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Evaluation of a Low-Cost UAS and Phenocams for Measuring Grapevine Greenness

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Evaluation of a Low-Cost UAS and Phenocams for Measuring Grapevine Greenness

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Master of Arts in
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ABSTRACT

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Timothy J. Hoheneder

Unpersoned aerial systems (UAS) could provide winegrowers with the potential to monitor vineyard productivity with ultra-high-resolution imagery and low operational costs. This ability could prove particularly valuable in the challenging cool-climate viticultural areas of Appalachia. Especially in this mountainous region of increasingly variable microclimates, there could be great value from an ability to use UAS-measured greenness to monitor wine grape phenology and predict harvest quality and quantity. In this study, I assess how UAS-measured greenness relates to three complementary measures of field-based: leaf angle measurements, phenocam measured greenness, and leaf spectral measurements of greenness. After correlating these field-based measures of greenness to UAS-measured greenness, I evaluate whether UAS-sensed greenness can predict spatial and temporal patterns in seasonal wine grape phenology.

I collected imagery every other week between June and September 2020 from a DJI Mavic 2 Pro UAS platform, focusing on three blocks of Marechal Foch varietal grapes at the Christian W. Klay Winery in Chalkhill, Pennsylvania. I also collect weekly leaf angle and greenness measurements from consumer-grade phenocams. From these data, I employed multivariate regression to assess the relationship of UAS-measured greenness to the three field-based measures of greenness. Based on these tests, I concluded that UAS-measured greenness is not highly correlated across space and time with field-based measures of greenness. I hypothesize this might be due to highly vertical leaf angles present on the grapes vines limiting the amount of assessable green area from the perspective of the UAS.

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1. Motivation and Objectives:

Unpersoned aerial systems (UAS) provide winegrowers a means to monitor vineyards with repeatable, ultra-high-resolution aerial imagery collected with low operational costs (Borgogno & Gajetti, 2017). The field of precision viticulture is a subset of the broader study of precision agriculture and is applied explicitly to grape and fruit wine production areas to improve agricultural practices through the implementation of spatially explicit technologies (Arnó Satorra, et al., 2009). As a part of precision viticulture, UAS imagery analysis can provide timely and spatially explicit information regarding the ecological status and productivity of individual grapevines (Pichon et al., 2019). Extensive surveys monitoring vine status can now be rapidly performed through UAS-based imagery sources and software to analyze image properties of individual grapevines. When analyzed, UAS imagery of individual grapevines combines with local knowledge of commercial vineyards and facilitates the development of more efficient vineyard management strategies. Ideally, a more complete understanding of spatial variability allows vineyards to evaluate the economic investment of management practices, providing geographic rationale for irrigation, fertilization, and labor operations (Bramley et al., 2003).

While aerial and satellite imagery is available for vineyard monitoring, infrequent revisits periods or economically infeasible costs associated with obtaining regular imagery prove a barrier to many vineyards. Additionally, for United States vineyards, commercial satellite imagery laws and restrictions capped maximum spatial resolution of imagery at 25cm, wherein the resolution was often too coarse to discern nuances associated with viticulture (Lejot, 2017). While ground-based measurement alternatives are also available, these systems also prove costly as a sensor must be identified for a specific purpose, purchased, employees trained to use the sensor, and conducting any surveys (Turner, 2011). UAS-based precision viticultural systems bypass these constraints as most UAS-based imagery is privately collected, leading to output spatial resolutions that can potentially be as low as 0.75cm/pixel (Lejot, 2017). Given the ultra-high spatial resolution, the nearly instantaneous ability to deploy a UAS into the vineyard, and the capability to outfit UAS platforms with sensors for user-defined purposes, the attraction to these autonomous platforms revolutionizes how a millenniums-old trade conducts itself. UAS-based surveys are a preferred alternative to traditional aerial or satellite imagery due to the low overhead cost of the UAS platform and the ability to frequently revisit the study site (Van Lersel et al., 2018).

The purpose of this study is to analyze the potential of UAS precision viticulture to track UAS-measured seasonal greenness in a vineyard spatially and temporally through a low-cost, consumer-grade UAS platform. Greenness is the quantity of green light reflected by vegetation which can be used to indicate the efficiency of various phenologic processes. Previous studies indicate greenness is highly correlated with several photosynthetically driven processes such as gross primary production, canopy leaf area, and carbon dioxide exchanges (Peichel et al., 2015, Reid et al., 2016, Richardson et al., 2018). While UAS-measured greenness has been incorporated previously in vegetation studies, I believe the approach to track greenness in viticulture from a UAS platform is entirely novel (Browning et al., 2013). Additionally, while previous studies identified that measuring single instance or short-term greenness from UAS

platforms is possible, there is no evidence of tracking seasonal greenness solely from UAS-based imagery (Browning et al., 2013, Van Lersel et al., 2018). Such, I believe this study's aim to measure seasonal greenness in a viticultural setting is also unique.

As visually described in **Figure 1**, my objectives are to:

- (1) Test the potential for UAS platforms to monitor seasonal greenness effectively and accurately in a vineyard setting
- (2) Relate spatial and temporal patterns of field-measured vine greenness to UAS-measured vine greenness.
- (3) Develop standardized UAS imagery and GeOBIA classification routines to extract UAS-measured vine greenness from individual vines

Fig. 1: Visual flowchart of data collection methods (ovals), derived data layers (rectangles), and statistical testing of the three project hypotheses (red arrows).

2. Study Area and Equipment:

2.1. Study Area:

The study area is the Christian W. Klay Winery, located in Chalkhill, Pennsylvania. The Christian W. Klay Winery is a 215-acre commercial vineyard owned and operated by John and Sharon Klay. I selected this vineyard site due to interest in evaluating the impacts of climate change upon agriculture in the Appalachian region of the United States. Appalachia has a unique opportunity to benefit from the viticultural industry because climate change has increased regional growing capabilities (Christmann et al., 2017). Precision viticulture could be extremely valuable in the emerging cool-climate viticultural areas of West Virginia, Pennsylvania, and Maryland. Warming temperatures, increased spatial and temporal variability in rainfall, and a longer growing season from climate change could bring improved growing conditions that translate to positive economic impacts from Appalachian viticulture (Fernandez & Zegre, 2019).

Ten actively producing Marechal Foch vines were randomly selected across three different blocks in the vineyard. I selected vines across three blocks to facilitate assessing spatial variability in UAS-measured greenness (**Fig. 2**). Soil morphology for the vineyard is that of a well-irrigated silty loam. The underlying lithology of the vineyard is sedimentary, with the Mississippian Wymys Gap fossiliferous limestone member being the most surficial unit (Kammer & Springer, 2008). Topographical variation includes 17.6m (57.75ft.) of total elevation change across the vineyard, where the lowest elevation of approximately 453.1m (1,486.55ft) is found in the northwestern portion of the study area and follows a gradual rise to a maximum extent of 482.8m (1584.0ft.) in the southern portion of the study area. According to vineyard managers, there are no known issues with flooding in the vineyard, and the property is classified as well-drained (Klay, Personal

Fig. (2): Location of Study Vines at the Christian W. Klay Winery Study Site

Communication). Shade from either topography or surrounding vegetation is not present during the day on the Marechal Foch rows.

2.2. Equipment:

I flew a DJI Mavic 2 Pro UAS owned by Dr. Trevor Harris of West Virginia University. The DJI Mavic 2 Pro weighs 907g before the addition of any additional onboard sensors. The primary sensor of the DJI Mavic 2 Pro is a 1" CMOS visible digital camera sensor that captures 20 million effective pixels per still image capture (5472x3648) and formats images into a .JPEG file type ("Mavic 2 Specs"). All images collected by this sensor were within the visible optical light electromagnetic spectrum (380-740nm) in a true color Red, Green, Blue band configuration. The average maximum flight time for the DJI Mavic 2 Pro is listed by the manufacturer to be up to 31 minutes if no additional payload is present. I flew all 2D single grid and 3D double grid flights within FAA Part 107 civil UAS regulations. Chalkhill, Pennsylvania, is within FAA Class G airspace and did not require advanced ATC flight authorization.

3. Hypotheses:

Building on findings from other global wine regions (Alessandrini et al., 2016, Moura et al. 2019, Sun et al. 2017), I hypothesize that:

- (H₁): Field-measured vine greenness will be highly correlated across space and time when compared between spectrometer and phenocam measures of vine greenness
- (H₂) UAS-measured vine greenness will be highly correlated across space and time when compared to spectrometer measures of vine greenness
- (H₃) UAS-measured vine greenness will be highly correlated across space and time when compared to phenocam measures of vine greenness

4. Materials and Methods:

4.1. Field Measurements of Greenness:

I employed field measurements to determine the canopy greenness of the ten study vines. Greenness is the measure of green light-reflectance that can be remotely sensed from plant species. Greenness functions to measure various plant-based properties such as the canopy density, vigor measurements, and overall ecological status (Ollinger, 2011). While NDVI could be a proxy for greenness, the ability to measure greenness based on individual grapevine canopies is also essential to observe as it directly measures the leaves' vigor or ecological functionality status with the optical spectrum. A higher amount of greenness means the plant is healthier and will produce at a higher level (Ollinger, 2011). I visited the Christian W. Klay Winery

<u>Field Measurement Number</u>	<u>Date of Field Measurements</u>	<u>Day of Year</u>	<u>Shape</u>
1	June 15th	167	Filled Circle
2	June 24th	176	Filled Square
3	July 9th	191	Filled Diamond
4	July 25th	207	Filled Triangle
5	August 8th	221	Hollow Circle
6	August 21st	234	Hollow Square
7	September 4th	248	Hollow Diamond
8	September 10th	254	Hollow Triangle

Table 1: Dates of Field Visits to the Christian W. Klay Winery

approximately eight times throughout the 2020 growing season to make field measurements from June 15th, proceeding véraison, through harvest on September 11th (**Table 1**).

4.1.1. Mean Leaf Greenness:

I measured mean leaf greenness (MLG) in the field using an ASD Fieldspec 3 spectrometer. The ASD Fieldspec 3 has a spectral range of 350-2500nm, a spectral resolution of 3nm within the visible spectrum at 700nm, and a sampling interval of 1.4nm for visible wavelengths (Elmer et al., 2020). On each of the ten study vines, I used the ASD Fieldspec 3 spectrometer to measure greenness using the green chromatic coordinate (GCC) (**Eq. 1**) of four vine leaves for each field site visitation date. I randomly sampled fully intact leaves for greenness within each vine canopy of the ten study vines. I selected fully intact leaves to ensure the ASD Fieldspec 3 only measured the sampled leaf and did not include background atmospheric reflection. After sampling each vine, I calibrated the ASD Fieldpsec 3 to a spectralon white reference disk. I recorded and logged all records of greenness electronically using the laptop computer that the ASD Fieldspec 3 directly attaches to and exported all files to a local desktop computer for further data analysis. I calculated the GCC employing 650nm as a single band measurement for the Red wavelength and 550nm and 450nm as measurements for Green and Blue wavelengths.

$$GCC = \frac{Green}{(Red + Green + Blue)}$$

Eq. 1: Green Chromatic Coordinate (GCC) Image Ratio for Vegetation

4.1.2. Phenocam-Measured Greenness:

I calculated the phenocam-measured greenness (PMG) coverage using 20MP RGB Moultrie Wingscapes Timelapse Cameras (phenocams) mounted adjacent to the grapevine canopy. A phenocam is a digital camera producing a time series of images used to track changes and responses in plant phenology. The Wingscapes Timelapse phenocams autonomously took a single image each hour between 11:00am and 4:00pm each day of study duration (**Fig. 3, Fig. 4**). I selected an image from each field visit at 1:00pm, as this time was close to solar noon and limited the effects of casted shadows in the images (Saitoh et al., 2012). A complete listing of imagery dates is identical to the field visit dates present in **Table 1**. Several incomplete sets of images exist throughout the study for various critical issues relating to camera positioning or status. Those critical issues are five images from Study Vine 2's camera accidentally being rotated by vineyard staff, four images Study Vine 4's camera failing to save images, and a leaf growing in front of Study Vine 10, disallowing three images.

I extracted greenness from the timelapse phenocam images by extracting a measure of greenness using the phenopix R package code (Fillipa et al., 2016). This code package allowed me to draw an area of interest on a single time-lapse image and extract mean average RGB DN values from that specific area I converted to GCC (**Fig. 4**). Given that the image extent does not change between images, the code generates a seasonal time series of greenness for each

timelapse phenocam imagery set. I repeated this process for each of the ten study vines, producing a separate phenocam-derived greenness curve for each phenocam image series.

Fig. (3): Moultrie Wingscapes Timelapse Camera Mounted Adjacent to Study Vine 5

Fig. (4): Phenocam Timelapse Image with Area of Interest (AOI) for GCC Calculation and Leaf Angle Measurement Area for Study Vine 8

4.1.3. Leaf Angle Measurements:

I measured the leaf angle of the 10 study vines using digital images from the Wingscapes Timelapse phenocams. From these images, I measured the mean leaf inclination of three different leaves using a digital protractor and recorded the mean angle of the leaves based upon the zenith and distance from leaf normal of observed leaves (McNeil et al., 2016) (**Fig. 4**). I recorded the mean leaf angle at the same time, and interval of phenocam-measured greenness as both originated from the same imagery source.

4.2. Collection of UAS Imagery:

4.2.1. 2D Single Grid Flight Pattern:

I flew the DJI Mavic 2 Pro in a 2D single grid flight pattern at 100ft. (30.48m) elevation to collect imagery. I used the Pix4Dcapture UAS flight planning mobile app to flight plan and collect imagery for the DJI Mavic 2 Pro UAS. I employed a standardized flight plan similar to the flight plan presented in **Figure 5**. I optimized my approach using the highest ground sampling distance (GSD) possible. The flight path is also optimized because I rotated the extent of my flight area to be aligned with vineyard block orientations, reducing unnecessary flight time capturing non-vineyard areas. I selected the maximum frontal and side overlap for images of 90% overlap to capture the greatest number of images for analysis and to limit the effects of BRDF most efficiently. For this flight pattern, I selected a 90° camera angle to minimize the effects of object lean. I flew the imagery close to solar noon to limit the effects of casted shadows away from nadir (Rahman et al., 2019). I flew imagery for each field visitation date using identical flight plans and imagery capture techniques. All dates of aerial imagery during the study were sunny and featured limited broken to no cloud cover. Dates of UAS imagery collection are identical to dates of field measurements (**Table 1**).

Fig. (5): Example 2D Single Grid Flight Pattern, Captured in the Pix4D Capture Interface

4.2.2. 3D Double Grid Flight Pattern:

The 3D Double Grid flight pattern is optimal for producing a digital canopy model (DCM) dataset to view the vineyard. I flew the first grid in a North-South orientation before flying in a perpendicular East-West orientation to produce the second grid. The change in flight orientation allows any objects within the imagery extent to be captured from multiple viewership angles to produce a DCM employing a structure from motion (SfM) technique of 3D imagery acquisition (Weiss & Baret, 2017). Each flight utilizes the default Pix4D Capture setting of a 70° camera angle with a modified 100% image overlap setting. As mentioned previously, a 100 feet (30.48m) flight altitude and flight extents are kept consistent across all imagery dates. A DCM model for analysis only requires this type of imagery to be flown once during maximum canopy extent.

4.3. Processing UAS Imagery:

4.3.1. Digital Canopy Model (DCM) and Orthomosaic Imagery Production:

To create the DCM and orthomosaic images, I applied standard routines in the Drone2Map software program. I utilized Drone2Map software to create orthomosaic images from the imagery collected from the 2D single grid flight patterns and produce a DCM from the 3D double grid imagery. Before processing, I eliminated images with moving objects, blurriness, sun glint, or any other factor or property deemed to be unsatisfactory from the datasets. I exclusively used images from each flight date and did not supplement orthoimages with images taken on separate flight dates. Drone2Map generates a report summary of the imagery products that includes a quality check of imagery products. Based upon the Drone2Map imagery quality report, all flights I conducted across all dates were satisfactory.

4.3.2. Radiometric Calibration for Orthomosaic Imagery:

Previous users of Drone2Map highlight that my low flight altitude and imagery processing routines mitigate the need for atmospheric correction (Stow et al., 2019). I employed a high degree of image overlap (90% image overlap) within the Pix4D Capture interface so that mosaicking of the imagery will also improve radiometric properties (**Fig. 5**). These procedural steps and collecting UAS imagery at solar noon with a high degree of overlap help mitigate the bidirectional reflectance distribution function (BRDF) related issues that can affect optical imagery (Laliberte et al., 2011).

4.3.3. Delineation of Grapevine Canopy:

I delineated grapevine canopies to extract UAS-measured greenness for the study vines. I placed 3D Flight Pattern orthoimagery from the DJI Mavic 2 Pro optical sensor into Trimble eCognition Developer alongside the 3D digital canopy model (DCM) imagery product to conduct a Geographic Object-Based Image Analysis (GeOBIA) procedure. Following the procedure of De Castro et al. (2018) and Mestas-Carrascosa et al. (2020), a multiresolution segmentation and classification procedure, I extracted only the grapevine canopy to compute the accuracy of my GeOBIA delineation. I used the same orthoimages collected by the UAS to hand delineate each of the vineyard blocks. De Castro et al. (2018) and Mestas-Carrascosa et al. (2020)

define an acceptable accuracy as correct classification above 90% overall accuracy within the confusion matrix. I conducted the GeOBIA delineation procedure in three sub-section procedures, with each procedure focusing on a specific portion of data management.

4.3.3.1. Manual Delineation:

I first manually delineated the orthoimages, so the extent of the grapevine canopy within each vineyard block could be classified. I performed all manual delineations utilizing UAS imagery products collected on September 4th, 2020. I manually delineated the three vineyard blocks within the ESRI ArcMap 10.5.1 software by outlining and digitizing grapevine row extents. The value of delineating orthoimagery into canopy extents provides an established basis to compare the GeOBIA classification against. I assumed that my hand delineation of vineyard canopies was expertly performed and entirely accurate. Given the imagery resolution and the complex shape of grapevine canopies, while I assume some degree of user error is present in the delineation, I do not consider this likely source of error.

4.3.3.2. GeOBIA Segmentation and Classification:

The second portion of the procedure is delineating the canopy extent using a Geographic Object-based Image Analysis (GeOBIA) methodology. Segmentation evaluates the original imagery and develops polygons of various spectral properties. The specific procedure followed for this GeOBIA segmentation and classification includes improvements that Puletti et al. (2014) and Kass et al. (2011) developed to classify non-vegetated interrow structures. The authors consider that while the spectral contrast between dark soils and green vines might be the most substantial classification technique, accuracy would improve by considering object geometry, specifically the linearity of grapevine row structures.

I completed the segmentation procedure using the Multiresolution Segmentation algorithm present in Trimble eCognition Developer. This algorithm separates pixels into similar structures of a defined size, objects, based upon pixel spectral properties. A spectral weighting was applied to the green wavelengths to be valued twice as high as any other band. Green reflectance serves as a proxy of the green grapevine canopies and better distinguishes canopy structures from darker soils or other vegetation (Taskos et al., 2013; Nolan et al., 2015). I considered a small shape factor of 15 for segmentation due to the relative size of the grapevine canopy in the imagery.

To classify grapevine canopies as being inclusive of vineyard structures or not. I selected four threshold properties in a Boolean AND fashion for polygon classification. First was the mean green reflectance value of the segmentation polygons. High levels of green light reflectance characterize pixels in the canopy, so I selected a digital number (DN) value of 100 as a threshold based upon a random sampling of potential canopy polygons. Pixels found above the threshold DN value were then subjected to a contrast test. Pixel contrast displays regions where the contrast between a single segmented polygon and at least one of its adjacent members was high. Only one adjacent member was selected as segmented polygons could also border other canopy segments. I defined a contrast value ratio of 145:95 for the green wavelength based upon sampled mean DN values of canopy segments and interrow segments. Third, based on the

recommendations of De Castro et al. (2018), I included a height-based segmentation rule to identify canopy areas better. Since the study area does not include interrow cropping in most areas, the height difference between vines and the block surface is substantial. I employed a height-based rule of vineyard canopies having to at least be 25cm from the surface, based upon DCM-listed heights. I chose a low height threshold as I theorized that soil would not reasonably be at the same height as vine canopies. Finally, I used polygon length to classify the segmented polygons fully. I defined the length as the maximum length within the polygon at any point from the defined compass bearing of the vineyard row. In all three blocks, there was no variation in row orientation bearing. I then sampled the length threshold across expected canopy polygons and defined inclusive polygons at greater than 15 pixels in length.

4.3.3.3. Comparison of GeOBIA and Manual Delineations:

Following the GeOBIA classification, I compared the GeOBIA classified vine rows and the manually delineated rows. I first merged all values of "Vine" polygons in the GeOBIA products into a single polygon unit. Once merged, I created a raster grid at an identical spatial resolution of the orthoimage using the spatial extent of the GeOBIA canopy extents as a mask. I performed the same extraction and simplification procedure on the manually delineated canopy areas to create a uniform comparison raster. Finally, I compared the extent of the GeOBIA delineation to the extent of the manual delineation using a Boolean overlap equation. Based upon the nature of raster overlap, I generated a confusion matrix for classification accuracy assessment using the number of pixels properly classified. No class-based weighting was applied when calculating the confusion matrix.

4.3.4. UAS-Measured Greenness:

Following the delineation of vineyard rows, I extracted UAS-measured mean greenness from each of the study vines in each vineyard block per imagery date. I extracted GCC values from an overlay mask area that coincided with any pixels within a 0.75m buffer of the vine trunk and within the canopy extent identified from the GeOBIA procedure (**Fig. 6**). After computing this greenness sampling region, I took the mean RGB DN pixel values from each greenness sampling region. Using these RGB values, I calculated the GCC value as a proxy for UAS-measured greenness (**Eq. 1**). I performed this procedure for each study vine in each block and across each date of UAS imagery.

4.3.5. Statistical Validation of Results:

Simple linear regression assesses the relationship of UAS-measured greenness against mean leaf greenness and phenocam-measured greenness (**Fig. 1; H₂, H₃**). I conducted regression analysis in the JMP Pro 13 statistical software suite. I compared the UAS-measured seasonal greenness of each unique study vine against the seasonal curves generated from measuring mean leaf greenness and phenocam-measured greenness independently. In addition to raw GCC values, I converted all GCC ratios from each dataset to a z-score value to normalize across different relative gain settings that might be present across the three sensors. I assessed the correlation and strength of the relationship between my variables based upon subsequent R^2 values. I tested for statistical significance indicated by a p-value ≤ 0.05 . Regression tests my

hypothesis that UAS-measured vine greenness can be effectively measured from a low-cost UAS Platform and will correlate highly across space and time when compared to two different field-measured greenness.

5. Results:

5.1. GeOBIA Delineation of Grapevine Canopy:

The overall classification accuracy for the GeOBIA procedure upon the grapevine canopy based upon the September 4th imagery is 96.00%, indicating a very high level of classification accuracy and precision (**Table 2**). Variances from true-positive and true-negative classifications are primarily found on the edges of the grapevine canopy in regions where green, interrow vegetation is present in the imagery. The largest source of false-positive classifications stems from large weeds and interrow vegetation present in vineyard rows that likely exceeded the height-based classification threshold of 25cm. As weeds and interrow vegetation are also green, neither provided enough spectral contrast to be identified separately from the canopy extent. In contrast, most false-negative classification regions were regions on the edge of the grapevine extent where the canopy might have been thin and not correctly recorded in the DCM, also leading to improper classification.

Fig. (6): GeOBIA Canopy Classification and GCC Extraction Area for UAS-measured Greenness Surrounding Study Vines 3 and 4

n=10,686,949	Manual			User's (%)
GeOBIA		Correct	Incorrect	
	Correct	1,642,231	135,777	92.36
	Incorrect	291,200	8,617,741	96.73
Producer's (%)		84.94	98.45	96.00

Table 2: Confusion Matrix for GeOBIA Vineyard Canopy Classification

5.2. Field-Based Measurements of Greenness:

Figure 7 and **Figure 8** indicate the seasonal profile of greenness in GCC measured by PMG and MLG against the day of year. The general linear trend in both field-measured seasonal greenness profiles displays that greenness slightly decreased on average as the growing season continued.

A comparison of seasonal, field-based measures of greenness calculated between PMG and MLG in terms of z-score values is present in **Figure 9**. Each datapoint aligns the PMG z-score to the MLG z-score for each study vine on each date of field study. PMG-MLG data points are not included for dates where I did not collect PMG measurements due to phenocam collection issues. The R^2 value representing the correlation between the two measures of greenness is 0.54, indicating a significant, positive relationship between the two variables that is visibly apparent in **Figure 9**.

Fig. (7): Mean Leaf Greenness against Day of Year for each Study Vine indicating a general trend of greenness slightly decreasing over time. The range of GCC values observed for MLG is 0.021

Fig. (8): Phenocam-Measured Greenness against Day of Year for each Study Vine indicating a general trend of greenness slightly decreasing over time. The range of GCC values observed for PMG is 0.014

Fig. (9): Relationship Between Seasonal, Phenocam-Measured Greenness and Mean Leaf Greenness Measurements Using Normalized Z-Scores. The relationship is significant with $R^2=0.054$

5.3. Leaf Angle Measurements:

The leaf angle found across 68 conglomerated mean leaf angle measurements across ten study vines all exceed an average inclination of 45° , indicating the Marechal Foch vines display highly vertical leaves (**Fig 10**). The average angle of inclination varied from a minimum of 58.6° to a maximum of 88.2° inclination. The average leaf angle found in the vineyard was an inclination of 74.3° . Based on the distribution of leaf angles, there is a bimodal distribution where the highest quantity of leaf angles measured centered on peaks of 70.0° and 80.0° .

Fig. (10): Distribution of Leaf Angle Measurements Across the 10 Study Vines. An Average Leaf Angle of 74.1° Indicates Highly Vertical Leaves

5.4. UAS-Measured Greenness:

Unlike the line graphs produced for field-based greenness measurements, the UAS seasonal greenness profile displays a general linear trend of greenness increasing over time (**Fig. 8, Fig. 9**). Additionally, a more substantial range is present for UAS-measured GCC values than for either of the two field-based measures of greenness, with GCC values having a full range of 0.109 for UAS-measured greenness compared to GCC ranges of 0.014 and 0.021 for PMG and MLG, respectively.

The R^2 value between UAS-measured greenness and MLG was 0.002 for GCC values and 0.04 for z-scores (**Fig. 12**), indicating no significant correlation for either metric. The R^2 value between UAS-measured greenness and PMG was 0.001 for GCC values and 0.008 for z-scores (**Fig. 13**), indicating no significant correlation between the two measures of greenness.

Fig. (11): UAS-Measured Greenness against Day of Year for each Study Vine indicating a slight increase in greenness over time. The range of GCC values observed for UAS-measured greenness is 0.109

Fig. (12): Relationship Between Seasonal, Mean Leaf Greenness and UAS-Based Greenness Measurements as GCC Values. The relationship is not significant with $R^2=0.02$

Fig. (13): Relationship Between Seasonal, Phenocam-Measured Greenness and UAS-Based Greenness Measurements as GCC Values. The relationship is not significant with $R^2=0.001$

6. Discussion:

Based upon the R^2 values correlating UAS-measured greenness against MLG and PMG, there is little evidence that a low-cost UAS platform can adequately measure greenness across space and time in a vineyard. All correlations of UAS-measured greenness against field-measured greenness contained an R^2 value between 0.001-0.04, displaying a lack of any significant relationships (**Fig. 12, Fig. 13**). While I did observe a significant, positive relationship between the two field-based measurements of greenness (**Fig. 9**), there is no quantitative indication to support that a low-cost UAS can effectively measure seasonal greenness. Other studies concluded that UAS-measured GCC values were more accurate than other greenness indices; these studies were exclusively conducted on a single image or short-term study basis in a non-viticultural lens (Larrinaga & Brotons, 2019; Li et al., 2020, Van Lersel et al., 2018).

The success of this study is the effectiveness of low-cost phenocams effectively measuring trends in seasonal greenness compared to the more expensive personal spectrometer or UAS-based platforms. Phenocams succeeded in this study due to the biophysical properties of the grapevine canopy leaves. Sampled leaf angles in the vineyard all exceeded 55° mean leaf inclination and were regularly measured over 65° from normal (**Fig. 10**), indicating highly vertical leaves. These highly vertical leaves are represented well in planimetric, side-view phenocam imagery and thinly in UAS imagery collected from above (**Fig. 4**). A more vertical leaf angle, an inclination greater than 45° , provides a reduced green leaf area surface for the UAS

to collect greenness across. In comparison, while leaf angle is independent of generating 1D spectrometry measurements, the side-based 2D viewership of the phenocams and vertical leaves provided a more significant green-leaf surface to extract greenness measures accurately.

A more vertical leaf angle, an inclination greater than 45° , provides a reduced green leaf area surface for the UAS to collect greenness across from the overhead 3D canopy perspective. Associated with the reduced green-leaf area, returns converged on the top of the grapevine canopy due to the overhead perspective of the UAS. Previous studies indicate that top of the canopy leaves often display more vertical leaf angles confirming they likely provide less viewership to UAS-based measurements of greenness (McNeil et al., 2016). Similarly, there is confirmation that greater canopy reflectance decreases with higher leaf angle measurements even with significant variation in leaf angle distribution amongst an individual species. This confirmation indicates UAS-measured greenness likely was negatively influenced by the vertical leaf angles exceeding 60° (Asner, 1998). Given that 67 of 68 leaf angle measurements were at or exceeded 60° , there was a high density of these low-viewership leaves. While previous studies indicate methods for rapidly measuring leaf angle distribution with a UAS and leaf angle measurements within a vineyard setting, there is little literature on how leaf angle varies across different species and varieties of grapevines (Bailey & Mahaffee, 2017, McNeil et al., 2016).

Pertaining to camera settings, consistent, accurate calculation of GCC based upon RGB DN values proved difficult due to the sensitivity levels of the UAS digital camera sensor. As indicated in previous studies, the rate of inconsistency, overexposure, and underexposure in UAS-based RGB imagery produced inaccurate estimations of DN values (Pádua et al., 2018). Based solely upon the range of GCC values calculated, UAS-based measurements had the broadest range of values with a numerical range of 0.109, compared to ranges of 0.021 and 0.014 for MLG and PMG-measured GCC accordingly (**Table 3**). This noisier range of DN values for UAS-measured greenness represents more significant variability in what the onboard UAS sensor collected, leading to more randomized, uncorrelated results across collection date and study vine when compared to significantly correlated results between PMG and MLG greenness (**Fig. 12, Fig. 13**). It is possible to filter settings in the onboard camera favor producing vibrant, colorful images during flight that align with hobbyist applications of UAS platforms (Grant, 2017). While ideal for recreation imaging purposes, the more vivid, dynamic range the onboard UAS camera provides is not beneficial for repeatable spectral measurements over multiple imaging dates when taken in tandem with presented biophysical issues in measuring greenness.

<u>GCC Collection</u> <u>Method</u>	<u>GCC Range</u>
MLG	0.021
PMG	0.014
UAS	0.109

Table (3): Range of GCC Values by GCC Collection Method. UAS-Measured Greenness Displays a GCC Range over Five Times as Large When Compared to MLG or PMG Methods

Conversely, while colorful settings are hindrances when conducting quantitative spectrometry measurements, a more comprehensive color range in UAS imagery is valuable for classification-based precision viticulture applications. The vibrant, high contrasting imagery of grapevine canopies aided GeOBIA classification accuracy as spectral contrast was an input segmentation-classification parameter. The high color contrast between dark soils and bright green vegetation maintains a practical purpose in segmentation and classification procedures as the overall GeOBIA classification accuracy was 96.0% accurate (**Table 2**). As noted above, many of the improperly classified regions, false-positive and false-negative, lack spectral differentiation due to green, vegetated interrows. The lack of contrast, despite the DCM, made these regions more difficult to classify correctly, leading to decreased measures of classification precision, 92.36%, and recall, 84.94%, from the classification (**Table 2**). However, the addition of the DCM, varying from previous models, did improve the accuracy where height was an effective classifier given the smallest number of classified pixels are false-positives (Matthews & Jensen, 2012; Pádua et al., 2018). Conversely, many of the false-negative regions classified in the GeOBIA algorithm are located on the border of the grapevine canopy where high spectral contrast was present, but the canopy was thin enough that the DCM lacked the height-based signature. In these scenarios, the algorithm likely identified these sectors as interrow vegetation, lacking the spectral contrast but not being elevated enough for the algorithm to classify them as canopy inclusive. Instances of this paradox are found in the GeOBIA segments, where false-negative areas improperly classified as part of the interrow are often only a cluster or two of leaves that the DCM did not record. However, given the incredibly high performance of the GeOBIA procedure, the remedy to this issue is a higher resolution DCM or smaller shape factor parameter, which given an assumed increase in processing time, likely produces negligible improvements.

While vineyard status ideally remains independent from outside influences during the active growing season, in reality, this simply isn't the case. During the term of fieldwork, flocks of birds routinely fed upon the grapes present on the vines and utilized the woody structures of the vines for nesting materials. In fact, one of the study vines, SV4, included a nest for most of the growing season following berryburst. While one of the three observed blocks containing study vines was relatively unaffected, two blocks were heavily affected by bird activity. Birds removed enough fruit and leaves from study vines that a tangible effect on canopy density was present. Birds historically are viewed as a pest on vineyard harvests, but there is little literature indicting them as affecting spectrometric hindrances within viticulture (Wang et al., 2019). However, the removal of leaves by birds within the grapevine canopy likely influenced measuring the seasonal greenness in this study. A less dense canopy, viewed by UAS imagery, evidently returned a more inconsistent GCC index. A thinner canopy affected the UAS-based greenness extraction procedure because of the identical area of interest employed across greenness extraction dates. These changes were not reflected in field-based measurements as green leaves were selected for spectrometry measurements independent of canopy density, and birds did not noticeably remove leaves present in the phenocam GCC extraction AOI.

Spatial resolution and flight duration are likely to increase in the upcoming years for commercial-grade UAS platforms (Borgogno Mondino & Gajetti, 2017). Higher quality imagery likely represents improvements in any GeOBIA delineation procedures cascading into improving the accuracy of UAS-based greenness extraction across space and time. The addition of other UAS-based remote imagery products such as LiDAR point cloud models indicating grapevine canopy structure would also likely increase canopy classification accuracy. Jurado et al. (2020) recently developed a procedure for classifying grapevine trunk locations based upon UAS-sourced point clouds; however, their model only performed well in low-density grapevine canopies. Relatedly, increased flight duration improves the amount of imagery that can be gathered within a single flight, potentially limiting radiometric calibration issues when comparing imagery across multiple flights, which proved problematic in this study. If classification could independently improve for trunk identification and canopy area delineations, a technique for recording grapevine trunks during the earlier growing season and classifying seasonal canopy areas could prove helpful in tandem to vineyards for vine development monitoring.

Given the novelty of this study's methodological approach creating a seasonal profile of UAS-measured greenness, it is unknown whether more expensive UAS sensors or platforms would improve seasonal accuracy or further justify UAS imagery being detached from accurately assessing greenness. Similar applications with traditional remote sensing products, as seen in Sun et al. (2017), regress NDVI and LAI satellite imagery returns against grape harvest yields. While this study did not regress UAS-measured seasonal greenness versus quantitative harvest yields, the potential to develop a greenness-yield relationship solely based upon UAS imagery is plausible. Matthews (2014) explored a similar topic finding a significant correlation between UAS-measured grapevine canopy area against several harvest properties. Relating seasonal greenness against harvest properties might prove a more fruitful path given that Matthews similarly considered the potential of low-cost UAS platforms. Additionally, this study only considered the role of inexpensive UAS platforms collecting in the visible spectrum. In industry, vineyards typically will purchase specialized sensors proven to fit specialized applications and needs over the most cost-effective platform (Sassu et al., 2021). Specialized precision viticultural platforms are currently available for applications such as grass mowing and interrow monitoring through the Vitirover autonomous UGV platform (Vitirover Solutions, Saint-Émilion, France). While manufacturers have produced aerial platforms within the larger field of precision agriculture, there is no precedent for an explicit precision viticultural UAS commercially available yet.

7. Conclusion:

Compounding the lack of accurate spectral measurements with variable natural factors present in a commercial vineyard, it would be unwise to expect a similar approach to this study to work in the future without significant technological improvements. While it is indeed possible to measure and monitor seasonal greenness using a commercial-grade UAS platform across space and time, the ability to do so accurately was not proven. Based upon the strength of the

relationship found in this study, UAS-based greenness measurements offer no advantage to previously existing field-based measurements.

Given that the extensive range and spectral noisiness found in UAS-measured DN values over space and time, it is also unlikely that a shift to another ecological metric or wavelength range would produce meaningful improvement. These low-cost UAS platforms are engineered for hobbyists and should not be expected to undertake rigorous quantitative academic endeavors. While the lack of spectral discrimination hindered the ability to track seasonal greenness accurately, it ironically aided in identifying canopy areas against interrow regions when combined with a DCM. The model performed exceptionally well overall, and most error-prone regions of the classification have identifiable solutions to improve canopy classification. The addition of LiDAR point cloud models to classify vineyard canopies, especially when interrows are present, could represent a considerable, tangible improvement for vineyard managers and academic researchers alike with obtaining ecological metrics solely from canopy areas.

The cost of portable spectrometry units is also prohibitive to deployment in many commercial vineyards. However, the significant relationship between a portable spectrometer and phenocams measuring greenness proves there are cheaper, spatially sensitive alternatives to produce seasonal greenness profiles. Low-cost phenocams might be the most effective tool for vineyard greenness measurements, given the low cost and the ability to immediately deploy multiple phenocams into the field. However, this is contingent on whether leaf angles are predominantly vertical and do not vary significantly amongst grapevine canopies or varieties.

8. Statement of Competing Interests:

The author of this paper declares no competing or conflicts of interest for this research. Supplemental funding for this research was provided by the NASA West Virginia Space Grant Consortium and a grant from the Trevor and Sylvia Harris Scholarship through the West Virginia University Department of Geology & Geography.

9. Appendix I:

9.1. Legend for Imagery Date Symbolology:

Imagery Date	Symbol
June 15th	Filled Circle
June 24th	Filled Square
July 9th	Filled Diamond
July 25th	Filled Triangle
August 8th	Hollow Circle
August 21st	Hollow Square
September 4th	Hollow Diamond
September 10th	Hollow Triangle

9.2. Legend for Study Vine Symbolology:

Study Vine	Color
SV1	Red
SV2	Light Red
SV3	Gold
SV4	Olive
SV5	Green
SV6	Teal
SV7	Blue
SV8	Orange
SV9	Pink
SV10	Black

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