UTILIZATION OF REMOTE SENSING TECHNOLOGY TO DETECT RIESLING VINEYARD VARIABILITY

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Abstract:
Context and purpose of the study – Vineyard blocks can vary spatially with respect to several viticulturally significant qualities such as soil variables, vine vigor, vine physiology, yield components, and berry composition. The ability to detect this variation enables the application of precision viticulture, whereby intra-vineyard variability can be readily identified and corresponding responses can be made. Although it has been well established that this variation can exist, its detection is often difficult, with vineyard blocks spanning large areas and variation occurring over several variables. The aim of this project was to determine if remote and proximal sensing technologies could be used to detect this vineyard variation in six Ontario Riesling vineyards over a 3-year period.
Material and methods – Six commercial Riesling vineyards across the Niagara Peninsula in Ontario, Canada were selected and 80-100 grapevines, in a ≈8 m x 8 m grid pattern, were identified and geolocated. From these vines, the following variables were measured in 2015-2017: soil moisture, vine water status (leaf water potential, leaf ψ; leaf stomatal conductance, g_s), vine size, yield components, berry composition, winter hardiness, and grapevine leaf roll-associated virus (GLRaV) infection. Furthermore, two sensing technologies—a ground-based red/green/blue (RGB) proximal sensing system (GreenSeeker), and an unmanned aerial vehicle (UAV) with two sensors (RGB and thermal), collected electromagnetic reflectance from each vineyard block. These data were transformed into normalized difference vegetation index (NDVI). Lastly, replicate wines were made from grapes harvested from areas of low vs high NDVI. Wines were subjected to sensory sorting and the sorting data were subjected subsequently to correspondence analysis, creating a Chi-square metric map that displayed the wines and their descriptors on a descriptor-based space. The overall hypothesis was that maps produced from NDVI data could be used to detect variation in other variables such as leaf ψ, g_s, berry composition, and GLRaV status, as well as implicate wine quality.
Results – NDVI maps demonstrated similar spatial configurations to maps of yield, vine size, berry weight, water status, and berry composition. Spatial zones corresponding to high NDVI were associated with zones of high vine water status, vine size, yield, titratable acidity (TA) and low soluble solids and terpene concentration. NDVI data as well as vine size, leaf ψ, g_s, GLRaV infection, winter hardiness, and berry composition consisted of significant spatial clustering within the vineyard. Both the proximal and UAV technologies produced maps of similar spatial distributions; however, the GreenSeeker NDVI data provided more significant relationships with agricultural data compared to the UAV NDVI. Direct positive correlations were observed between NDVI vs. vine size, leaf g_s, leaf ψ, GLRaV infection, yield, berry weight, and TA and inverse correlations with soluble solids and terpene concentration. Wines created from areas of high vs low NDVI differed slightly in basic wine composition (pH, TA, ethanol). Sensorially, panelists were often able to distinguish between wines made from high vs. low NDVI zones and associate those wines with specific descriptors. Ultimately, remote sensing demonstrates the ability to consistently detect areas within a vineyard differing in several important variables, which have implications for vine physiology, berry composition, and wine sensory attributes.
Keywords: Viticulture, Remote Sensing, Terroir, UAV, Precision viticulture, GIS

1. Introduction

The Ontario wine industry produces ≈ 80,000 tonnes of grapes including cultivars such as Riesling, Chardonnay and Cabernet franc as well as Cabernet Sauvignon, Merlot and Pinot noir (www.grapegrowersofontario.com). Riesling is currently the second most widely planted white wine cultivar after Chardonnay. Soils in the Niagara Region are variable due to glacial activity > 10,000 years ago, and many vineyards are situated on several soils that can range widely in texture, depth of solum, and water-holding capacity [Kingston and Presant, 1989]. This soil variability can impact vine vigor, yield, and vine water status.

GreenSeeker and other ground-based (proximal sensing) technologies might allow identification of unique zones within vineyards without use of aircraft using continuous compilation of NDVI data from vine canopies [Drissi et al., 2009; Mazzeto et al., 2009, 2011]. If unique zones are identified easily from the ground, it is possible that different wine products of varying price points could be created from these zones with minimal cost from the producer. Data validation is required to determine relationships between proximally-sensed data and other variables of agricultural relevance, but the proximally-sensed data are relatively easy to access. Proximal sensing technologies are relatively recent introductions and their evaluation in viticulture is uncommon. Proximal sensing correlated with vine size and berry color in Merlot vineyards in Greece [Stamatiadis et al., 2006] and downy mildew levels in Italian vineyards [Mazzeto et al., 2011]. A linear correlation to stable isotope content in leaves (^{13}C and ^{15}N) provided relationships between canopy reflectance and both water status and N fertilizer uptake [Taskos et al., 2014; Stamatiadis et al., 2009]. Despite these advances research into proximal sensing has mainly been limited to agronomic crops [Barker and Sawyer, 2010] and thus far little viticulture-related work has been carried out in Canada [Reynolds et al., 2016a,b].

Attempts have been made with limited success to identify unique zones using remote sensing (RS) and to thereafter associate these remotely-sensed regions with variables such as vine water status, soil moisture, vine vigor, yield, and berry composition. Although less laborious than manual data collection and subsequent production of a multitude of maps, use of aircraft is costly and RS in agricultural systems is often imprecise [Stamatiadis et al., 2006]. Data that are collected must be converted to vegetation indices (VIs), e.g., normalized difference vegetative index (NDVI) through appropriate computer software [Hall et al., 2002; Ledderhof et al., 2016, 2017; Marciniak et al., 2015, 2017]. Moreover, validation of data acquired by RS is still necessary to determine whether ostensibly-unique zones are relevant based on physiology, productivity, and berry composition. One particular challenge involved masking of cover crop spectral reflectance from all images to assess the vine canopy-specific NDVI and other VIs [Ledderhof et al., 2016, 2017; Marciniak et al., 2015, 2017].

In viticultural applications, RS has been used in modelling vegetative growth, and to infer grape composition from those measurements. Remotely sensed multispectral data were used to delineate a Chardonnay vineyard into small-lot production zones, based on vine size (weight of cane prunings; vigor). Vigor zones were also related to vine water status and grape composition variables [Johnson et al., 2001]. Relationships between VIs and vegetative growth were further explored, with strong, positive correlations between the VIs and vine size [Dobrowski et al., 2003]. Relationships established in the first season were able to predict vine size in the second season. The ability of RS to directly predict grape composition variables was explored in Australia, showing that re-sampling the image to a final pixel size approximately equal to the distance between rows, effectively combining vine size and density information into a single pixel, resulted in the strongest correlations to color and phenols [Lamb et al., 2004]. In Languedoc temporally stable relationships occurred between zones delineated based on NDVI and vegetative growth, vine water status, and yield [Acevedo-Opazo et al., 2008].

Overall, RS can be a useful tool for monitoring vineyard vegetative growth, and for making inferences about grape composition from multispectral measurements. In Ontario, NDVI data from aircraft-based RS was associated with numerous variables in Riesling [Marciniak et al., 2015, 2017] and Pinot noir [Ledderhof et al., 2016] vineyards, including leaf ψ, yield components, and berry composition. RS proved to be a good tool to determine Pinot noir anthocyanins and phenols, in addition to water status, yield and vine size [Ledderhof et al., 2016]. These studies were unique by studying cover-cropped vineyards, and using protocols for excluding the spectral reflectance contributed by inter-row vegetation. Aircraft-based RS has been used for making inferences about grape composition from multispectral measurements [Post et al., 2000]. However, employment of UAVs for RS in vineyards is a relatively new area of research, heretofore untested in Canada, and capable of acquiring high-resolution spatial data without high cost of aircraft. As with proximal sensing there has been little published, and most have confirmed their ability to acquire NDVI and related images [Turner et al., 2011; Guillen-Climent et al., 2012; Matese and Di Gennaro, 2015]. Relationships were explored between photosynthesis and chlorophyll fluorescence by hyperspectral imagery captured via UAVs [Zarco-Tejada et al., 2013a]. Significant relationships were observed between photosynthesis and chlorophyll fluorescence vs. remote measurements, as well as between both chlorophyll a/b and leaf carotenoids vs. several UAV-based VIs [Zarco-Tejada et al., 2013c]. UAVs were likewise utilized for assessment of vineyard water status by correlation of stem water potential (ψ) with NDVI [Baluja et al., 2012]. Further relationships were elucidated between several VIs [NDVI, photochemical reflectance index, renormalized difference vegetation index, red edge inflection point (REIP)] vs. leaf ψ and stomatal conductance (g_s)[Zarco-Tejada et al., 2013b]. Nutritional stresses have been detected by UAVs; e.g., NDVI was correlated with levels of Fe chlorosis, leaf carotenoid pigments, and grape leaf and berry anthocyanins [Meggio et al., 2010].

It has been increasingly evident that many vineyards in Ontario, British Columbia, and California are infected by both grapevine leafroll-associated virus (GLRaV) as well as grapevine red blotch virus (GRBV). GLRaV is one of the most destructive and widespread diseases in all grape-growing regions globally. Yield losses from GLRaV can reach 20-40% [Habili and Nutter, 1997], depending on cultivar, rootstock, soil type, vine age, and climate. Many large Ontario vineyards have attained the designation as "underperforming" by wineries, based on basic fruit maturity characteristics such as reduced total soluble solids, TSS) and color. Technologies must be developed and implemented to detect zones of virus infection before entire vineyard blocks become unsuitable for quality winemaking. Discovery of evidence of correlations between both remotely- and proximally-acquired vegetation indices (VIs) such as NDVI and the titer of GLRaV and GRBV, as well as unique spectral signatures of leaves of virus-infected vines based upon spectral technology would be of significant benefit to the industry worldwide. These tools may be particularly valuable for white wine cultivars such as Riesling and Sauvignon blanc, since they are mostly asymptomatic for GLRaV and GRBV.

2. Materials and methods

2.1 Sites and cultivars

Six Riesling vineyards (1-2 ha) in the Niagara Region were chosen. The sites represented the following sub-appellations: Niagara Lakeshore (Buis), Creek Shores (Pondview), St. Davids Bench (Chateau des Charmes), Lincoln Lakeshore north (George), Lincoln Lakeshore south (Hughes), Beamsville Bench (Cave Spring). Soil types [Kingston and Presant, 1989] varied substantially in these sub-appellations from well-drained coarse-textured Tavistock and Vineland series (Niagara Lakeshore, Lincoln Lakeshore north), to moderately-well drained Chinguacousy (Creek Shores, Beamsville Bench), and poorly-drained Jeddo (Lincoln Lakeshore south) and Beverly/Toledo soils (St. Davids Bench). These soils provided a range of water-holding capacities that impacted vine water status.

2.2 Geolocation

Vineyard blocks were GPS-delineated to determine shape using a Trimble Handheld GPS, equipped with TerraSync software (Trimble Navigation, Sunnyvale, CA). Sentinel vines (80-100) were identified in a ≈ 8m x 8m grid within each vineyard and geolocated by the aforementioned GPS system. Post-collection differential correction was performed using GPS Pathfinder Office (Trimble Navigation) to ≈30-50 cm accuracy using the Port Weller, ON base station correction. Field measurements and berry samples were taken on these vines in all vintages.

2.3 Soil moisture, leaf water potential (ψ), and stomatal conductance (g_s)

Vineyard soil water content (SWC) was measured at 20 cm depth by time domain reflectometry using the Field Scout TDR 300 Soil Moisture Meter (Spectrum Technologies, East Plainfield, IL). Measurements occurred at berry set, lag phase, and veraison on all sentinel vines. Vine water status was measured using midday leaf ψ by pressure bomb (Soil Moisture Equip., Santa Barbara, CA). Measurements were made only at designated leaf ψ vines (≈ 20 per vineyard block), on the same days as SWC measurements, from 1000h-1400h (ca. solar noon), under full sun. Leaf g_s was measured by a hand-held porometer (Decagon Devices, Pullman, WA) on leaf ψ vines.

2.4 Yield components and vine size

Harvest dates were at the discretion of vineyard managers. Fruit from each sentinel vine was harvested, cluster number determined, and fruit weighed using a portable field scale. Dormant cane prunings and weighed to determine vine size.

2.5 Berry analysis

A 100-berry sample was taken from each sentinel vine at harvest and frozen at -25°C. Each sample was weighed to determine mean berry weight, and placed in a beaker in a water bath at 80°C for 1 hr to dissolve precipitated tartrates. Samples were homogenized in a juicer and juice samples (≈35 mL) were clarified by centrifugation at 4500 *g* for 10 minutes. TSS were measured by refractometer (UV Corp., Buffalo, NY), pH by an Accumet pH meter (Fisher, Mississauga, ON), and titratable acidity (TA) by titration to an 8.2 pH endpoint with 0.1N NaOH with a PC-Titrate autotitrator (Man-Tech, Guelph, ON). Free volatile and potentially-volatile terpene concentrations (FVT, PVT; mg/kg) were analyzed on 250-berry samples taken from leaf ψ vines using a distillation method [Dimitriadis and Williams, 1984] modified by Reynolds & Wardle [1989]. Absorbances were measured using an Ultrospec 2100 Pro UV-VIS spectrophotometer (Biochrom, Cambridge, UK).

2.6 Spatial mapping

GPS coordinates from vineyard blocks and sentinel vines were imported into a GIS environment (ArcGIS 10.3; Environmental Systems Res. Inst., Redlands, CA) and linked to all point data collected from sentinel vines. Spatial interpolation techniques (inverse-distance weighting; diffusion interpolation with barriers for remotely-sensed data) were applied to these data to estimate values of vineyard variables at unsampled locations.

2.7 Hand-held spectral signatures

There has been limited experience in measurement of unique spectral signatures in GLRaV [Naidu et al., 2009] and GRBV [Mehrubeoglu et al., 2016]. Prior to appearance of virus symptoms in leaves, spectral reflectance in the visible and near-infrared (NIR) ranges was measured on leaves from virus-free and GLRaV-infected vines. An EPP2000 (UV-Vis-100 nm) spectrometer, controlled by a laptop computer running SpectraWiz software (Stellarnet, Tampa, FL) was used to record reflectance spectra [Ledderhof et al., 2016, 2017; Marciniak et al., 2015, 2017]. A custom-built enclosure was used to hold the leaf and 5-W halogen bulb light source.

2.8 Proximal sensing

A GreenSeeker unit (Trimble Navigation, Englewood, CO) mounted on a four-wheel-drive vehicle was used to collect NDVI data in 2015-2017 on dates close to soil moisture and leaf ψ data collection. Data were imported into Farmworks software (Trimble) and spatial maps created. Shapefiles were imported into the ArcGIS geodatabase. GPS coordinates identical to the sentinel vines were identified and NDVI data corresponding to these coordinates were extracted for statistical analyses.

2.9 UAV and sensors

Flights - The 2015 and 2016 UAV flights corresponded to the veraison SWC, leaf ψ, and GreenSeeker data collection. Image acquisition was performed according to previously-reported methods with a Robotic Aviation Responder (ING Robotic Aviation, Orléans, ON) supplied by Air-Tech Solutions, Inverary, ON [Reynolds et al., 2016a]. Two sensors were used for image acquisition. The first operated in the visible and NIR portions of the electromagnetic spectrum (Mini-MCA 6; Tetracam, Chatsworth, CA) utilizing five spectral bands (blue, green, red, red edge, NIR) equipped with an incident light sensor. The second sensor operated in the thermal–IR portion of the spectrum (A65 thermal imaging camera; FLIR Systems, Burlington, ON).

Image acquisition, pre-processing, processing - Image acquisition was performed over each vineyard block according to published protocols [Reynolds et al., 2016a]. Once assembled and corrected NDVI-red, NDVI-green, Greenness Ratio, and REIP were calculated on mosaics. Pixel values corresponding to sentinel vines were extracted and compiled into a geodatabase that included all field based variables (e.g. leaf ψ).

2.10 Virus titer determination

All vines designated for leaf ψ and g_s measurements were sampled in September 2016 to determine GLRaV titer. Total RNAs were isolated from leaf samples using a recently-developed method [Xiao et al., 2015]. The resulting total RNAs were used in reverse transcription using primers specific to GLRaV-2 and 3, followed by amplification through PCR using broad-spectrum primers to first identify virus presence in the samples [Meng et al., 2006]. To determine virus titer for the purpose of comparison and correlation to the data collected using UAV and GreenSeeker, qPCR was conducted by Power SYBR Green PCR Master Mix and StepOnePlus qPCR (Applied Biosystems).

2.11 Wine composition and sensory evaluation

Replicate wines were made from high and low NDVI zones in 2016 and 2017 using standard protocols. Wines were analyzed for TA and pH using aforementioned methods; ethanol was measured by GC using a six-point calibration with 1-butanol as an internal standard. Labeled free sorting tasks (Chollet et al., 2014) were carried out on wines from both vintages in 2018 to determine if sensory differences could be detected between wines from low vs high NDVI vineyard zones. A contingency table was then used in a correspondence analysis (Chollet et al., 2014) creating a Chi-square metric map that displayed the wines and their descriptors on a descriptor-based space.

2.12 Data analysis

Basic linear correlations and regressions were performed on the ground-based, proximally-sensed, and UAV data to determine relationships, particularly those between proximally sensed/UAV data vs. ground-based data using XLStat (Addinsoft, Paris, France). Principal components analysis was likewise performed. Maps were created for all variables using ArcGIS. *K*-means clustering and Moran's *I* were used to verify spatial relationships.

3. Results and discussion

3.1 Principal components analysis

NDVI acquired by GreenSeeker and UAV were directly correlated at five of six sites (Fig. 1A-D). Direct correlations between NDVI were also observed for g_s but were limited for SWC and leaf ψ. NDVI was also associated with yield, berry weight, and vine size, and inversely with Brix and pH. Inverse relationships between NDVI and both FVT and PVT were also observed in some vineyards. These relationships were consistent with those previously observed in this investigation [Reynolds et al., 2016a,b], as well as previous studies [Marciniak et al., 2015, 2017].

3.2 Map analysis

Spatial maps from one vineyard in 2016 are in Fig. 2. Zones of high UAV-based NDVI were spatially-associated with GreenSeeker-based NDVI. Other direct correlations included leaf ψ, TA, and FVT. Four of six vineyards had significant GLRaV infections. High GLRaV titer was directly associated with low NDVI in some vineyards based on map analysis. This is consistent with observations in Cabernet franc where low NDVI was associated with GLRaV symptoms [Reynolds, 2017].

3.3 Regression analysis

There was no obvious statistical relationship between UAV-based NDVI and GLRaV titer (data not shown). As with PCA and map analysis, UAV-based and GreenSeeker-based NDVI were directly correlated in four of six vineyards (data not shown), but were inexplicably inversely correlated in one. Other relationships included direct correlations between UAV-based NDVI and leaf ψ, g_s, vine size, and TA, and inverse relationships between NDVI and Brix, pH, and PVT (Fig. 1E-H). Many of these relationships confirmed those observed in PCA and map analysis. These trends confirmed those observed in previous seasons or other studies [Ledderhof 2016, 2017; Marciniak et al., 2015, 2017; Reynolds et al., 2016a,b].

3.4 Wine composition and sensory sorting

Wine composition did not differ between treatments, with the exception of pH, which differed between low and high NDVI wines in multiple sites in 2016 and 2017 (data not shown). In 2016, pH differed between treatment wines in two sites and in 2017 in four sites. There was a tendency for TA values to be higher and pH to be lower in high NDVI wines in both seasons for all sites. Ethanol values were virtually the same between treatments in both years. Tasters were successful in sorting two groups of wines in 2016 and 2017 for most sites based on NDVI (data not shown). Correspondence analysis in some circumstances associated high NDVI wines with descriptors such as 'neutral', 'acidic', and 'citrus', and low NDVI wines with 'floral', 'tree fruit', and 'tropical fruit'. This suggests that NDVI might be used to delineate zones within blocks with potentially higher quality levels.

4. Conclusions

UAV-derived NDVI data were related to those from GreenSeeker as well as many other variables of viticultural significant, particularly leaf ψ, g_s, vine size, and yield. There was little relationship between NDVI and GLRaV titer in the six vineyards investigated. Other VIs such as NDVI-red, NDVI-green, red edge inflection point, NDRE, and many others may be better indicators of virus titer. Riesling was in general less responsive than Cabernet franc in terms of relationships between NDVI and other physiological and viticultural variables.

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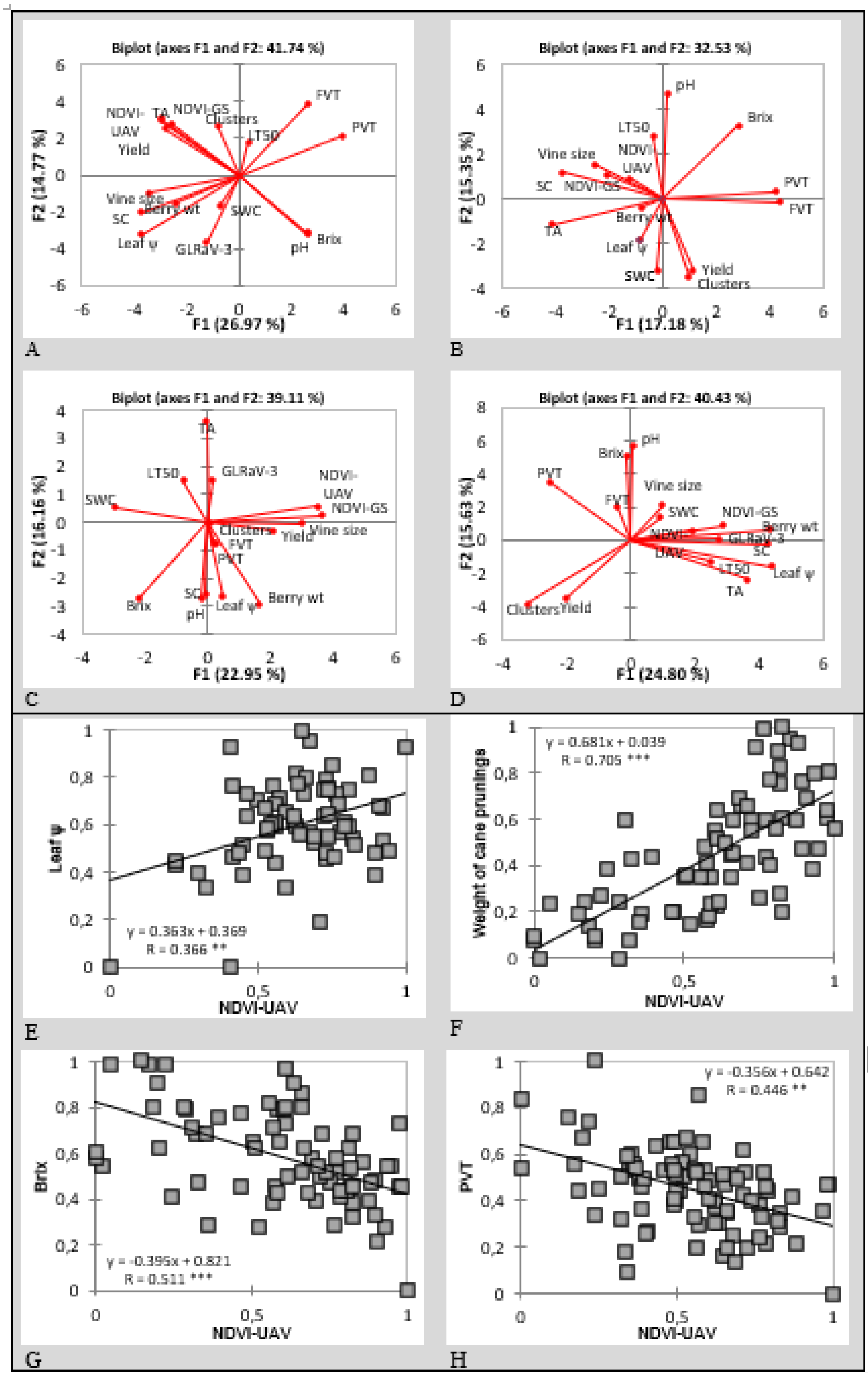

Figure 1. A-D: Principal components analysis of four typical Ontario Riesling vineyards, 2016. A: Buis, Virgil, ON; B: Pondview, Virgil, ON; C: Chateau des Charmes, St. Davids, ON; D: George, Vineland, ON. Abbreviations: GS: GreenSeeker; GLRaV: Grapevine leafroll-associated virus; LWP: Leaf water potential; SWC: Soil water content; SC: Stomatal conductance; TA: Titratable acidity. E-H: Relationships between UAV NDVI and viticultural variables in three typical Ontario Cabernet franc vineyards, 2016. E: George, Vineland, ON; F,G: Chateau des Charmes, St. Davids, ON; H: Cave Spring, Beamsville, ON.

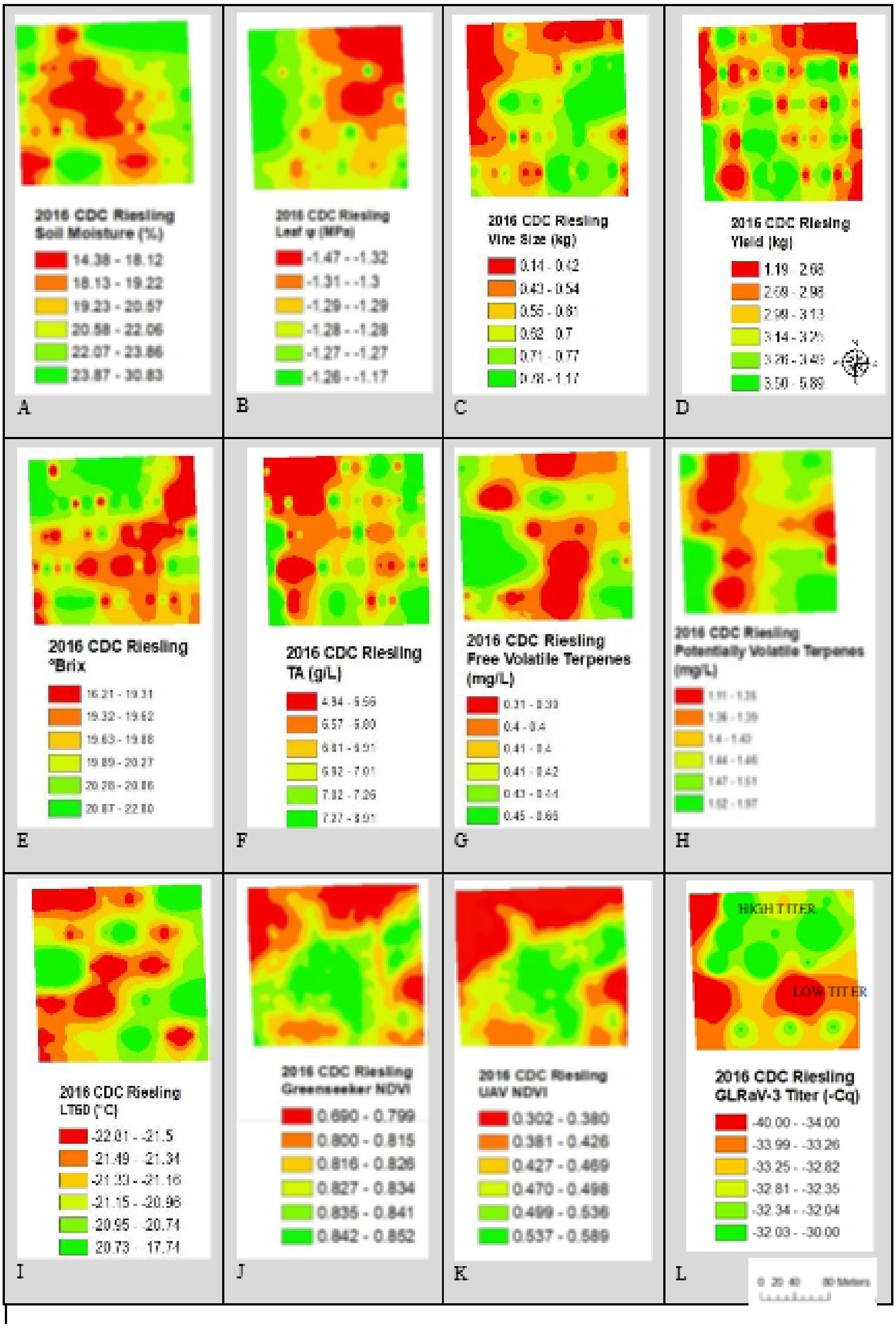

Figure 2. Spatial maps of the Chateau des Charmes Riesling vineyard, St. Davids, ON, 2016. A: Soil water content (%); B: Leaf water potential (MPa); C: Vine size (kg); D: Yield (kg); E: Brix; F: Titratable acidity (g/L); G: Free volatile terpenes (mg/L); H: Potentially-volatile terpenes (mg/L); I: LT50 (ºC) J: NDVI acquired by GreenSeeker; K: NDVI acquired by UAV; L: GLRaV titer (Cq).