

Discriminating Spectral Signatures Among and Within Two Closely Related Grapevine Species

Matthew Maimaitiyiming, Allison J. Miller, and Abduwasit Ghulam

Abstract

Several North American *Vitis* species are used to breed scions and rootstocks, including *V. riparia* and *V. rupestris*. However, the degree to which *Vitis* species can be distinguished using remote sensing is not well known. Here we explore whether two North American *Vitis* species and genotypes growing in a common garden can be discriminated with leaf and canopy hyperspectral reflectance factor data (350-2500 nm) using independent *t*-test and derivative analysis. Foliar properties and spectral indices of the grapevines were evaluated with analysis of the variance (ANOVA) and pair-wise Bonferroni adjusted *t*-tests. The results showed that *V. riparia* and *V. rupestris* can be distinguished at the leaf level spectra of visible, near- and infrared spectral regions. At the canopy level, genotypes were spectrally discriminated with limited success. The Photochemical Reflectance Index (PRI) demonstrated the highest potential not only to differentiate two species, but also two genotype pair groups within *V. rupestris*. This finding was also true for the PRI calculated with simulated EO-1 Hyperion data. These capacities to distinguish *Vitis* species, and to a lesser extent genotypes, using spectral signatures have important applications in remote monitoring of vineyards for plants health and also for locating wild *Vitis* populations for future crop improvement efforts.

Introduction

Grapes (*Vitis* spp.) are the most economically important berry crop in the world. The European grapevine *V. vinifera* is the primary species used to produce wine and table grapes (Myles *et al.*, 2011); however, like many clonally propagated woody perennials, cultivated grapevines are usually two distinct genotypes that are grafted to one another. The above-ground part of the plant (the scion) produces the stem, leaves, flowers, and berries, and the below-ground part (the rootstock) makes the lower stem and roots. In most regions of the world, grafting allows grape growers to retain the economically valuable berry-producing varietal (e.g., Cabernet Sauvignon, Chardonnay) while introducing resistance to soil-borne pests and pathogens through rootstocks.

North American *Vitis* species have played a vital role in the global grape industry both through the generation of rootstocks as well as through their contributions to hybrid scions. For example, while approximately 90 percent of US grape acreage consists of *V. vinifera* cultivars in California, the vast majority of these are grafted to rootstocks derived from native North American grape species including *V. berlandieri*, *V. riparia*, and *V. rupestris*. In the Midwestern and Eastern United States, abiotic and biotic stress preclude most cultivation of

even grafted *V. vinifera* ssp. *vinifera*; instead, in these areas cultivated grapevines are hybrid scions derived from crosses between *V. vinifera* ssp. *vinifera* and one of the native North American *Vitis* species. Today, grape growing is becoming a more significant component of rural agricultural development in these areas. For example, in Missouri, grape and wine is a \$1.6 billion industry with a 16 percent annual growth rate (Stonebridge Research, 2010). Despite the importance of native North American species for rootstock and scion breeding, relatively little is known about our capacity to differentiate different *Vitis* species remotely.

Given the increasing importance of North American *Vitis* species, two ongoing challenges in the grape and wine industry are to locate wild North American *Vitis* germplasm for breeding, and to monitor plant health in hybrid vineyards in an efficient manner. In this study, we use spectral signatures to determine whether closely related native grape species could be distinguished from one another remotely. These approaches and results have potential applications in ongoing efforts to locate native germplasm for breeding, and also in vineyard management, where grape growers are looking for new ways to efficiently monitor plant health.

This study focuses on two native North American grapevines (*V. riparia* and *V. rupestris*) both of which are used in the generation of hybrid scions and rootstocks. *Vitis riparia* and *V. rupestris* present an interesting system for comparing spectral responses of plants because they are likely each other's closest relatives (Zecca *et al.*, 2012; Miller *et al.*, 2013), but are differentiated morphologically in terms of leaf shape and leaf ion concentration, which has strong implications for monitoring crop health using remote sensing techniques. Natural populations of *V. riparia* and *V. rupestris* have evolved to inhabit different types of environments: *V. rupestris* occurs on rocky, dry creek beds in Missouri and surrounding states (Fernald, 1987). Its closest wild relative, *V. riparia*, is found in moister soils and in forests throughout the northeastern quarter of the United States (US Forest Service, 1949). *V. riparia* and *V. rupestris* present an ideal system in which to explore differences in spectral signatures because they are closely related but have diverged morphologically in leaf traits; further, they are easily cloned which means that spectral reflectance factor data can be collected from multiple replicates of the same genotype, offering a robust statistical framework for analysis.

We leverage an experimental vineyard of *V. riparia* and *V. rupestris* housed at the Missouri Botanical Garden (MBG) to test the hypothesis that two unique *Vitis* species, as well as different genotypes within each species, can be detected remotely. The plants in the MBG experimental vineyard are

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own-rooted; they are not grafted. In 2013 the research vineyard containing these two species was established at the MBG, Saint Louis, Missouri. The vineyard includes multiple clones of each of four genotypes *V. riparia* genotypes and multiple clones of each of five *V. rupestris* genotypes. This experimental design presents an important opportunity to compare spectral signatures among and within species growing under common conditions.

Remote sensing can be used to map and monitor spatio-temporal dynamics of crops and different vegetation communities provided that different species are spectrally distinct within the landscape. Spectral signatures of plants are expressions of canopy biochemical and structural properties including leaf area index (LAI), leaf/canopy water content, chlorophyll concentration, leaf internal structure, leaf angle orientation and specific leaf area (SLA, leaf area per unit mass). It has been suggested that plants may show similar spectral profiles because they are composed of the same spectrally active materials, e.g., pigments, water, cellulose, etc. (Baret *et al.*, 1987; Jacquemoud and Baret, 1990). Under common conditions, how do the spectral signatures of distinct species, and distinct genotypes within species, differ from one another? Understanding the spectral bands significant for discrimination of genotypes and species are always promising and critical in remote sensing based monitoring of crop health (Burkholder *et al.*, 2011; Cho *et al.*, 2008).

Leaf chemical properties are principal determinants of plant physiology and biogeochemical processes in terrestrial ecosystems (Hedin, 2004; Wang *et al.*, 2010). Numerous studies show that empirical relationships exist between leaf spectral properties and leaf morphological and physiological conditions (Adams *et al.*, 1993; Adams *et al.*, 2000; Baret *et al.*, 1987; Curran *et al.*, 2001; Pacumbaba, Jr. and Beyl, 2011). Therefore, many optical vegetation indices have been explored pertaining to biochemical compositions in the leaf and canopy levels to investigate the spectral differences among the species (Blackburn, 1998; le Maire *et al.*, 2004; Lovelock and Robinson, 2002).

Previous studies have examined the potential of hyperspectral data in characterizing grapevine species, focusing primarily on discriminating common varieties of *Vitis vinifera* L. (Diago *et al.*, 2013; Lacar *et al.*, 2001; Parton *et al.*, 2012; Renzullo *et al.*, 2006). Several attempts have been made to assess the capability of airborne hyperspectral data for discrimination and mapping of grapevine varieties with some success (Ferreiro-Armán *et al.*, 2006; Lacar *et al.*, 2001). Studies using hyperspectral reflectance factor data to quantify the differences in spectral and biophysical properties of two closely related rootstock grapevine species or their genotypes within species have not been reported. Recent studies found that the chance of success of species separability using satellite data can be higher with multitemporal composite EO-1 Hyperion images at 30 m spatial resolution (Somers and Asner, 2013).

Building on this work, here we attempt to differentiate two grapevine species using remote sensing. This work is directly relevant to the grape and wine industry because some vineyards are composed of unique hybrids derived from different combinations of species or more commonly, different varieties (genotypes). If species and genotypes could be differentiated remotely, this opens up the possibility of identifying and monitoring individual varieties remotely. This is particularly important considering that the upcoming satellite-based hyperspectral missions including Environmental Mapping and Analysis Program (EnMap), Hyperspectral Infrared Imager (HypIRI) and Precursore Iperspettrale della Missione Applicativa (PRISMA) will provide unparalleled opportunities in satellite remote sensing of individual plant species and their response to abiotic stress under climate change. These

developments call for further studies to explore the link between field-measured hyperspectral spectra and available or upcoming satellite hyperspectral missions, which allow understanding the performance of spectral indices on crop monitoring at leaf, canopy, and satellite scales without atmospheric disturbance.

Work completed in this study provides an important baseline for understanding the dynamics of differentiating species and genotypes used in grapevine breeding. Specifically, the research described here tests the following hypotheses: (a) Spectral reflectance factor properties of two *Vitis* species are unique and can be used to discriminate the species at the leaf, canopy, and satellite levels, and (b) Spectral reflectance factor properties differ among genotypes within species.

Materials and Methods

The Study Site Description

The fieldwork was conducted in two experimental plots at the MBG, Saint Louis, Missouri (38°36'50.76"N, 90°15'32.04"W) during the growing season of the study organisms. However, only two measurements collected on 24 July and 07 August 2013 were used due to the optimal weather conditions in these days. Thirty-three *V. riparia* (four genotypes, one to eight clones/genotype) and 31 *V. rupestris* (five genotypes, one to eight clones/genotype) were received from the United States Department of Agriculture Grape Germplasm Research Unit (USDA - GGRU) in Geneva, New York. Accessions arrived as canes during Winter 2013. In the MBG greenhouses, the canes were first stored in dark, cool conditions on a heating pad from February through mid-April, and were then moved into standard greenhouse conditions where leaf flush, flower emergence, and in some cases, fruiting occurred. On 23 May 2014, the plants were transplanted into the common vineyard in the Kemper Center for Home Gardening at MBG. The first plot consisted of eight rows with three plants in each row. The second plot contained 10 rows of four plants each. Rows on both plots were oriented North-South and trained on a single-wire vertical trellis system. The plots were separated with a nearly two-meter wide sidewalk. Table 1 shows the specific number of individual grapevine species and genotypes studied in this paper.

Spectral Data Collection

Canopy reflectance, more specifically, hemispheric conical reflectance factor (HCRF; Schaepman-Strub *et al.*, 2006) was acquired between 12:00 to 1:00 pm local time, under

TABLE 1. SPECIES AND GENOTYPES SURVEYED;
N = NUMBER OF CLONES PER GENOTYPE

Species	Genotype	n	Total (species)
<i>V. riparia</i>	GVIT 775	8	32
	Okoboji	8	
	B 50	8	
	B 75	8	
<i>V. rupestris</i>	B 38	7	29
	R-67-2	7	
	R-66-9	6	
	R-66-3	5	
	R-65-44	4	
Total		61	

clear-sky conditions by using high resolution full range PSR-3500 (Portable Spectroradiometer, Spectral Revolution, Inc., Lawrence, Massachusetts). The wavelength range of PSR-3500 is 350-2500 nm with a resolution of 3.5 nm in the 350-1000 nm range, 10 nm in the 1000-1900 nm range, and 7 nm in the 1900-2500 nm range. The 1.2 m long fiber optic with 25° circular field of view (FOV) was attached to the device and pointed to 1 m above the canopy without shading in nadir orientation holding with pistol grip, which has a low reflectance and impact resistance ABS thermoplastic handle. This resulted in a FOV with radius of 0.2 m and an area of about 0.13 m². Care was taken to ensure that the FOV of the spectrometer covers the grapevine canopy, excluding background effects (e.g., soil). A reference spectrum was taken from a 99 percent reflectance Spectralon calibration panel (Labsphere, Inc., North Sutton, New Hampshire) before target measurement and repeated for every other five measurements to re-adjust the base line to account for any change in illumination.

Following the canopy reflectance factor measurement, PSR-3500 was equipped with a specifically developed leaf clip with a bifurcated fiber-optic connected to both the device and 5 watt tungsten halogen lamp light source. The leaf clip is made from the same material as the reference panel and enables us to take leaf reflectance factor (HCRF) with both spectrally white and black backgrounds. The white background is used to take reference spectra. The third leaf back from the top of the growing vine was held with the leaf clip, and the measurements were taken with a black background after taking the reference spectrum as the purpose of the measurement was to obtain the pure adaxial reflectance factor (first surface spectrum). To effectively detect the spectral differences between the two grapevine species, the measurement took place at two different growth stages with a ten-day interval in average.

In both cases, PSR-3500 was configured to average automatically 40 spectra per sampling, and the raw spectra bandwidth was interpolated to 1 nm. This resulted in 2,151 individual spectral bands. The spectral bands 1887-1978 and 2418-2500 were excluded from the canopy reflectance due to strong atmospheric water absorption. Getac® PS336 PDA preloaded with DARWin software (Compact V.1.2.4903, Spectral Revolution, Inc., Lawrence, Massachusetts) was used to manipulate the device and assisted for quick data collection.

Spectral Separability Analysis

We investigated the spectral separability of *V. riparia* and *V. rupestris*, and of genotypes within each species at the leaf and canopy levels. The collected reflectance factor spectra in different growing stages and conditions were averaged and an independent t-test was applied as our intention was band-by-band spectral comparison. Averaging of spectral data may also help us identify those consistent spectral features, which are not affected by the abiotic environment or growing stage and unique to the specific species or genotypes. p-values were calculated to determine the statistical significance of the spectral separability (Zar, 1996). The vegetation reflectance factor spectra, regardless of the canopy or leaf levels, indicate a certain degree of absorption characteristics from 350 to 2500 nm due to the presence of pigments, water, and dry matter. However, the recorded data are always subject to contamination caused by scattering, viewing geometry, and changing illumination. Derivative analysis has been a desirable tool to suppress background noise, accentuate individual absorption features and resolve the over-lapping spectral features (Butler and Hopkins, 1970; Tsai and Philpot, 1998; Sawut *et al.*, 2014). Therefore, we treated the reflectance factor spectra with 1st- and 2nd- derivative processing. The derivative calculations were performed with Savitzky-Golay (SG) methods (2 degrees and 5 points) of GRAMS/AI software (V. 9.1, Thermo Fisher Science, Inc, Waltham, Massachusetts). The variances

were pooled when inequality was detected in each species and genotype grouping in order to achieve the best estimate of the variances.

Fresh and Dry Leaf Weight Measurement

The leaves, used for leaf reflectance factor measurement, were destructively collected and sent to the lab for fresh leaf weight measurement using a balance. After weight measurement, the samples contained in a paper envelope were oven-dried for one hour at about 75°C. When there is no change in weight, the dry leaf weight of the samples were determined.

Leaf Area Index Measurement

The LAI-2200 Plant Canopy Analyzer (LI-COR, Inc., Lincoln, Nebraska) was used to make indirect measurements of LAI. The LAI of each grapevine is estimated with eight measurements of Plant Canopy Analyzer pointing at the four compass directions and using a 45° view cap (four readings above the plant, four readings below the plant). The sensor was located at the base of the individual plant while below the canopy measurement. Fieldwork was conducted at dusk or dawn in order to minimize the effects from the scattering of direct sunlight through the leaf canopy.

Leaf Bio- and Photochemical Properties

Chlorophyll index (CI), developed by Gitelson and Merzlyak (1994), was calculated based on 1 nm interpolated leaf reflectance factor from spectroradiometer data. CI was formulated as follows:

$$CI = \frac{R_{750} - R_{705}}{R_{750} + R_{705}} \quad (1)$$

where R is the reflectance factor value and subscripts are wavelengths in nm. Then, CI was converted into total chlorophyll content (total chl; $\mu\text{g cm}^{-2}$) following Richardson *et al.* (2002).

Using the interpolated leaf reflectance factor spectra, we calculated the photochemical reflective index (PRI) proposed by Gamon *et al.* (1997) as:

$$PRI = \frac{R_{531} - R_{570}}{R_{531} + R_{570}} \quad (2)$$

To avoid negative values for PRI, we scaled the PRI as Letts *et al.* (2008):

$$sPRI = \frac{PRI + 1}{2} \quad (3)$$

The PRI is sensitive to changes in xanthophyll pigments, which is a key indicator of photosynthetic light use efficiency; therefore, the rate of carbon dioxide uptake by foliage per unit energy absorbed.

Simulated Sensor-Specific Indices

No hyperspectral satellite data were available for our study area during the experiment period. Simulation of satellite spectra using the spectral response function provides insights on the use of the methods at satellite levels. Since both NASA's Hyperion and planned HypSIRES sensors have 10 nm spectral resolutions, we decided to use Hyperion spectral response function for the simulation. Leaf level reflectance factor were convolved using sensor-specific spectral response function to simulate EO-1 Hyperion following Equation 4:

$$\rho_{\text{Hyperion}}(\lambda) = \frac{\int_{\lambda_{\min}}^{\lambda_{\max}} \rho_{\text{leaf}}(\lambda) f(\lambda) d\lambda}{\int_{\lambda_{\min}}^{\lambda_{\max}} f(\lambda) d\lambda} \quad (4)$$

where ρ_{Hyperion} is simulated EO-1 Hyperion reflectance factor spectra of band λ ; $f(\lambda)$ is the spectral response function of the simulated band λ ; $\rho_{\text{leaf}}(\lambda)$ is the measured reflectance factor at band λ ; and λ_{min} and λ_{max} are the lower and upper bounds of leaf spectra. We calculated the SPRI and CI indices using 528.7 nm, 569.4 nm, 701.6 nm, and 752.47 nm spectral bands of simulated EO-1 Hyperion data based on Equations 1 and 3, respectively.

Foliar Statistical Analysis

Initially, we tested for differences between nine genotypes of *V. riparia* and *V. rupestris* in five leaf, structural, bio- and photochemical properties including fresh, dry leaf weight, LAI, total chlorophyll content and SPRI. Three steps were taken to evaluate the potential leaf traits to discriminate between species. First, between species, a one-way analysis of variance (ANOVA) was used to examine whether differences exist between genotype means of species. Secondly, within species, one-way ANOVA was conducted in separate species to compare the leaf traits within four genotypes of *V. riparia* and five genotypes of *V. rupestris*, respectively. Finally, a multiple comparisons test using Bonferroni adjusted t-test, which can reduce the chance of committing Type I error, was carried out in order to determine which pairs of genotype means differ (Zar, 1996). We applied the Bonferroni multiple comparisons procedure with $\alpha = 0.05$ to the data. The alpha level was adjusted downwards by dividing 0.05 by four (number of *V. riparia* genotypes) and five (number of *V. rupestris* genotypes), e.g., $0.05/4 = 0.0125$ and $0.05/5 = 0.01$.

Results

Leaf Reflectance Factor Spectra Separability

Figure 1 shows the mean leaf reflectance factor spectra of *V. riparia* and *V. rupestris*. It was obvious from visual inspection that *V. rupestris* had higher reflectance factor values in almost all the wavelength regions (350-2500 nm). To show the consistency of the reflectance factor differences and confirm they were not detected by chance, we employed an independent t-test to investigate the spectral separability through band-by-band comparison. The results indicated that spectral differences between *V. riparia* and *V. rupestris* were statistically significant across three wavelength regions: 350-1400 nm ($p < 0.01$), 1480-1870 ($p < 0.01$), and 2100-2400 nm ($p < 0.04$).

We also tested the leaf spectral separability between subspecies by examining four genotypes within *V. riparia* and five genotypes within *V. rupestris* species (Figure 2). Over the full spectral region, we identified wavelength-specific differences between the Okoboji and both B 50 and GVIT 775 subspecies within *V. riparia*, and between R-67-2 and both B 38 and, R-66-3 subspecies within *V. rupestris*. Within *V. riparia*, a spectrally separable continuous region (730-1450 nm) ($p < 0.03$) and some discontinuous SWIR regions were detected between B 50 and Okoboji leaf spectra (Figure 2a). Similar results were found when comparing GVIT 775 and Okoboji genotypes, but there were more wavelength-specific differences in the SWIR region, and they were consistent than found in the B 50 and Okoboji group (Figure 2b). Within *V. rupestris*, two wavelength regions, 1390-1585 nm and 1740-2470 nm ($p < 0.04$), showed statistically significant difference for B 38 and R-67-2 genotype group (Figure 2c). Moreover, R-66-3 and R-67-2 spectra were spectrally separable in the 990-2500 nm ($p < 0.04$), and there were some subtle spectral separability in the VIS region (Figure 2d).

Figure 3 shows the 1st derivative (1st-d) of the leaf reflectance factor spectra between the *V. riparia* and *V. rupestris*. The number of bands significant for discrimination derived from 1st-d transform were much fewer compared to those

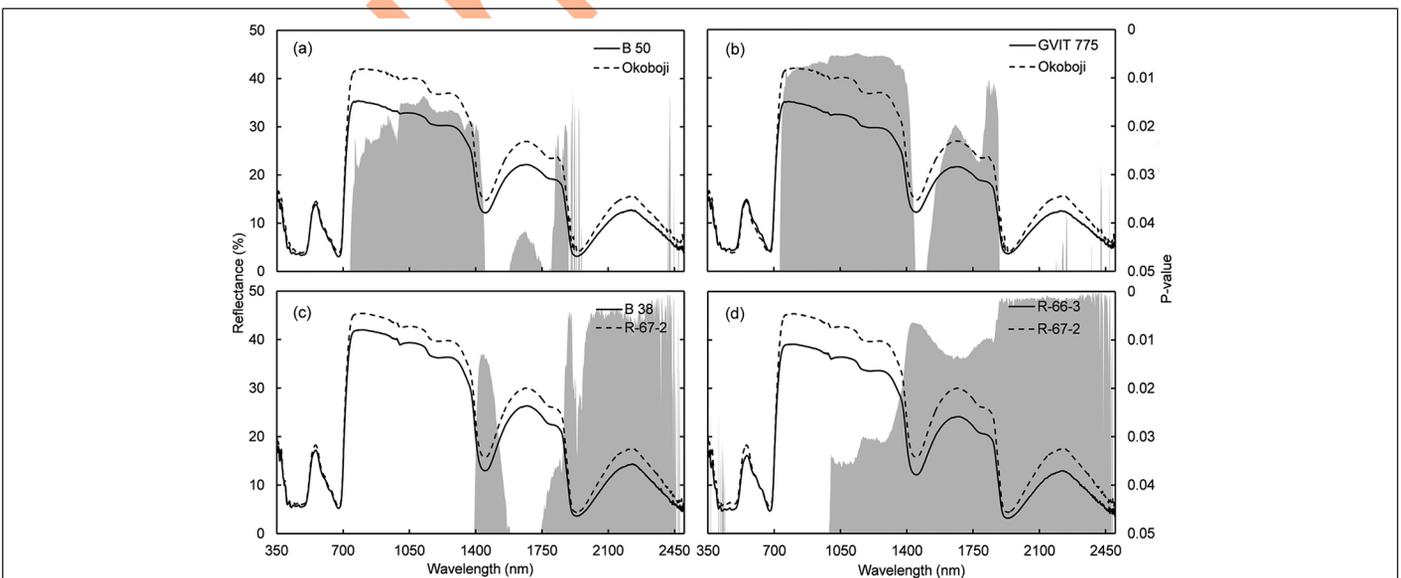
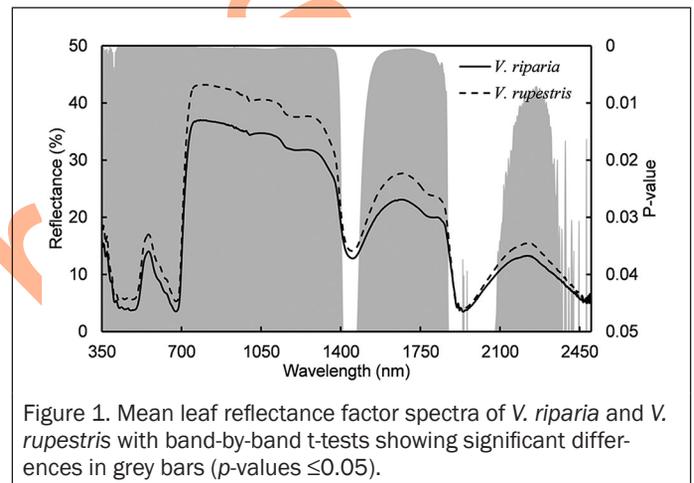


Figure 2. Mean leaf reflectance factor spectra of (a) B 50 and Okoboji within *V. riparia*, (b) GVIT 775 and Okoboji within *V. riparia*, (c), B 38 and R-67-2 within *V. rupestris*, (d) R-66-3 and R-67-2 within *V. rupestris*, and (e) with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

identified in the reflectance factor analysis (Figure 1). However, the spectral regions where genotypes were statistically separable were not the same in the 1st-d data and the original raw reflectance factor data (Figure 4). Specifically, the 710-750 nm ($p < 0.05$) and the 705 - 755 nm ($p < 0.03$) regions were found as spectrally separable for the B 50 and Okobojo and GVIT 775 and Okobojo groups, respectively, within *V. riparia* species (Figure 4a and 4b). Similarly, within *V. rupestris* species R-66-3 and R-67-2 group was separable in the 550-600 nm ($p < 0.02$) and 710-750 nm ($p < 0.04$) regions (Figure 4c), and the R-66-9 and R-67-2 group was separable in 510-612 nm ($p < 0.02$) region (Figure 4d). In all cases above, the 1st-d

was capable of finding variably spaced spectral signatures throughout the VIS, NIR, and SWIR regions.

We also calculated the 2nd derivative (2nd-d) of the leaf reflectance factor spectra and found several spectrally separable regions. In this study, we only present the 2nd-d results at VIS spectral range (400-750 nm) because these are the spectral regions where the influence of chlorophyll-a and b carotenoids is predominant. Between *V. riparia* and *V. rupestris*, spectrally separable bands are sparsely distributed over the VIS wavelength range and are primarily centered in the 650-700 nm ($p < 0.02$) region (Figure 5a). Among genotype comparison groups, similar trends were detected. The most obvious group

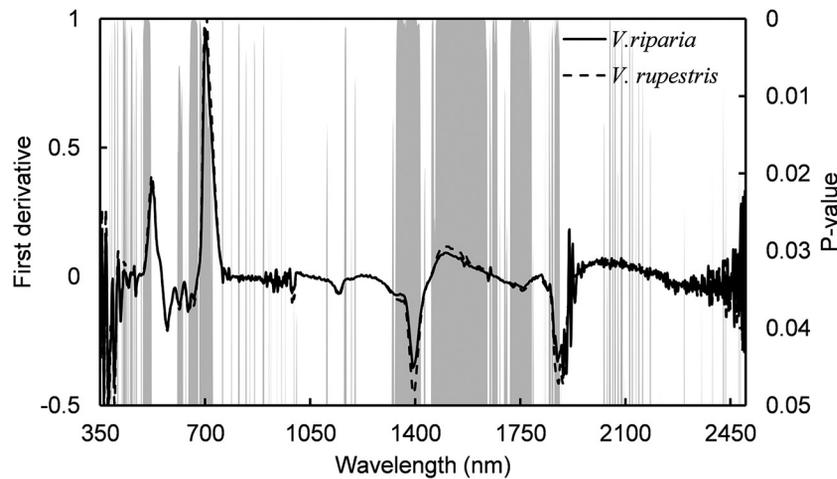


Figure 3. Mean 1st-d leaf reflectance factor spectra of *V. riparia* and *V. rupestris*, with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

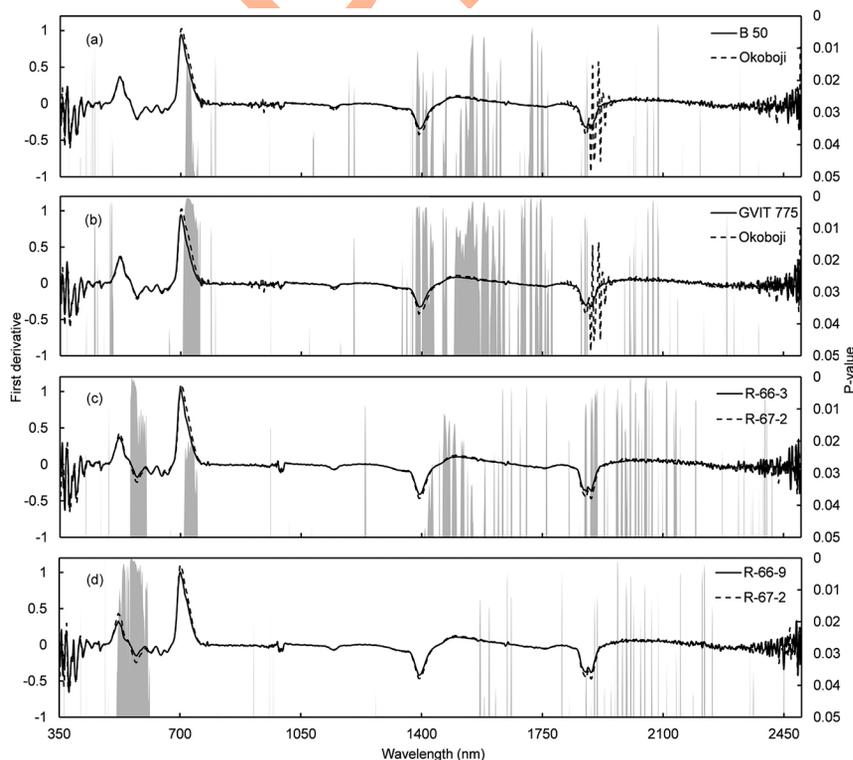


Figure 4. Mean 1st-d leaf reflectance factor spectra of (a) B 50 and Okobojo within *V. riparia*, (b) GVIT 775 and Okobojo within *V. riparia*, (c) R-66-3 and R-67-2 within *V. rupestris*, and (d), R-66-9 and R-67-2 within *V. rupestris*, with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

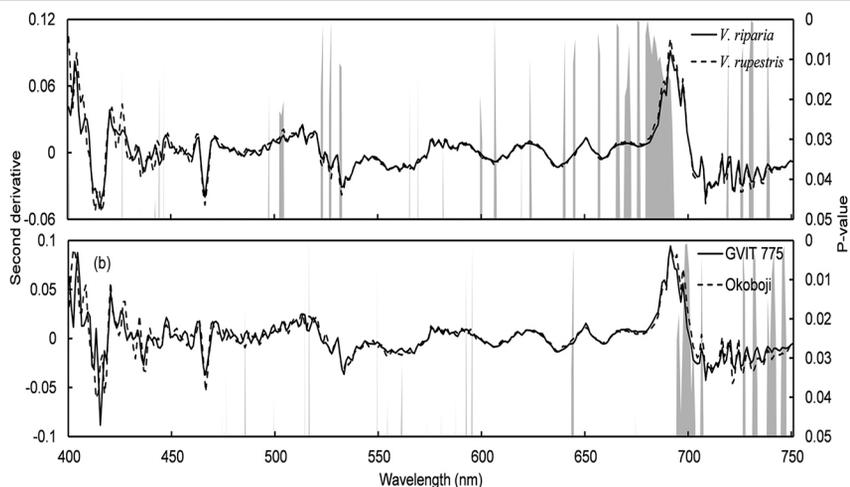


Figure 5. Mean 2nd-d leaf reflectance factor spectra of (a) *V. riparia* and *V. rupestris*, (b) GVIT 775 and Okoboji within *V. riparia*, and (c) with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

was GVIT 775 and Okoboji where distinct spectral signatures were located in the 690-750 nm ($p < 0.02$) region (Figure 5b).

Canopy Reflectance Factor Spectra Separability

We analyzed the canopy reflectance factor spectra with the same method that we used for leaf reflectance factor spectra. Again, the mean canopy reflectance factor spectra of two grapevine species were distinguished visually (Figure 6). Interestingly, *V. riparia* had higher reflectance factor values in portion of VIS, full NIR, and SWNIR spectral regions than *V. rupestris*, which was opposite to what we found in leaf reflectance factor spectra (Figure 1). Possible causes of this observation will be explored in the Discussion Section. In the VIS and NIR spectral regions, the number of spectrally separable bands in canopy reflectance factor spectra was reduced substantially compared to leaf level spectra. In contrast, the number of spectrally separable bands expanded in the SWIR spectral region together with an increase in their statistical significance ($p < 0.01$).

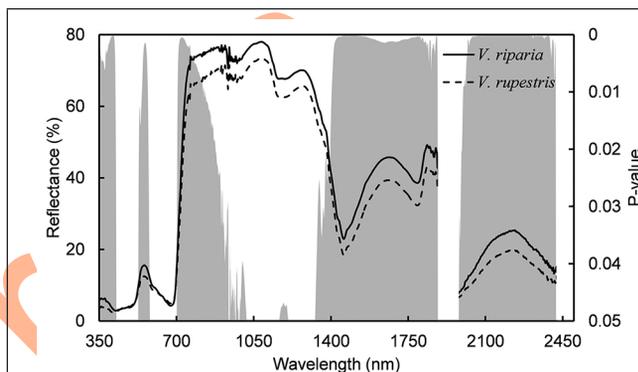


Figure 6. Mean canopy reflectance factor spectra of *V. riparia* and *V. rupestris* with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

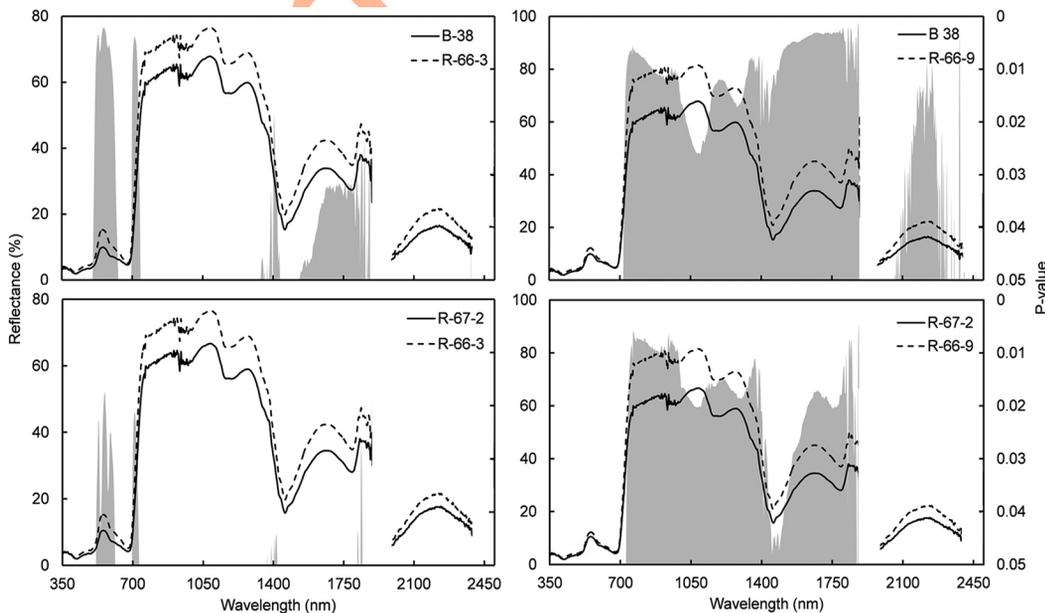


Figure 7. Mean canopy reflectance factor spectra of (a) B 38 and R-66-3 within *V. rupestris*, (b) B 38 and R-66-9 within *V. rupestris*, (c) R-67-2 and R-66-3 within *V. rupestris*, (d) R-67-2 and R-66-9 within *V. rupestris*, with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

Although there were not spectrally separable bands among the *V. riparia* genotypes, we were able to identify them in *V. rupestris* genotype groups. Some of these separable bands were not even found in leaf spectra comparison groups. For instance, the B 38 and R-66-3, B 38, and R-66-9, and R-67-2 and R-66-9 genotype groups were spectrally separable in VIS, NIR, and SWIR regions (Figure 7a, 7b, and 7d). The R-67-2 and R-66-3 group, which also had separable bands in leaf reflectance factor spectra (Figure 2d), was discriminated in VIS band range (517-612 nm and 696-731nm) ($p < 0.04$) (Figure 7c).

The 1st-d canopy reflectance factor spectra enabled us to detect wavelength specific differences that were not shown in the raw canopy reflectance factor data. Figure 8 presents the evidence that more spectrally separable bands between two grapevine species were identified in VIS and NIR regions. Among genotypes, the 1st-d calculation not only revealed significantly different VIS bands in the B-38 and R-66-9 group (Figure 9a), but also identified a new genotype group R-65-44 and R-66-9 which had separable bands through the VIS and NIR regions and part of the SWIR region ($p < 0.03$) (Figure 9b).

The 2nd-d canopy reflectance factor spectra were also analyzed for species and genotype groups. However, 2nd-d was only capable of detecting significantly different bands at the species level (Figure 9c). This finding was very similar to the result that we found with our 1st-d analysis. There were also few numbers of separable bands in genotype comparison groups (data not shown).

Foliar Separability

We found by examining growing grapevines of nine genotypes that foliar properties differ noticeably between species. Fresh and dry leaf weight of *V. riparia* was significantly higher than that of *V. rupestris* ($F_{1,59} = 19.92$, $p < 0.01$ and $F_{1,59} = 44.49$, $p < 0.01$, respectively) (Figure 10a and 10b). Correspondingly, the LAI had higher values among *V. riparia* genotypes than

V. rupestris. The *V. rupestris* LAI had a broader data range compared to the ranges of all other properties discussed here. However, the difference in LAI between the two species was not statistically significant ($F_{1,59} = 0.13$, $p = 0.72$) (Figure 10c). Similarly, *V. rupestris* genotypes differed from *V. riparia* genotypes with their lower total chlorophyll content, but again the difference was not significant ($F_{1,59} = 2.37$, $p = 0.13$) (Figure 10d). As we expected, sPRI, an indicator of epoxidation state of xanthophyll, was significantly lower in *V. riparia* than in *V. rupestris* ($F_{1,59} = 15.52$, $p < 0.01$) (Figure 10e). We expected this because these two grapevine species have different drought tolerance characteristics.

Among genotype pairs of *V. riparia*, the results of one-way ANOVA did not show significant differences in any of the foliar properties. Therefore, we did not perform a Bonferroni adjusted t-test. Within *V. rupestris* species, one-way ANOVA results

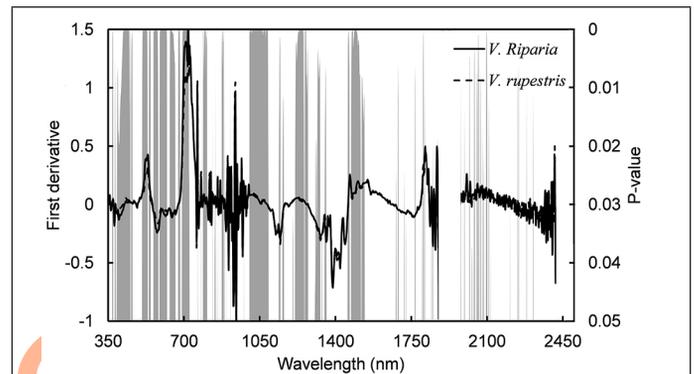


Figure 8. Mean 1st-d canopy reflectance factor spectra of *V. riparia* and *V. rupestris*, with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

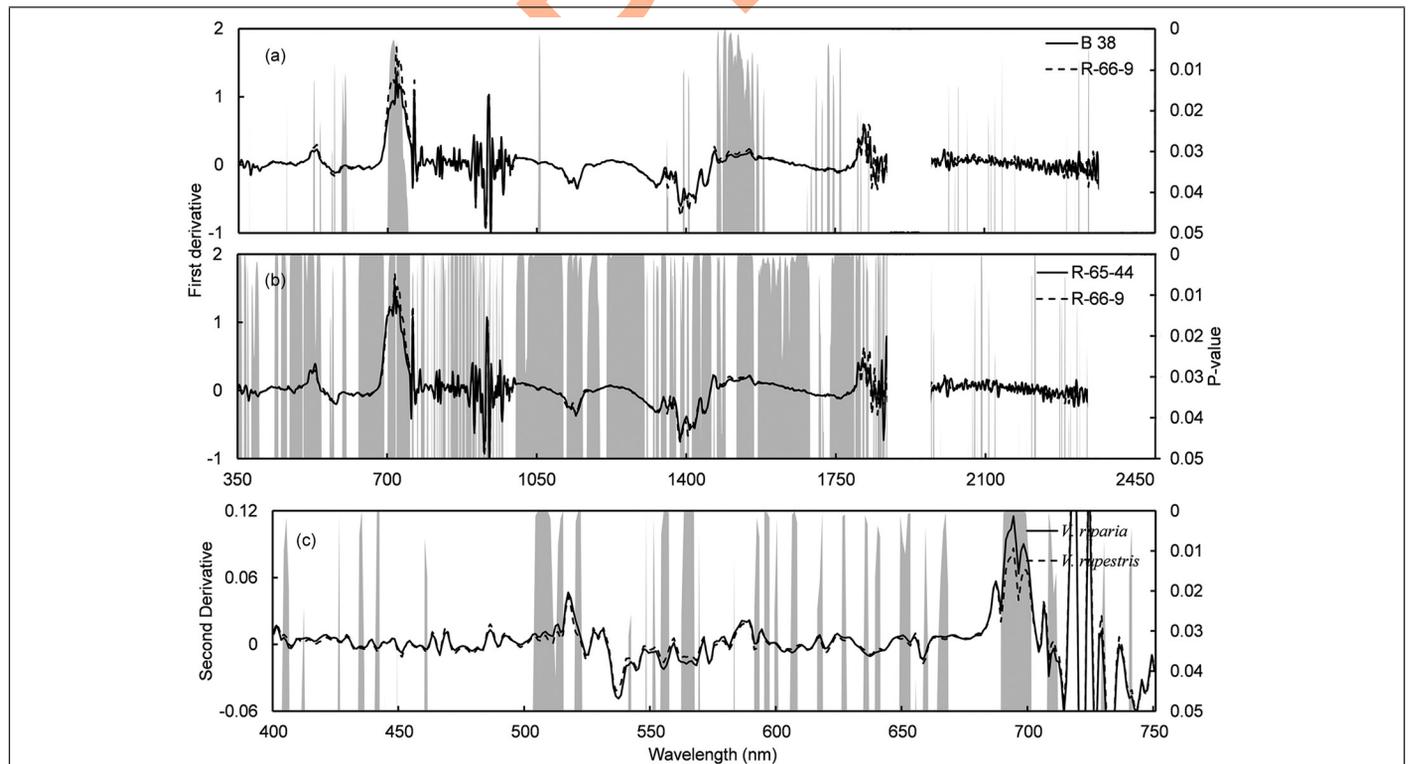


Figure 9. Mean 1st-d canopy reflectance factor spectra of (a) B 38 and R-66-9 within *V. rupestris*, (b) R-65-44 and R-66-9 within *V. rupestris*, (c), Mean 2nd-d canopy reflectance factor spectra of *V. riparia* and *V. rupestris*, with band-by-band t-tests showing significant differences in grey bars (p -values ≤ 0.05).

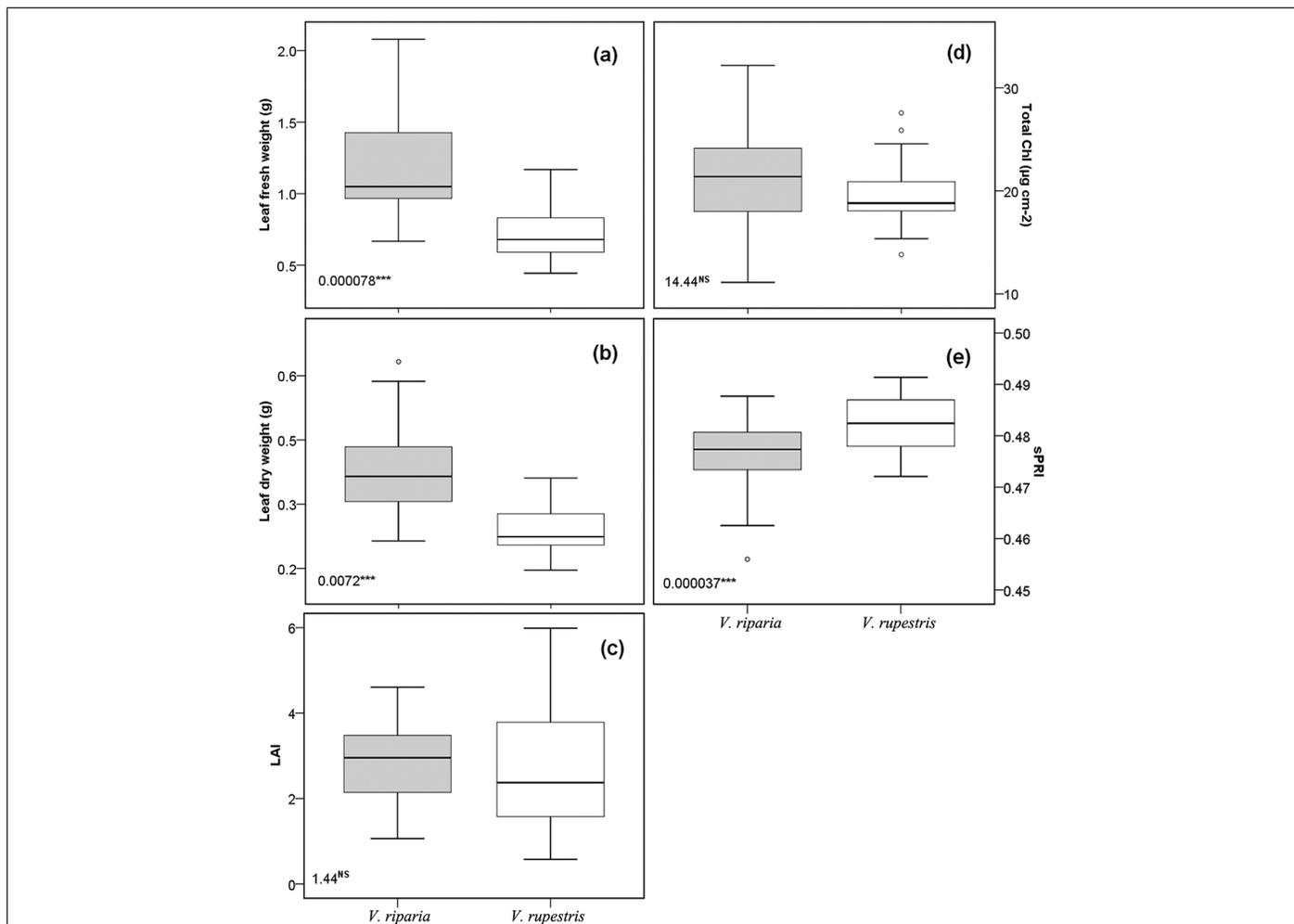


Figure 10. Variation in foliar properties of grapevine species and genotypes within the species: (a) leaf fresh weight, (b) leaf dry weight, (c) LAI, (d) total chlorophyll content, and (e) scaled photochemical reflectance index. Dots outside of the box plots represent outliers and whiskers indicate the 5th and 95th percentiles. Solid lines inside the box represent the median; the colored area represents the 25th and 75th percentile. The mean square error (MSE) from the ANOVA and level of significance is also shown (*** $p < 0.01$).

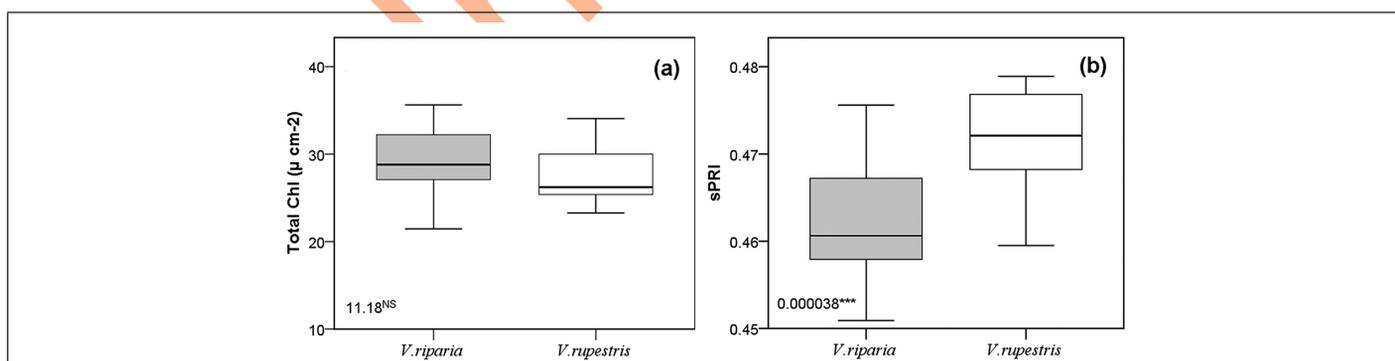


Figure 11. Variation in foliar properties of grapevine species and genotypes within the species: (a) total chlorophyll content, and (b) scaled photochemical reflectance index. Whiskers indicate the 5th and 95th percentiles. Solid lines inside the box represent the median; the colored area represents the 25th and 75th percentile. The mean square error (MSE) from the ANOVA and level of significance is also shown. *** $p < 0.01$

indicated that there was a significant difference only in SPRI values ($F_{4,24} = 15.52$, $p < 0.01$). Based on a Bonferroni adjusted t-test, we determined that two pairs of *V. rupestris* genotypes, B 38 and R-66-3 ($t = 5.24$, $p < 0.01$) and R-67-2 and R-66-3 ($t = 4.71$, $p < 0.01$), could be differentiated using SPRI.

Separability Analysis Based on Simulated EO-1 Hyperion Indices

The results of ANOVA performed on simulated Hyperion indices, did not show significant differences for total chlorophyll content between two species ($F_{1,59} = 3.60$, $p = 0.06$). *V. riparia* had higher total chlorophyll content than its counterpart, and this is consistent with the results found at leaf and canopy

level. The results of using SPRI to differentiate between grapevine species were highly significant ($F_{1,59} = 39.15$, $p < 0.01$) (Figure 11).

In addition, the results of ANOVA analysis of genotypes within species were similar to the results found at leaf level. We did not perform a Bonferroni adjusted t-test because the ANOVA test did not reveal significant difference within *V. riparia* genotypes for either total chlorophyll content or SPRI. However, ANOVA results showed that there was a significant difference between SPRI values of *V. rupestris* genotypes ($F_{4,24} = 4.30$, $p < 0.01$). We identified four statistically separable pairs of *V. rupestris* genotypes: B 38 and R-66-3 ($t = 2.88$, $p < 0.01$), R-67-2 and R-66-3 ($t = 3.69$, $p < 0.01$), B 38 and R-65-44 ($t = 2.58$, $p < 0.05$), and R-67-2 and R-65-44 ($t = 3.94$, $p < 0.01$). The latter two pairs were not separable at leaf level.

Discussion

The results of spectral analysis showed that *V. riparia* and *V. rupestris* genotypes can be spectrally discriminated at the leaf and canopy scales. Although there was no single band that could be used to discriminate between species and genotype pairs within species at either leaf or canopy scales, the results of statistical analysis used to identify such spectrally separable bands had a confidence level of $p \leq 0.05$. The VIS spectral region is dominated by leaf pigment constituents, and inconsistency in the NIR and SWIR regions is caused by differences in leaf and canopy water content that are associated with changes in LAI (Ceccato *et al.*, 2001; Ustin *et al.*, 2004). Therefore, the combination of these factors plays a crucial role in discriminating species and genotypes with reflectance factor spectra. The VIS and NIR regions were the most useful for species and genotype discrimination. This is supported by statistical results from previous studies using the same or other statistical tests (Asner *et al.*, 2008; Lacar *et al.*, 2001; Manevski *et al.*, 2011; Schmidt and Skidmore, 2003). The SWIR was also important for discriminating plant species and genotypes, and it was almost as effective in identifying spectral differences as the VIS and NIR regions. This finding was somewhat different from previously reported selective significance of the SWIR spectrum (Thenkabail *et al.*, 2004; Van Aardt, 2000).

At leaf level, the overall spectral curve shape of the two grapevine species was similar but with different absorption depth; highly significant lower reflectance factor in the full wavelength region (350-2500 nm) of *V. riparia* indicates that its leaf water content and pigment constituents are higher, on average, than the *V. rupestris* ($p \leq 0.05$). This observation is strongly supported by fresh and dry leaf weights that are the core components of equivalent water thickness (EWT), SLA and total chlorophyll content. Surprisingly, even though no significant differences were found in calculated total chlorophyll content between species and genotype pair groups, statistically significant differences were detected in VIS region after treating the reflectance factor data through derivative processing.

The distinguishing capability of leaf and canopy spectra may vary because the photons reflected back to the sensor at canopy scale is affected by absorption and multiple scattering. The spectral separability decreased markedly at canopy level especially in the VIS and shorter NIR regions, whereas spectral separability increased in longer NIR and SWIR regions. Moreover, at canopy level *V. riparia* had higher reflectance factor values than *V. rupestris* in portions of VIS, full NIR, and SWIR spectral regions which is opposite to what we found in leaf spectra. This may be associated with the higher canopy pigment concentrations, LAI, and lower canopy water content of *V. riparia* compared to *V. rupestris*. In contrast, Cho *et al.* (2008) found systematically higher VIS and NIR reflectance factor values at the leaf scale than at the canopy scale. These

different results may be caused by the methodology used in leaf spectra collection. It is worth noting that the wavelength region 1125-1300 nm known to be dominated foremost by variations in canopy water content (Asner *et al.*, 2006), did not show significantly different bands at the canopy scale. This is supported by LAI data that is not significant between two species. Therefore, we agree with Cho *et al.* (2008) that the change in reflectance factor values from the leaf to the canopy scale is not only due to the LAI but also due to the complexity of the canopy (e.g., foliage clumping and the presence of twigs, flowers, and shadow).

In two species, the spectrally separable genotypes were found using leaf spectra analysis and these wavelength-specific bands were located only in the NIR and SWIR regions. There were new groups of spectrally separable genotypes within *V. rupestris* detected using canopy spectra. The statistically significant differences were not only in NIR and SWIR regions, but also in the VIS region. In addition, the genotype groups that had separable bands in NIR and SWIR regions at leaf scale revealed separable bands in the VIS region at canopy scale; however the groups lost their spectral separability found at leaf scale. Due to the similarity of spectra, the most difficult genotype groups to discriminate were those paired with B 75 within *V. riparia* or with R-65-44 paired groups within *V. rupestris*. In fact, the analysis of those paired groups produced the lowest number of significantly different bands in their spectral discrimination.

Spectral derivatives are a well-known approach to use instead of spectral reflectance factor because of their ability to reduce variability caused by changes in illumination and background reflectance (Curran *et al.*, 1991; Elvidge and Chen, 1995; Laba *et al.*, 2005). Additionally, both the amplitude of the 1st-d and 2nd-d of reflectance factor spectra and the derivatives of the VIS spectral region can isolate the pigment expressions in this spectral region because they are strongly related to pigment concentrations (Boochs *et al.*, 1990; Sims and Gamon, 2002; Yoder and Pettigrewcrosby, 1995). Concerning the performance of 1st-d and 2nd-d, the two grapevine species displayed differences with 1st-d spectra in NIR and SWIR regions at both leaf and canopy level. In addition, new sets of spectrally separable bands were identified by 1st-d at canopy scale. Nonetheless, the separability in NIR and SWIR regions were not as great when 2nd-d spectra were tested. Among genotype groups that had separable bands in NIR and SWIR regions at leaf scale, the 1st-d processing identified those separable bands, particularly in VIS region, together with a new genotype group that we also discriminated with VIS bands. Likewise, at canopy level, the 1st-d was able to detect spectrally separable VIS bands in only one comparison group and found another genotype group that was not discriminated with original raw spectra. The 2nd-d in genotype comparison did not perform as effectively as 1st-d did. The 2nd-d identified the spectrally separable bands in the VIS region that overlap with the separable bands found in 1st-d spectra. In all other cases, the 2nd-d spectra were separable in only very few bands or no bands throughout the full spectral region.

A change in spectral properties and a lowering of PRI values in plants exposed to various abiotic stresses has been previously reported (Ainsworth *et al.*, 2014; Meroni *et al.*, 2009; Naumann *et al.*, 2008; Richardson *et al.*, 2001). The mid-summer heat would be the only main stress that the grapevines would be exposed to in this study. The PRI variation between two species may demonstrate variations in xanthophyll cycle pigments between species with different capacities for photosynthetic efficiency (Nichol *et al.*, 2006). Decreased PRI values for *V. riparia* indicated a lower xanthophyll epoxidation state and may be a reflection of the reduced photosynthetic rates relative to the *V. rupestris*. This result was expected since the

V. rupestris is considered more drought resistant than *V. riparia* (Padgett-Johnson *et al.*, 2003). Drought-tolerant plants are able to keep higher photosynthetic rates for extended period at lowered cell volume and water potential (Proctor, 2000). This is also supported by other studies that show drought-tolerant plant species can maintain normal metabolism while tolerating elevated ionic concentrations in the cytoplasm and external environment (Schroeter *et al.*, 1999). The PRI derived from simulated EO-1 Hyperion data was consistent with leaf level measurements even though we only considered the spectral resolution of Hyperion sensor while radiometric and spatial resolution, sensor geometry and signal-to-noise ratio were not accounted for. This further confirmed that PRI is a useful indicator of plant physiological status at multiple scales.

In general, other than previously mentioned leaf biochemical and biophysical parameters, the identified spectral regions used to discriminate species and their genotypes are related to foliar chemistries such as lignin, starch, protein, and cellulose concentrations (Curran, 1989).

It is worth noting that the organisms used in the study *V. riparia* and *V. rupestris* are closely related species that are widely used in commercial vineyards as rootstocks. The results showed that the species when used as rootstocks, but not as genotypes within the same species, can be spectrally discriminated from one another at canopy and satellite scales indicating that satellite remote sensing can be used to monitor crop health. Results also showed that remote detection of *V. riparia* and *V. rupestris* species in its wild habitat are possible; this is critical for finding native germplasm that can be used in stress-tolerant plant breeding.

Conclusions

Spectral reflectance factor data acquired in the field together with foliar properties were used to discriminate two important rootstock grapevine species (e.g., *V. riparia* and *V. rupestris*) and their genotypes within the species. The main results of this study can be summarized as follows:

1. Our results suggest that the spectral reflectance factor data of grapevine species at leaf and canopy level provided useful information to identify a set of optimal bands significant for discrimination of two grapevine species and among genotypes within species. The wavelength regions include 350-1400 nm, 1480-1870 nm, and 2100-2400 nm at leaf level and 350-427 nm, 527-580 nm, 701-1023 nm, 1326-1884 nm, and 1979-2419 nm at canopy level. The set of optimal bands within NIR and SWIR regions were consistent at both leaf and canopy levels with respect to its capability to discriminate species. Although there were no spectrally separable bands among the *V. riparia* genotypes at canopy level, we identified the 730-1450 nm wavelength region has the potential to discriminate genotype pairs of B 50 and Okobojo and GVIT 775 and Okobojo at leaf level. Within *V. rupestris*, 1390-1585 nm and 1740-2470 nm wavelength regions were identified for B 38 and R-67-2 genotype groups and 990-2500 nm was identified for R-66-3 and R-67-2 genotype groups as specific wavelength regions at leaf level. In addition, at canopy level, 500-633 nm and 696-742 nm was identified for B 38 and R-67-2 and 517-612 nm and 696-731 nm was identified for R-66-3 and R-67-2 as optimal wavelengths regions.
2. The 1st- and 2nd-ds were vital for spectrally discriminating the grapevine genotypes especially in the vis spectral region. This was mainly due to the pigment concentration differences between species and among

genotypes. At leaf level, within *V. riparia* species 710-750 nm and 705-755 nm regions were found to be important for discriminating the B 50 and Okobojo and GVIT 775 and Okobojo groups, respectively. Similarly, within *V. rupestris* species, the R-66-3 and R-67-2 group was spectrally separable in 550-600 nm and 710-750 nm regions, and the R-66-9 and R-67-2 group was spectrally separable in the 510-612 nm region. At canopy level, the 1st-d identified a new genotype group (e.g., R-65-44 and R-66-9) that was not detected at leaf level and original raw spectra within *V. rupestris*.

3. Some of the foliar properties such as fresh and dry leaf weight enabled us to differentiate two grapevine species, while PRI not only showed great potential to discriminate species but also identified spectrally separable genotypes group pairs within the *V. rupestris* species.
4. This study is considered as a preparatory step towards building a spectral library of the important wild grapevine species for Missouri's thriving viticulture economy using field collected reflectance factor data. Therefore, these spectral data can be used as endmembers to identify natural populations of *V. riparia* and *V. rupestris* in hyperspectral images for the purposes of locating wild germplasm that could be used in breeding.

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