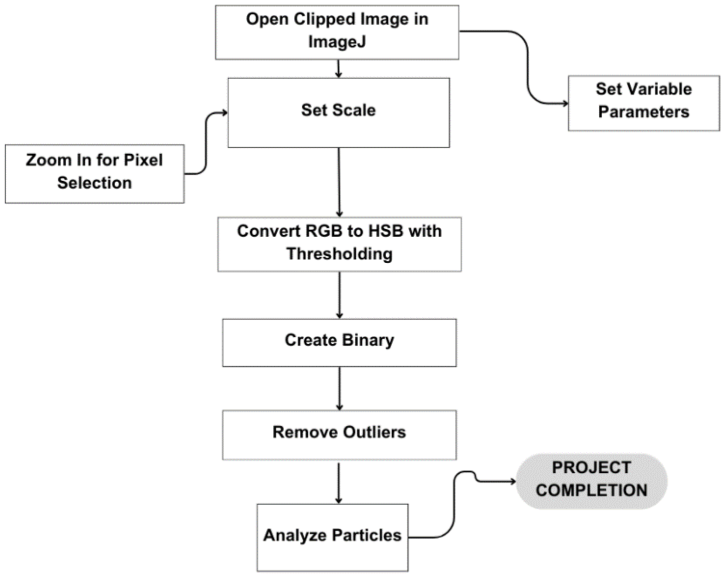
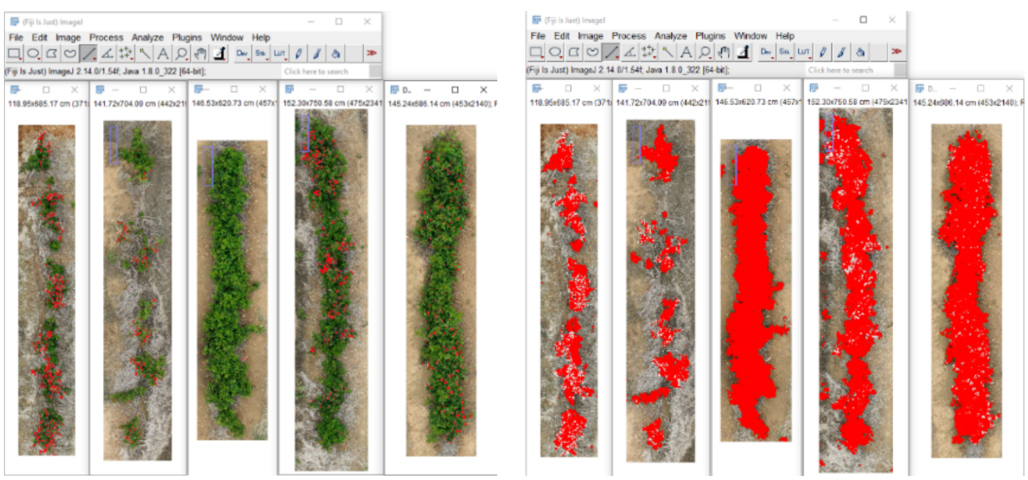


Figure 1.2. Comprehensive image processing flow diagram illustrating the sequential steps involved in the analysis and interpretation of UAV-captured imagery for assessments of flower and vegetation coverage for blackberry plots.

The segmentation process was essential to compute the Flower-Vegetation Ratio (FVR). To determine the differences in RGB, a single pixel was selected with a set scale of 0.32cm representing the ground sampling distance. Through the application of thresholding technique, the area (cm2) and percentage (%) coverage of flower and vegetation were extracted. This segmentation process identified the floral bloom from the RGB image. Figure 1.3 displays the outcomes of the picture processing. Following the thresholding procedure, a filtering process was employed to eliminate the presence of outliers through noise removal.



(A) (B)

Figure 1.3. Plant thresholding from UAV image: (A) clipped and rotated plots from UAV imagery with flower threshold selected at different flower coverage with HSB threshold colors of Hue 49-255, Saturation 0-40, Brightness 177-255; (B) clipped and rotated plots from UAV imagery with vegetation threshold selected at different vegetation coverage with HSB threshold colors of Hue 48-255, Saturation 0-255, Brightness 0-255.

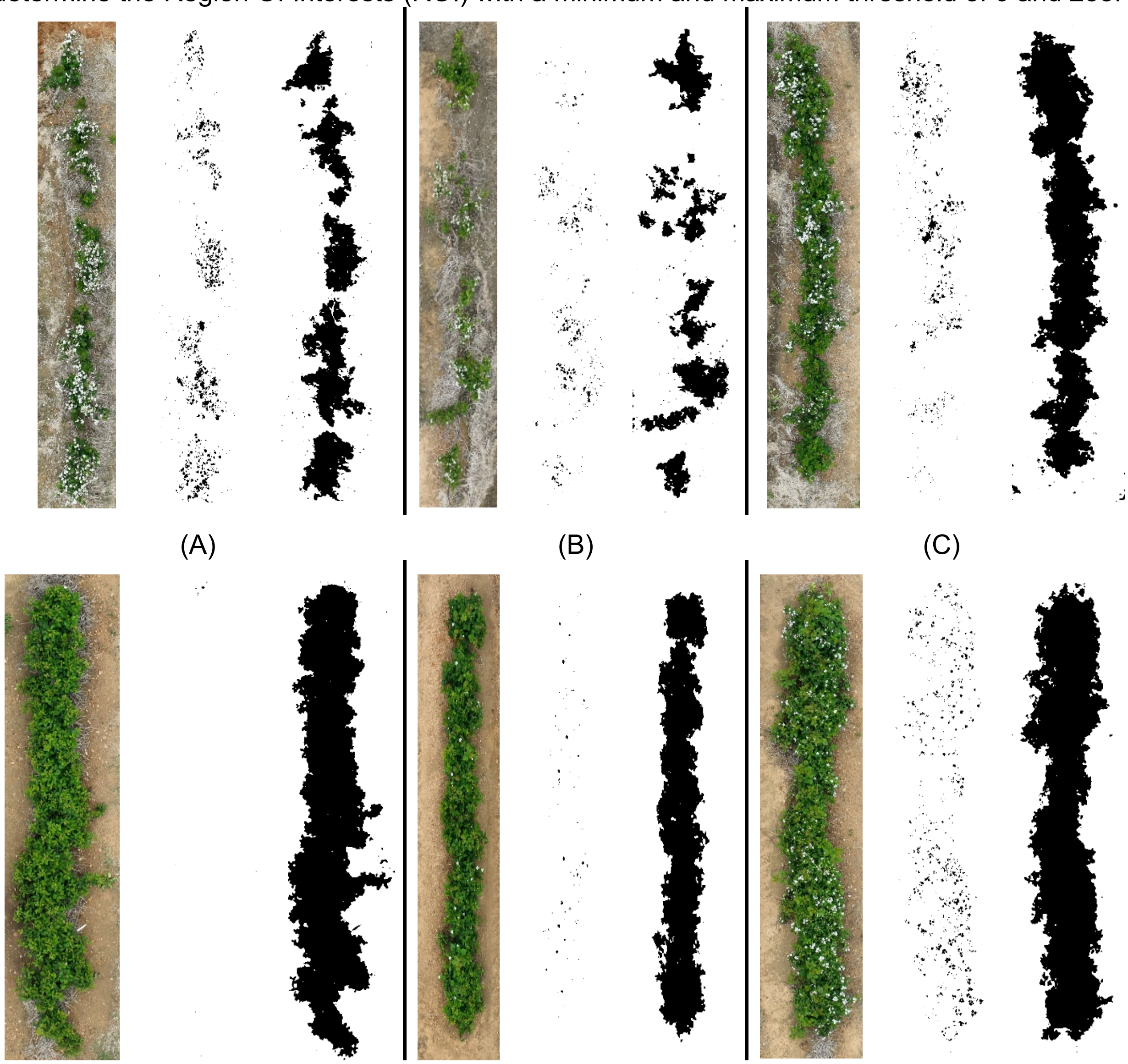
Based on area of flower and vegetation coverage in percentages, a flower-vegetation ratio was calculated for each plot. Additional data analysis of simple linear regression, paired sample t-test and Pearson’s correlation analysis was used to investigate the differences in FVR for various plots, the set scale used to determine FVR and the relationship between FVR and ground truth data (visual observations) respectively. All statistical analysis was performed in RStudio (R Core Team, 2021) online via Posit Cloud.

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

Where FVR = Flower Vegetation Ratio, FC = Flower Coverage (%) and VC = Vegetation Coverage (%).

Results

The data on the Flower Vegetation Ratio (FVR) which measured the proportion of flower covering to vegetation coverage, was examined using descriptive statistics to provide a summary of the average and range of values. Flower coverage per vegetation coverage was estimated to determine the flower density per plot, Figure 2.1 shows the binary segmentation results to determine the Region Of Interests (ROI) with a minimum and maximum threshold of 0 and 255.



(A) (B) (C)

(D) (E) (F)

Figure 2.1. Binary segmentation of flowers and vegetation from RGB images to illustrate segmentation effectiveness for different plot sizes: (A) clipped RGB image of plot 54 with binary of flowers and vegetation, FVR = 15.75; (B) clipped RGB image of plot 49 with binary of flowers and vegetation, FVR = 7.96; (C) clipped RGB image of plot 57 with binary of flowers and

vegetation, FVR = 7.10; (D) clipped RGB image of plot 77 with binary of flowers and vegetation, FVR = 0.16; (E) clipped RGB image of plot 67 with binary of flowers and vegetation, FVR = 0.83; (F) clipped RGB image of plot 78 with binary of flowers and vegetation, FVR = 5.08.

The mean FVR was 1.756 (n=123), indicating the average ratio between floral and vegetation coverage throughout the plots with a standard deviation of 1.976. The minimum and maximum FVRs were 0.000 and 15.575 respectively. Figure 2.2 depicts the distribution of FVR which was a right-skewed distribution.

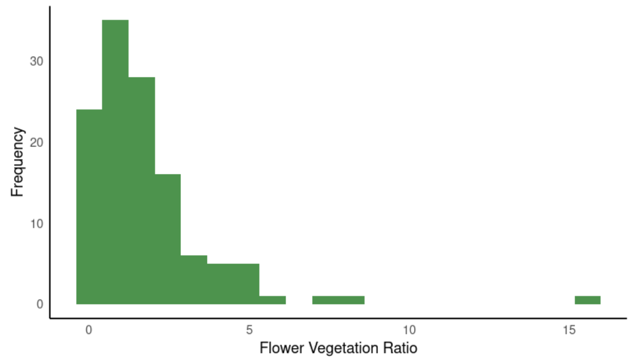


Figure 2.2. Histogram of Flower Vegetation Ratio (n=123).

A paired samples t-test was performed to compare the means of FVR from area (cm^2) and FVR from percent coverage (%) to determine whether there are noteworthy disparities between these two variables. The study showed that there was no statistically significant difference between the means of FVR from area (cm^2) and FVR from percent coverage (%) ($t\ (122) = 1.017$, $p = .311$) validating the set-scale based on the ground sampling distance of image captured.

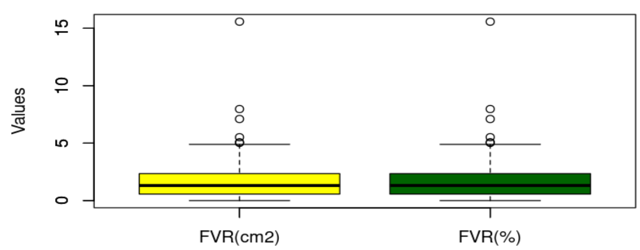


Figure 2.3. Paired box plot for FVR from area (cm2) and FVR from percent coverage (%).

Simple Linear Regression (SLR) analysis was used to determine the correlation between Vegetation Coverage (%) as a predictor variable and Flower Coverage (%) as a response variable. The regression analysis showed a statistically significant positive correlation between the variables Vegetation Coverage (%) and Flower Coverage (%) ($\beta = 0.031$, $SE = 0.006$, $t = 5.404$, $p < .001$). The intercept of the model was calculated to be -0.322 (standard error = 0.160, t-value = -2.010, p-value = .047). The model accounted for 19.44% of the variation in floral coverage percentages, as indicated by the coefficient of determination ($R^2 = .1944$, Adjusted $R^2 = .1878$). The model's F-statistic was 29.21, indicating a statistically significant fit, as evidenced by a p-value of less than .001.

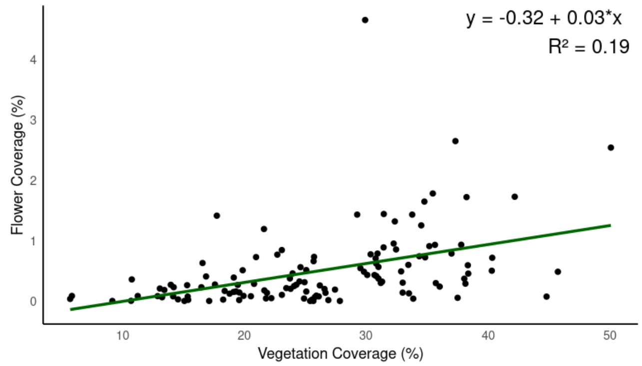
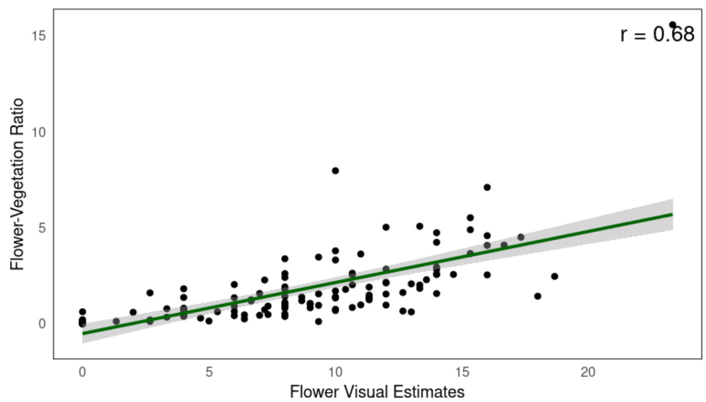


Figure 2.4 Correlation of Vegetation Coverage (%) and Flower Coverage (%).

A Pearson correlation analysis was performed to evaluate the magnitude of the linear association between the Flower-Vegetation Ratio and Visual Estimates. The analysis showed a Pearson correlation coefficient (r) of 0.675, suggesting a moderate to strong positive association. The positive correlation indicates that there is a direct relationship between higher levels of vegetation and higher visual perceptions of vegetation or floral density.



2.5. Correlation between Flower Visual Estimates and Flower-Vegetation Ratio.

Discussion

The objective of this study was to investigate the efficacy of Unmanned Aerial Vehicles (UAVs) in identifying and measuring the extent of floral distribution in agricultural environments, with a particular emphasis on blackberry blossom coverage. The paired t-test performed to compare two methods of quantifying the coverage: direct area measurement in area (FVR (cm^2)) and percentage coverage calculations (FVR (%)). The t-statistic was found to be 1.017, with a corresponding p-value of .311. There was no statistically significant difference between the two methods, indicating that both methods yield equally reliable findings for measuring the amount of blackberry blossom coverage, validating the set-scale during image analysis in ImageJ (Treder et al., 2021). Based on these findings, it can be inferred that both the area-based and percentage-based methodologies can be used to measure blackberry flower coverage without any substantial decrease in accuracy or precision. This output has significant implications for agricultural research and operations, since it allows for the selection of the most suitable approach based on specific operational or logistical requirements, without compromising the accuracy and dependability of the data obtained.

The Simple Linear Regression analysis revealed a positive correlation between Vegetation Coverage (%) and Flower Coverage (%). This finding highlights the usefulness of vegetation metrics in predicting flower density and improving real-time flower monitoring in precision agriculture. Nevertheless, the model explains 19.44% of the variability in bloom coverage, indicating the potential advantages of incorporating other technology to enhance the accuracy and resilience of the predictive model. This study confirms the results of recent research that emphasizes the dependability and precision of unmanned aerial vehicle (UAV)-based photography in agricultural surveys for flower detection (Bairwa & Agrawal, 2014; Piani, Bortolotti & Manfrini, 2021). However, in contrast to the work of Horton, Cano, Bulanon and Fallahi, (2017), which focused on the importance of multispectral imaging in improving detection accuracy, this study exclusively used regular RGB imaging, offering a more feasible choice for settings with limited resources.

For this study, the flower-vegetation ratio accounted for all aspects of the plant's vegetation, where vegetation coverage included flower coverage. Rzanny, Mäder, Deggelmann, Chen and Wäldchen (2019) in their study aimed at obtaining suitable images for automated plant identification for flowers and leaves concluded that it would be beneficial to have multi-organ observations made of front and lateral perspectives of flowers. Though the total vegetation for the research included the plant multi-organs of flower and vegetation, flower coverage was largely accounted for through aerial view.

The lack of considerable disparity in measurement methodology implies that less complex and resource-demanding techniques, such as percentage estimates derived from RGB photos, can be equally successful as more direct area measurements in certain situations. Additionally, the use of open-source ImageJ software provides horticultural farmers with a means to analyze data and for management decisions. This result is vital for practical use, as it suggests that farmers might use simpler technologies without sacrificing the precision required for making effective decisions.

The conformity in measuring methodologies corresponds with the wider body of literature suggesting that unmanned aerial vehicles (UAVs) equipped with red-green-blue (RGB) cameras are adequately precise for numerous agricultural purposes (Piani et al., 2021; Volpato et al., 2021). Nevertheless, it is crucial to acknowledge that although the comparability of data collection techniques adopted for this study confirms the adaptability of UAV technologies, other variables such as time of day and UAV flight altitude may still influence data precision and must be meticulously controlled during flight operations.

Conclusion

The study showcased the development and analysis of UAV image-based methodology for estimating flower density in blackberry crops. The study employed visible (RGB) images to observe and measure the flower density specific to vegetation cover. The results demonstrated positive correlation between flower-vegetation ratio and flower visual estimates for all plots. Additionally, the results for flower density determination using area coverage and percentage coverage of flower and vegetation are statistically insignificant from a paired t-test analysis. The performance of both the set-scale using the ground sampling distance and thresholding were useful in determining the flower and vegetation coverage per blackberry plot. Though there were outliers signifying flower coverage being greater than vegetation coverage, there was a significant relationship between flower coverage and vegetation coverage. In general, the research findings demonstrate that less resource-intensive techniques, such as RGB image-based estimations, are useful in flower density estimations. Conclusively, the utilization of UAV and remote sensing do not only advance current agricultural methods but also offers a means to achieve more sustainable and precise farming techniques through crop management and plant breeding. Further studies should prioritize the improvement of these methods, investigating the use of multispectral and hyperspectral imaging capabilities to amplify the accuracy and precision of crop monitoring systems. In addition, future research could explore the determination of flower density from orthophotos for large fields, thereby expanding the range and practicality of UAV-based technology in precision agriculture.

Acknowledgments

This research was supported by the intramural research program of the U.S. Department of

Agriculture, National Institute of Food and Agriculture, [Agricultural Genome to Phenome Initiative, grant no. 2022-70412-38454, 2021-70412-35233, and 2020-70412-32615].

This research was partially funded by the U.S. Department of Agriculture, National Institute of Food and Agriculture Specialty Crop Research Initiative award # 2020-51181-32156 and NIFA USDA SCRI award # 2019-67013-29196.

References

Ahmad, L., & Mahdi, S. S. (2018). Variable rate technology and variable rate application. Satellite Farming: An Information and Technology Based Agriculture, 67–80.

Aggelopoulou, A. D., Bochtis, D., Fountas, S., Swain, K. C., Gemtos, T. A., & Nanos, G. D. (2011). Yield prediction in apple orchards based on image processing. Precision Agriculture, 12, 448–456.

Akhter, R., & Sofi, S. A. (2022). Precision agriculture using IoT data analytics and machine learning. Journal of King Saud University - Computer and Information Sciences, 34(8, Part B), 5602–5618. https://doi.org/10.1016/j.jksuci.2021.05.013

Bairwa, N., & Agrawal, N. K. (2014). Counting of flowers using image processing. International Journal of Computer Applications, 3, 0975–8887.

Blackmore, S. (2016). Towards robotic agriculture. Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping, 9866, 8–15.

Bogue, R. (2017). Sensors key to advances in precision agriculture. Sensor Review, 37(1), 1–6.

Clark, J. R. (2008). Primocane-fruiting blackberry breeding. HortScience, 43(6), 1637–1639.

Clark, J. R., & Finn, C. E. (2014). Blackberry cult ivation in the world. Revista Brasileira de Fruticultura, 36, 46–57.

Da-Jiang Innovations, D. J. I. (n.d.). (n.d.). [Https://www.dji.com/Support/Product/Mavic-3.]. Support for DJI Mavic 3.

Deng, L., Mao, Z., Li, X., Hu, Z., Duan, F., & Yan, Y. (2018). UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras. ISPRS Journal of Photogrammetry and Remote Sensing, 146, 124–136. https://doi.org/10.1016/j.isprsjprs.2018.09.008

Dias, P. A., Tabb, A., & Medeiros, H. (2018). Apple flower detection using deep convolutional networks. Computers in Industry, 99, 17–28. https://doi.org/10.1016/j.compind.2018.03.010

Farjon, G., Krikeb, O., Hillel, A. B., & Alchanatis, V. (2020). Detection and counting of flowers on apple trees for better chemical thinning decisions. Precision Agriculture, 21(3), 503–521. https://doi.org/10.1007/s11119-019-09679-1

Gill, T., Gill, S. K., Saini, D. K., Chopra, Y., de Koff, J. P., & Sandhu, K. S. (2022). A comprehensive review of high throughput phenotyping and machine learning for plant stress phenotyping. Phenomics, 2(3), 156–183.

Gogul, I., & Kumar, V. S. (2017). Flower species recognition system using convolution neural networks and transfer learning. 2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN), 1–6. https://doi.org/10.1109/ICSCN.2017.8085675

Guo, J., Li, X., Li, Z., Hu, L., Yang, G., Zhao, C., Fairbairn, D., Watson, D., & Ge, M. (2018). Multi-GNSS precise point positioning for precision agriculture. Precision Agriculture, 19(5), 895–911. https://doi.org/10.1007/s11119-018-9563-8

Hočevar, M., Širok, B., Godeša, T., & Stopar, M. (2014). Flowering estimation in apple orchards by image analysis. Precision Agriculture, 15(4), 466–478. https://doi.org/10.1007/s11119-013-9341-6

Horton, R., Cano, E., Bulanon, D., & Fallahi, E. (2017). Peach flower monitoring using aerial multispectral imaging. Journal of Imaging, 3(1), 2.

International Society of Precision Agriculture. (2018). Association seeks definitive definition of "precision agriculture"—What's your vote? —PrecisionAg. https://www.precisionag.com/events/association-seeks-definitive-definition-of-precision-agriculture-whats-your-vote/

Lewers, K. S., Wang, S. Y., & Vinyard, B. T. (2010). Evaluation of blackberry cultivars and breeding selections for fruit quality traits and flowering and fruiting dates. Crop Science, 50(6), 2475–2491.

Lin, P., & Chen, Y. (2018). Detection of Strawberry Flowers in Outdoor Field by Deep Neural Network. 2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC), 482–486. https://doi.org/10.1109/ICIVC.2018.8492793

Liu, J., Xiang, J., Jin, Y., Liu, R., Yan, J., & Wang, L. (2021). Boost precision agriculture with unmanned aerial vehicle remote sensing and edge intelligence: A survey. Remote Sensing, 13(21), 4387.

Mu, X., He, L., Heinemann, P., Schupp, J., & Karkee, M. (2023). Mask R-CNN based apple flower detection and king flower identification for precision pollination. Smart Agricultural Technology, 4, 100151. https://doi.org/10.1016/j.atech.2022.100151

Piani, M., Bortolotti, G., & Manfrini, L. (2021). Apple orchard flower clusters density mapping by unmanned aerial vehicle RGB acquisitions. 2021 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), 92–96.

Radoglou-Grammatikis, P., Sarigiannidis, P., Lagkas, T., & Moscholios, I. (2020). A compilation of UAV applications for precision agriculture. Computer Networks, 172, 107148.

Ren, Y., Zhu, C., & Xiao, S. (2018). Small object detection in optical remote sensing images via modified faster R-CNN. Applied Sciences, 8(5), 813.

Rzanny, M., Mäder, P., Deggelmann, A., Chen, M., & Wäldchen, J. (2019). Flowers, leaves or both? How to obtain suitable images for automated plant identification. Plant Methods, 15, 1–11.

Sankaran, S., Khot, L. R., Espinoza, C. Z., Jarolmasjed, S., Sathuvalli, V. R., Vandemark, G. J., Miklas, P. N., Carter, A. H., Pumphrey, M. O., Knowles, N. R., & Pavek, M. J. (2015). Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review. European Journal of Agronomy, 70, 112–123. https://doi.org/10.1016/j.eja.2015.07.004

Schneider, C. A., Rasband, W. S., & Eliceiri, K. W. (2012). NIH Image to ImageJ: 25 years of image analysis. Nature Methods, 9(7), 671–675.

Singh, P., Pandey, P. C., Petropoulos, G. P., Pavlides, A., Srivastava, P. K., Koutsias, N., Deng, K. A. K., & Bao, Y. (2020). Hyperspectral remote sensing in precision agriculture: Present status, challenges, and future trends. In Hyperspectral remote sensing (pp. 121–146). Elsevier.

Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. Remote Sensing, 12(19), 3136.

Teodorescu, G., Moise, V., & Cosac, A. C. (2016). Spatial variation in blooming and yield in an apple orchard, in Romania. Annals" Valahia" University of Târgoviște-Agriculture, 10(1), 1–6.

Tiay, T., Benyaphaichit, P., & Riyamongkol, P. (2014). Flower recognition system based on image processing. 2014 Third ICT International Student Project Conference (ICT-ISPC), 99–102. https://doi.org/10.1109/ICT-ISPC.2014.6923227

Treder, W., Klamkowski, K., Tryngiel-Gać, A., & Wójcik, K. (2021). Application of ImageJ Software in the assessment of flowering Intensity and growth Vigor of Pear Trees. Journal of Horticultural Research, 29(2), 85–94.

Tsai, C.-M., & Yeh, Z.-M. (2008). Contrast enhancement by automatic and parameter-free piecewise linear transformation for color images. IEEE Transactions on Consumer Electronics, 54(2), 213–219.

United States Department of Agriculture (USDA-AMS). (n.d.). What is a Specialty Crop? | Agricultural Marketing Service. Retrieved May 24, 2024, from https://www.ams.usda.gov/services/grants/scbgp/specialty-crop.

Worthington, M. L., & Clark, J. R. (2019). Development of blackberry cultivars with novel plant architecture. XII I8nternational Rubus and Ribes Symposium: Innovative Rubus and Ribes Production for High Quality Berries in Changing 1277, 159–164.

Wu, Y., Zhang, C., Huang, Z., Lyu, L., Li, W., & Wu, W. (2022). Integrative analysis of the metabolome and transcriptome provides insights into the mechanisms of flavonoid biosynthesis in blackberry. Food Research International, 153, 110948.

Yahata, S., Onishi, T., Yamaguchi, K., Ozawa, S., Kitazono, J., Ohkawa, T., Yoshida, T., Murakami, N., & Tsuji, H. (2017). A hybrid machine learning approach to automatic plant phenotyping for smart agriculture. 2017 International Joint Conference on Neural Networks (IJCNN), 1787–1793. https://doi.org/10.1109/IJCNN.2017.7966067

Zhang, C., Craine, W. A., McGee, R. J., Vandemark, G. J., Davis, J. B., Brown, J., Hulbert, S. H., & Sankaran, S. (2020). Image-based phenotyping of flowering intensity in cool-season crops. Sensors, 20(5), 1450.