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# Developing Education, Research, and Extension Training on Precision Agriculture Phenotyping Tools at HBCU Communities

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**ABSTRACT.** *Precision agriculture aims to improve crop yields and assist management decisions using high-technology sensors and analysis tools, which involve data acquisition, data processing, and data analysis expertise of crops to determine associate crop solutions and outcomes. Florida A&M University (FAMU) Center for Viticulture and Small Fruit Research (CVSFR) is recognized internationally for excellence in warm climate grape research and facilitator of outstanding academic programs for experiential learning and student training. The Center is the only specialized research program among the 1890 colleges and universities dedicated to grape and wine, and it is a national leader in muscadine grape research. Currently, there is a critical need to develop education, research, and extension training on precision agriculture phenotyping tools at FAMU CVSFR. We developed a website that utilizes the digital image recognition algorithm that automatically calculates the muscadine grape canopy cover and berry cover from a digital camera/smartphone. This pilot platform has been used in students' experiential learning on precision agriculture phenotyping tools and data analytics as well as in agricultural extension in muscadine vineyards.*

***Keywords.*** *Data Sharing, HBCU Education and Outreach, Muscadine Vineyards, Precision Agriculture Phenotyping Tools, Sensors and Image Processing*

## Introduction

With the advancements of machine learning and artificial intelligence in digital agriculture, especially precision agriculture phenotyping sensors and tools. There is a gap between HBCU (Historically Black Colleges and Universities) education, research, outreach, and the advances in precision agriculture phenotyping technologies. To address this need, this project aims to develop education, research, and extension training on precision agriculture phenotyping tools at HBCU communities, by coordinating and enhancing available educational resources from top R1 institutions and determine best approaches for expanding cross-disciplinary training in plant phenotyping data collection, sharing, and analysis. We (1) developed educational materials focused on plants phenotyping tools applications, data collection (sensors, cameras, and smart phones), data sharing, and image processing; (2) launched an undergraduate research training program on precision agriculture phenotyping tools and applications for Minorities in Agriculture, Natural Resources, and Related Sciences at FAMU; (3) organized one Field Day at FAMU Center for Viticulture and Small Fruit Research for general public especially for growers, producers to collect and analyze plant phenotyping data in the Muscadine Vineyard by using the platform we developed.

Within the first objective, we focused on developing four educational modules. Firstly, we developed an image processing algorithm to estimate grapevine canopy using RGB images (Liang et al. 2018, 2021, and 2023). Canopy cover (CC) directly relates to crop water use, yield (Westgate et al., 1997), disease, and weed development (Ma et al., 2001). Rapid canopy development in crops leads to greater biomass accumulation, greater yield potential, and the fully CC suppresses early season weed. We used 4 muscadine grape (Muscadinia sp.)  wine cultivars (2 red: 'Noble' and 'Floriana'; 2 white: 'Carlos' and A-27-10) at the 2 phenological stages: 'mature leaf' and 'mature berry' at Viticulture Center. Secondly, we developed a website as the platform for users to upload images from digital camera/smart phone and calculate canopy cover automatically. Percentage of CC and grape pixel numbers can be analyzed and displayed at website. As users upload pictures of crop canopy, it also allows extension professionals to visually examine grapevine growth and yield. Third, we developed a module focused on introducing hyperspectral imaging technologies for plant phenotyping. Hyperspectral imaging (HSI) technology has been increasingly applied in plant phenotyping projects at different scales from plant tissues, whole plants, to canopy levels. It is mainly because HSI has great potential in measuring plant responses to various abiotic and biotic stresses at an earlier stage before being visible to human eyes. Most current HSI systems are expensive, and their signal quality is compromised by various noise factors, such as the changing ambient light, leaf slopes, and so on. In 2017, the "LeafSpec" handheld hyperspectral leaf imager was developed at Purdue, which overcomes most of the noise challenges (Wang et al., 2020). Last but not the least, we developed a module focused on "A Taste of Florida Viticulture".

This project makes precision agriculture phenotyping tools and technology more accessible, particularly to those with limited resources, will engage HBCU communities that are currently underrepresented in the precision agriculture field, and develop precision agriculture phenotyping tools and training activities tailored to multiple scientific communities and different career stages.

## Materials and Methods

The sections discussed below included software of Grapevine detection, followed by description of field sites, data collection procedures, preliminary data evaluation procedures, and finally website design.

### The image processing software – Grapevine Canopy Image Analyzer (GCIA)

*Experiment site and data collection*

In this study, the grapevine canopy cover (GCC) images were taken at two wine cultivars fields (Variety: Noble and Floriana) at the Viticulture and Small Fruit Research Center of Florida A&M University (30.4797, -84.1733). The vine cultivars of Noble and Floriana were harvested in late September, 2022. In addition to GCC images, leaf area index (LAI) was manually taken at two grapevine cultivar fields using LP-80 Ceptometer (METER Group, U.S.). LAI values were compared to GCC and grape yield. Simultaneously, images (2532×1170 pixels) were taken with smart phone camera (Apple model iPhone 12) mounted on a tripod set normal to the canopy 1.5 m from row axis and 1 m aboveground. Manual images and LAI were collected at the same time at each plot around 9:00 AM to 11:00 AM to guarantee data and image quality.

**Determination of grapevine canopy cover and grape**

Canopy cover images of grapevine were taken on nine dates in 2022 (June 7th, June 27th, July 5th, July 12th, August 3rd, August 12th, August 29th, September 7th, and September 13th). Images (2532×1170 pixels) were taken with smart phone camera (Apple model iPhone 12) mounted on a tripod set normal to the canopy 1.5 m from row axis and 1 m aboveground. Thirty representative canopy images from research plots during different growth stages were randomly selected to classify color groups and train an in-house designed software grapevine canopy image analyzer (GCIA) for estimating grapevine canopy cover (GCC) and grape cover (GC). GCIA utilized a supervised classifier based on Mahalanobis distance (Md) method to estimate CC and GC, which was used to determine soybean leaf area (Liang et al. 2018) and dry edible beans leaf area (Liang et al. 2021; Liang et al., 2023). The Md (Eqn. 1) measured the similarity between an unknown sample group and a known sample group.

$$Md = \sqrt{(X-Y)^T S^{-1}(X-Y)} \tag{1}$$

where X is a three-dimensional vector (R, G, B), which represented pixels from the image to be processed. Y is a three-dimensional vector ($\bar{R}$, $\bar{G}$, $\bar{B}$), which represented the average of reference pixels (reference group) for each class to be identified. The Mahalanobis color distance standardizes the influence of the distribution of each feature considering the correlation between each pair of terms. In the case of RGB color images, S is computed as (Eqn. 2):

$$S = \begin{bmatrix} \sigma_{R_{ref}R_{ref}} & \sigma_{R_{ref}G_{ref}} & \sigma_{R_{ref}B_{ref}} \\ \sigma_{G_{ref}R_{ref}} & \sigma_{G_{ref}G_{ref}} & \sigma_{G_{ref}B_{ref}} \\ \sigma_{B_{ref}R_{ref}} & \sigma_{B_{ref}G_{ref}} & \sigma_{B_{ref}B_{ref}} \end{bmatrix} \tag{2}$$

and as an example, the elements of S are calculated as:

$$\sigma_{G_{ref}R_{ref}} = \sigma_{R_{ref}G_{ref}} = \frac{\sum_{i=1}^{n}(R_i-\bar{R})(G_i-\bar{G})}{n-1} \tag{3}$$

where σ is covariance of R, G, B reference group colors, $R_i$, $G_i$, $B_i$ are the values of the $i^{th}$ match (i=1, 2, 3, ….n), and $\bar{R}$, $\bar{G}$, $\bar{B}$ are the mean color values for R, G, B in the given image, respectively.

In this study, eight reference groups of pixels were selected to generate the classification, in which every group represented relevant characteristics of grapevine canopy cover (4 groups), grape cover (1 groups), and background classes (2 group). The eight groups were identified as: light green leaves, light yellow leaves, dark green leaves, greyish green leaves, purple grape, shadow, and blue board background. If any of these classes were not present, or a new group or class appeared on the image, the number and/or the group labels would be modified. Each reference group was manually selected from a set of 30 GC images and a set of 20-30 color pixels with R, G, B, values in each reference group was chosen. The 30 canopy images were used to train GCIA to determine which pixel belongs to which group. After training GCIA, Md was computed over a set of 400 images. GCIA was written in C++ programming language (Stroustrup, 1995) and was programed on our developed peer learning agricultural network (PLAN) website (https://phrec-irrigation.com). Identified GCC and GC were shown as original color and purple color, respectively, and the background was shown as pink color in the output images. The GCC percentage was calculated using green area pixel number ($N_G$), purple area pixel number ($N_p$), and background pixel number ($N_B$) (Eqn.4). The GC percentage was also calculated in Eqn. 5.

$$GCC = \frac{N_G}{N_G+N_p+N_B} \times 100\% \tag{4}$$

$$GC = \frac{N_P}{N_G+N_p+N_B} \times 100\% \tag{5}$$

**The GCIA software refinement**

After evaluating the images from grapevine field days (280 images), most of the GC were detected but light pink grapes were not detected in the output images. Upon inspection of the problematic images, the color pixels of pink color were selected and pink color group was developed in grape class.

**Correlations of leaf area index (LAI), GCC, GC and grape yield**

Correlation was run between the GCC and LAI in each image at different sampling dates. The relationship of grapeyield at camera extent and GC in the image was also tested (SAS, 2022, Institute SAS Inc., Cary, NC). The coefficients of determination ($R^2$) was computed.

## Results and Discussion

**Performance of Grapevine Canopy Image Analyzer (GCIA)**

Depending on computer or smartphone GPU, it takes 3-6 seconds to process and display one image using GCIA. An example on sampling date 8/12/2022 of processed surface area of grapevine canopy by Md method is shown in Figure 1. Identified green leaves, berries, and background are shown as original, purple, and pink colors, respectively in the output image displayed at PLAN website (Figure 1). It can be seen that shadow pixels and background pixels were properly filtered. The classifiers for 7 reference groups performed well. The average GCC and GC percentage were 62.6% and 19.2%, respectively (Figure 1). As users upload pictures of grapevine canopy, it also allows extension professionals to visually examine grapevine growth and yield.

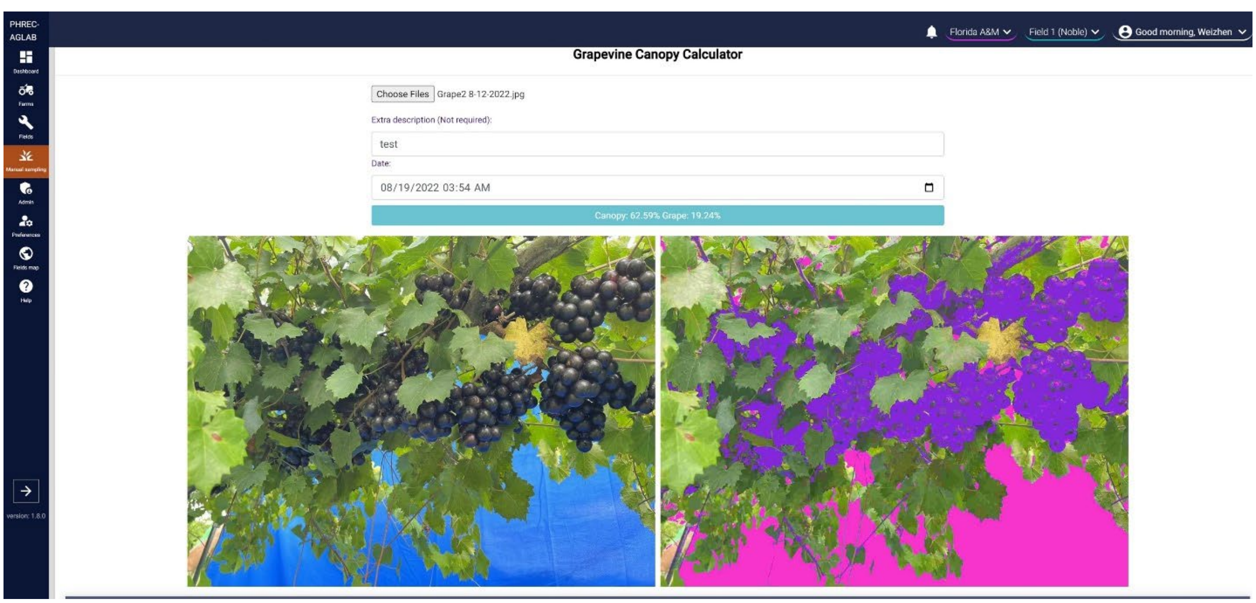
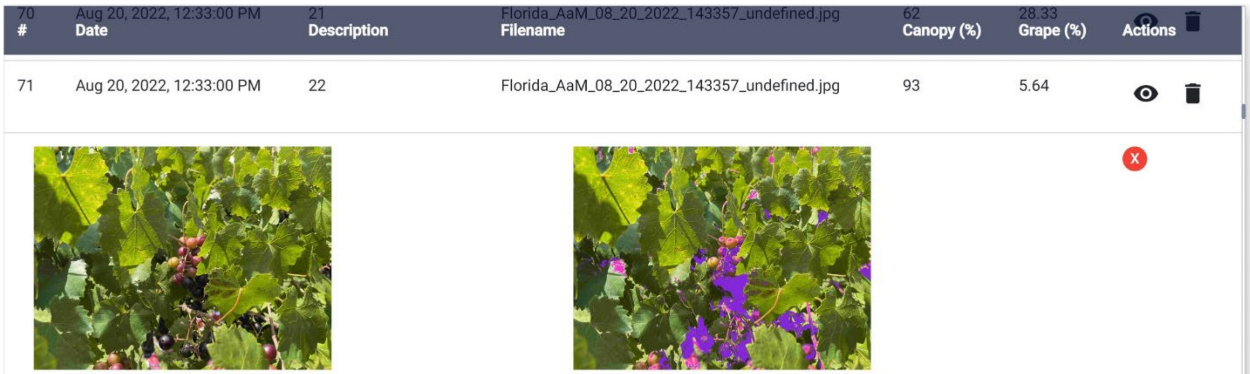


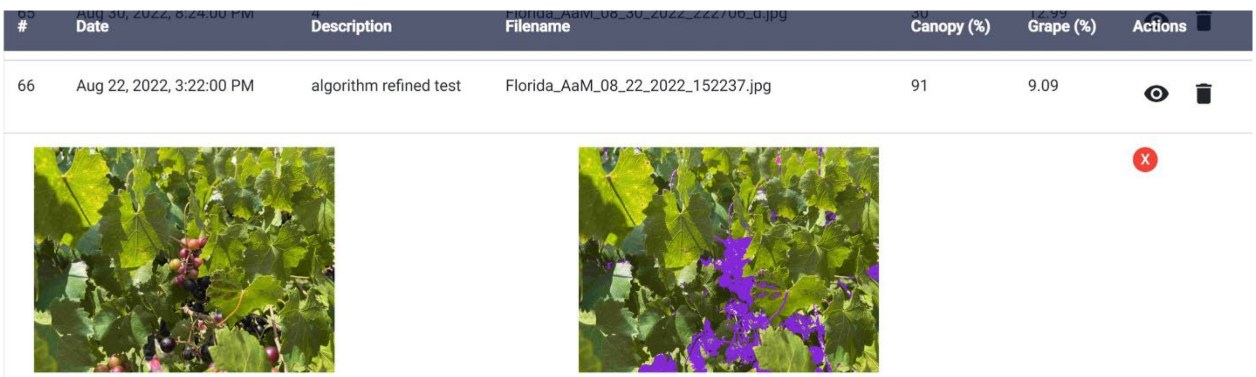

Figure 1. An example of original and processed canopy GCC and GC image collected by smartphone and uploaded to website on 8/12/2022. (The GCC and GC on processed image were 62.6% and 19.24%, respectively.

## Refinement of Grapevine Canopy Image Analyzer (GCIA)

The refinement of GCIA was utilized the images from grapevine field days. Most of the GC was detected (Figure 2a) but some of the light pink grapes were not detected in the output images. Upon inspection of the problematic images, the color pixels of pink grape were selected and new pink color group was developed in grape class. The refined GCIA increased accuracy of GC (Figure 2b).




(a) Original GCIA: GCC and GC were 93% and 5.64%, respectively

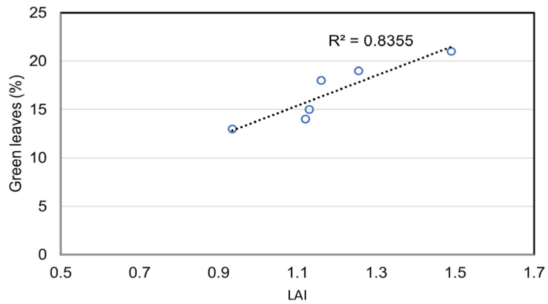



(b) Refined GCIA: GCC and GC were 91% and 0.1%, respectively.

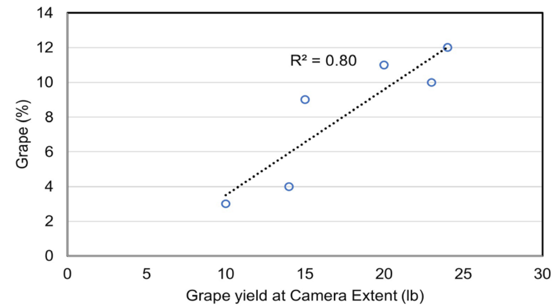
Figure 2. An example of image processed by original and refined GCIA. Image collected by smartphone and uploaded to website on 8/22/2022.

## Correlations of leaf area index (LAI), GCC, GC and grape yield

The green leaves of GCC and leaf area index (LAI) of grapevine (*Floriana* as example) showed linear relationship among 6 grapevines (Figure 3a). The GC in image (Figure 1) and yield at camera extent also represents linear relationship among 6 grapevines (Figure 3b)




(a)




(b)

Figure 3: (a) Linear correlation between LAI and green leaves (%) and (b) Linear correlation between grape yield at camera extent and grapes (%)

## Conclusion

This project produced four leading-edge precision agriculture phenotyping educational modules: Module 1 development of image processing algorithm to estimate grapevine canopy using RGB images; Module 2 website development for users to upload images from digital camera/smart phone and calculate canopy cover automatically; Module 3 introducing hyperspectral imaging technologies for plant phenotyping and GIS server for geo-referenced imaging measurements; Module 4 A Taste of Florida Viticulture Lecture. With these modules, we showcase both easy-to-obtain and the most advanced imaging technologies to limited resource students and farmers to get started in learning digital applications utilizing sensing and data infrastructure to improve the agricultural production efficiency.

We successfully launched an undergraduate research training program on precision agriculture phenotyping tools and applications for Minorities in Agriculture, Natural Resources, and Related Sciences at FAMU. By leveraging the current resources, students were trained to conduct firsthand fieldwork as well as to develop different types of data collection and data analysis skills. Students also had an increased experiential learning on a precision agriculture phenotyping tool and its application. We successfully organized one Field Day at FAMU Center for Viticulture and Small Fruit Research for general public especially for growers, producers to collect and analyze plant phenotyping data in the Muscadine Vineyard by using the platform we developed (> 500 participants).

## Acknowledgment

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