APPLICATION OF REMOTE SENSING BY UNMANNED AERIAL VEHICLES TO MAP VARIABILITY IN ONTARIO RIESLING AND CABERNET FRANC VINEYARDS

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Abstract. The objective of this investigation was to verify usefulness of proximal sensing technology and unmanned aerial vehicles (UAVs) for mapping variables e.g., vine size (potential vigor), soil and vine water status, yield, fruit composition, and virus incidence in vineyards. Twelve Niagara Peninsula sites (six each of Riesling and Cabernet franc) were chosen in 2015. Data were collected from a grid of vines (≈ 80 per vineyard) geolocated by GPS. Soil moisture and leaf water potential (ψ) data (three times during the growing season; June to September) and yield components/berry composition were collected. Ground based GreenSeeker™ data were likewise acquired June to September, while multi-spectral UAV data were obtained at veraison and processed into geo-referenced high spatial resolution maps of biophysical indices (e.g., NDVI). Following harvest, yield/berry composition maps were also prepared. These data layers in conjunction with growing/dormant season sentinel vine data [e.g. soil moisture, leaf ψ, vine size, winter hardiness (LT_{50})], were used for map creation. Vine size, LT_{50}, yield, berry weight, and berry composition data were correlated in several vineyards to NDVI and other data acquired with the UAV and GreenSeeker™, while soil and vine water status, and yield components showed direct relationships with NDVI. Spatial relationships were also apparent from examination of the maps. Principal components analysis confirmed these relationships. Map analysis to determine spatial relationships was accomplished by calculation of Moran's I and k-means clustering. NDVI values were considerably higher in GreenSeeker maps vs. those from UAV flights. Water status zones, and those of several fruit composition variables, were correlated with UAV-derived NDVI. Preliminary conclusions suggest that UAVs have significant potential to identify zones of superior fruit composition.

Keywords: Precision viticulture, drones, leaf water potential, soil moisture

1 INTRODUCTION

The Ontario wine industry produces ≈ 65,000 tonnes of grapes and consists of cultivars such as Riesling, Chardonnay, and Cabernet franc, with lesser quantities of Merlot, Cabernet Sauvignon, and Pinot noir (www.grapegrowersofontario.com). Soils are characterized as variable as a result of widespread glacial activity over 10,000 years ago, and consequently many vineyards are situated on several soil series that can range widely in texture, depth of solum, and water-holding capacity [1]. This variability in soil characteristics can impact vine vigor, yield, and water status. A significant growth in the number of small artisanal wineries has permitted production of wines that are unique to individual vineyard sites and in some cases unique to specific vineyard blocks. In the past 10-15 years this interest has expanded to include identification of unique portions of vineyard blocks, some < 1 ha, that might be capable of producing extremely high-value wines based upon yield, vine size, or water status-based quality levels.

The recent introduction of Greenseeker and other proximal sensing technologies might allow growers to identify unique zones within vineyards without use of aircraft [2-4]. If unique zones can be 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 would be required as with remote sensing to determine relationships between proximally-sensed data and other variables of agricultural relevance, but the proximally-sensed data are relatively easy to access. Ground-based (proximal sensing) technologies are relatively recent introductions and their evaluation in viticulture is uncommon. Their initial use was for continuous compilation of NDVI data from vine canopies [2-4]. Proximal sensing correlated with vine size and berry color in Merlot vineyards in northern Greece [5]. NDVI sensors explained variation in biomass; its relationship to vine size was nonlinear and was best described by a quadratic regression. A linear correlation to stable isotope content in leaves (^{13}C and ^{15}N) provided evidence that canopy reflectance detected plant stresses as a result of water shortage and limited N fertilizer uptake [6,7]. It was also successful in detection of downy mildew disease levels in Italian vineyards [4]. Despite these advances research into proximal sensing has mainly been limited to agronomic crops such as corn [8,9] and thus far no work in Canada has been carried out.

Attempts have been made with limited success to identify unique zones using remote sensing 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 remote sensing in agricultural systems is often imprecise [5]. The data that is collected must be converted to variables, e.g., normalized difference vegetative index (NDVI) through computer software such as ENVI [10-13]. Moreover, validation of data acquired by remote sensing is still necessary to determine whether ostensibly-unique zones are relevant from a standpoint of physiology, productivity, and berry composition. One particular challenge involved masking of cover crop NDVI from all images to assess the vine canopy-specific NDVI [12,13].

In viticultural applications, remote sensing has been used in modelling vegetative growth, and to infer grape composition from those measurements. Johnson et al. [14] used remotely sensed multispectral data to delineate a Chardonnay vineyard into small-lot production zones. They found that vine size was related to vigor zones identified by airborne images. Vigor zones were also related to vine water status and grape composition variables. Thus, indirectly, remote sensing was used to predict vineyard status and grape composition, with direct implications for wine quality [14]. Relationships between vegetation indices (VIs) and vegetative growth were further explored by Dobrowski et al. [15]. There were strong, positive correlations between the extracted VIs and pruning weights (vine size) in two years. Additionally, relationships established in the first season were able to predict the vine size in the second season [15].

The ability of remote sensing to be used to directly predict grape composition variables was explored by Lamb et al. [16]. They found 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. Strongest negative correlations between NDVI and color and phenols occurred around veraison [16]. In Languedoc (France), Acevedo-Opazo et al. [17] performed a study on remotely sensed VIs, vine water status, and grape composition on a number of winegrape cultivars in non-irrigated vineyards. Temporally stable relationships occurred between zones delineated based on the NDVI and vegetative growth, vine water status, and yield. These zones were also consistent with soil type. They concluded that a combination of remotely sensed data with intimate vineyard knowledge, especially of the soil, is needed to predict grape composition and ultimately wine quality [17].

Overall, remote sensing has been proven as a useful tool for monitoring vineyard vegetative growth, and for making inferences about grape composition from multispectral measurements. In Ontario, NDVI data from remote sensing was associated with numerous variables in Riesling vineyards, including vine water status, yield components, and berry composition [12,13]. Similar applications were made in Pinot noir vineyards [11]. Remote sensing proved to be a good tool to determine color and phenolic potential of grapes, in addition to water status, yield and vine size [11]. These studies were unique by employing remote sensing in cover-cropped vineyards and thereafter using protocols for excluding the spectral reflectance contributed by the inter-row vegetation.

Remote sensing has likewise been used for making inferences about grape composition from multispectral measurements [18,19]. However, employment of UAVs for remote sensing 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 has confirmed their ability to acquire NDVI and related images [20-22]. Zarco-Tejada et al. [23] explored relationships between photosynthesis and chlorophyll fluorescence by hyperspectral imagery captured via UAVs. Significant relationships were demonstrated between photosynthesis and chlorophyll fluorescence vs. remote measurements. Other relationships were demonstrated between both chlorophyll a/b and leaf carotenoids vs. several VIs based on multispectral images acquired by UAVs [24]. UAVs were likewise utilized for assessment of vineyard water status by correlation of stem water potential with NDVI [25]. Further relationships were elucidated between several VIs including NDVI vs. leaf water potential and stomatal conductance [26]. Additionally, photochemical reflectance index (PRI), renormalized difference vegetation index (RDVI), and red edge index were correlated to water status variables [26]. Other stresses such as those nutritional in nature have been detected by UAVs; e.g. NDVI was correlated with levels of iron chlorosis, leaf carotenoid pigments, and grape leaf and berry anthocyanins [27].

2 MATERIALS AND METHODS

Sites and cultivars. Six each of Cabernet franc and Riesling vineyards (1-2 ha in area) in different Niagara sub-appellations were chosen. The sites represented the following sub-appellations: Niagara Lakeshore (Buis), Creek Shores (Lambert), St. Davids Bench (Chateau des Charmes), Lincoln Lakeshore north (George), Lincoln Lakeshore south (Hughes; Kocsis), Beamsville Bench (Cave Spring). Soil types [1] 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.

Geolocation. Vineyard blocks were GPS-delineated to determine shape using a Trimble Handheld GPS, equipped with TerraSync software (Trimble Navigation Ltd., 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 Ltd.) to sub-metre accuracy (≈30-50 cm) using the Port Weller, ON base station correction. Field measurements and berry samples were taken on these vines in all vintages.

Soil moisture, leaf water potential (ψ), and stomatal conductance (G_s). Vineyard soil moisture (SM) was measured by time domain reflectometry (TDR) using the Field Scout TDR 300 Soil Moisture Meter (Spectrum Technologies, East Plainfield, IL). The volumetric water content mode was used. A pair of 20-cm stainless steel probes were used for measurements at all sentinel vines. Measurements took place at berry set, lag phase, and veraison on all sentinel vines. Two measurements ≈ 10 cm from the vine trunk were taken. Vine water status was measured using midday leaf ψ by pressure bomb (Soil Moisture Equipment, Santa Barbara, CA). Measurements were made only at designated leaf ψ vines (≈ 15 per vineyard block), on the same days as SM 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 those vines used for leaf ψ.

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. Mean cluster weight was calculated from these data. Cane prunings were retained and weighed to determine vine size during dormancy.

Berry analysis. *Basic composition.* 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 one hour to dissolve precipitated tartrates. Samples were homogenized in a commercial juicer. Soluble solids were measured using a benchtop refractometer (UV Corp., Buffalo, NY). Berry pH was measured using an Accumet pH/ion meter and VWR Symphony electrode (Fisher, Mississauga, ON). Juice samples (≈35 mL) were clarified by centrifugation at 4500 *g* for 10 minutes. The remaining juice (≈20 mL) was retained at -25°C for subsequent color analysis (Cabernet franc). Titratable acidity was measured on centrifuged juice, titrated to an endpoint of pH 8.2 with 0.1N NaOH using a PC-Titrate autotitrator (Man-Tech Associates, Guelph, ON).

Colour/hue, total anthocyanins, total phenols (Cabernet franc; monoterpenes (Riesling). Re-frozen samples were centrifuged at 4500 *g* at 4°C. Absorbances were measured using a spectrophotometric method at 420 nm and 520 nm using an Ultrospec 2100 pro UV-VIS spectrophotometer (Biochrom Ltd., Cambridge, UK). Color intensity was calculated as A420+A520, and hue as A420/A520. Total anthocyanins were quantified using the pH shift method [28]. Total phenols were quantified using the Folin-Ciocalteu method [29] and expressed as mg/L gallic acid. Monoterpenes were analyzed on 250-berry samples taken from leaf ψ vines using a distillation method [30] modified by Reynolds & Wardle [31]. Free volatile and potentially-volatile terpene concentrations were expressed in mg/kg.

Spatial mapping. GPS coordinates from vineyard blocks and sentinel vines were imported into a GIS environment (ArcGIS 10.3; Environmental Systems Research Institute, Redlands, CA) and linked to all point data collected from sentinel vines. Spatial interpolation techniques (i.e., kriging) applied to these data were used to estimate the value of vineyard variables at unsampled locations. This permitted further spatial data analyses; including the integration of these data with the remote-sensing datasets.

Proximal sensing. A GreenSeeker unit (Trimble Navigation, Englewood, CO) mounted on a four-wheel-drive vehicle was used to collect Normalized Difference Vegetation Index (NDVI) data on dates close to soil moisture and leaf ψ data collection. An additional reading was collected mid-September. Data were imported into Farmworks software (Trimble Navigation, Englewood, CO) and spatial maps created. Shapefiles were thereafter 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.

UAV and sensors. The 2015 UAV flight corresponded to the veraison soil moisture, leaf ψ, and GreenSeeker data collection. Image acquisition was performed using the ING Robotic Aviation Responder (ING Robotic Aviation, Orléans, ON), a UAV supplied by Air-Tech Solutions, Kingston, ON. The UAV was powered by an electric motor providing 30 min of endurance and a 9-kg payload, and equipped with an autopilot system allowing a 1000-m visual range and 5-km radio line of sight. The UAV was flown at a 122-m elevation and a 60 km/h maximum speed. Two sensors were used for image acquisition. The first operated in the visible and near-infrared portions of the electromagnetic spectrum (EMS) (Mini-MCA 6; Tetracam, Inc., Chatsworth, CA) utilizing five spectral bands (blue, green, red, red edge, near-infrared) equipped with an incident light sensor. It ensured acquisition at a resolution of 7.8 megapixels, representing a spatial resolution of 4 cm at an altitude of 100 m. The second sensor operated in the thermal–infrared (IR) portion of the EMS (A65 thermal imaging camera; FLIR Systems, Burlington, ON). It ensured acquisition of imagery in the thermal-IR range covering 7500 to 13500 nm at a resolution of 0.3 megapixels, which represents a spatial resolution of 9 cm at a 100-m altitude. Equipment onboard also consisted of a GPS and an inertial station to correct anomalies in flight attitude (i.e., yaw, pitch, and roll) and ensuring the verticality and orientation of imaging. This equipment was complemented by a ground receiving station that provided real-time feedback on the position of the aircraft and its imaging.

Image acquisition, pre-processing, processing. Image acquisition was performed over each vineyard block. Data were stored onboard and retrieved after the flight mission. Geometric correction was performed to correct the image geometry. Geometric distortions caused by changes in UAV attitude and altitude were corrected using the information provided by the inertial station. Radiometric correction was performed to correct the effects of vignetting and bidirectional reflectance. The series of images acquired during each flight was assembled into mosaics by selecting the overlapping areas near nadir to limit the viewing angle and the problems of directional effects. Once assembled and corrected NDVI was 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).

Data analysis. Basic 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 SAS 9.4 (SAS Institute, Cary, NC). PCA was likewise performed by XLStat (Addinsoft, Paris, France). Maps were created for all variables using ArcGIS. K-means clustering and Moran's I were used to determine spatial relationships.

3 RESULTS AND DISCUSSION

PCA. UAV NDVI and NIR indices were correlated with vine size in all Riesling vineyards (Fig. 1). Other noteworthy associations included UAV indices and berry weight (five sites), TA (two sites—Buis, George), and proximally-sensed NDVI (four sites). Inverse correlations of note with UAV data included soil moisture and leaf ψ (five sites). Direct correlations were also noted for NDVI/NIR and at least one LT_{50} measurement for four sites: LT_{50} 03 (Buis), LT_{50} 01 (Pondview), LT_{50} 02 (Hughes, Cave Spring). Yield and cluster number were not consistently related to VIs; they were inversely correlated in three sites (Buis, Hughes, Pondview) but unrelated in two others. UAV NDVI was likewise correlated with vine size in all Cabernet franc vineyards (data not shown). Other noteworthy associations included UAV indices and soil moisture (three sites), leaf ψ (two sites), berry weight (five sites), TA (three sites), yield/cluster number (four sites), and proximally-sensed NDVI (four sites).

Maps. Maps for Buis Riesling vineyard 2015 are depicted in Fig. 2. The UAV NDVI map showed a low NDVI zone on the west side of the vineyard (Fig. 2A). This corresponded closely with highest regions from the thermal camera (Fig. 2B), and lowest regions of NDVI by GreenSeeker (Fig. 2C), leaf ψ (Fig. 2D), to a limited degree soil moisture (Fig. 2E), vine size (Fig. 2F), berry weight (Fig. 2G), and TA (Fig. 2I), and higher LT_{50} (i.e. less winter hardy; Fig. 2H). Conversely, those high-NDVI zones identified by the UAV were typically also high in terms of thermal camera data, NDVI by GreenSeeker, leaf ψ, soil moisture, vine size, berry weight, and TA, and lower in LT_{50} (i.e. more winter hardy). The Cabernet franc vineyard (data not shown) likewise showed clustering in the UAV data with low NDVI and high thermal zones in the south end of the block. These corresponded to low NDVI areas delineated by GreenSeeker, low soil moisture and leaf ψ areas, low vine size and berry weight, and higher LT_{50} zones. These showed some spatial correlation with high TA and low Brix areas, but pH and overall yield were not strongly related spatially.

In most other vineyard blocks the NDVI maps based upon drone flights were comparable to maps created from GreenSeeker data. There were occasional situations in which maps from thermal data were inversely correlated spatially with NDVI (data not shown). Most frequent spatial correlations in Riesling with UAV and GreenSeeker NDVI zones were leaf ψ, G_s, vine size, berry weight, and TA. Noteworthy inverse spatial correlations included soil moisture and yield.

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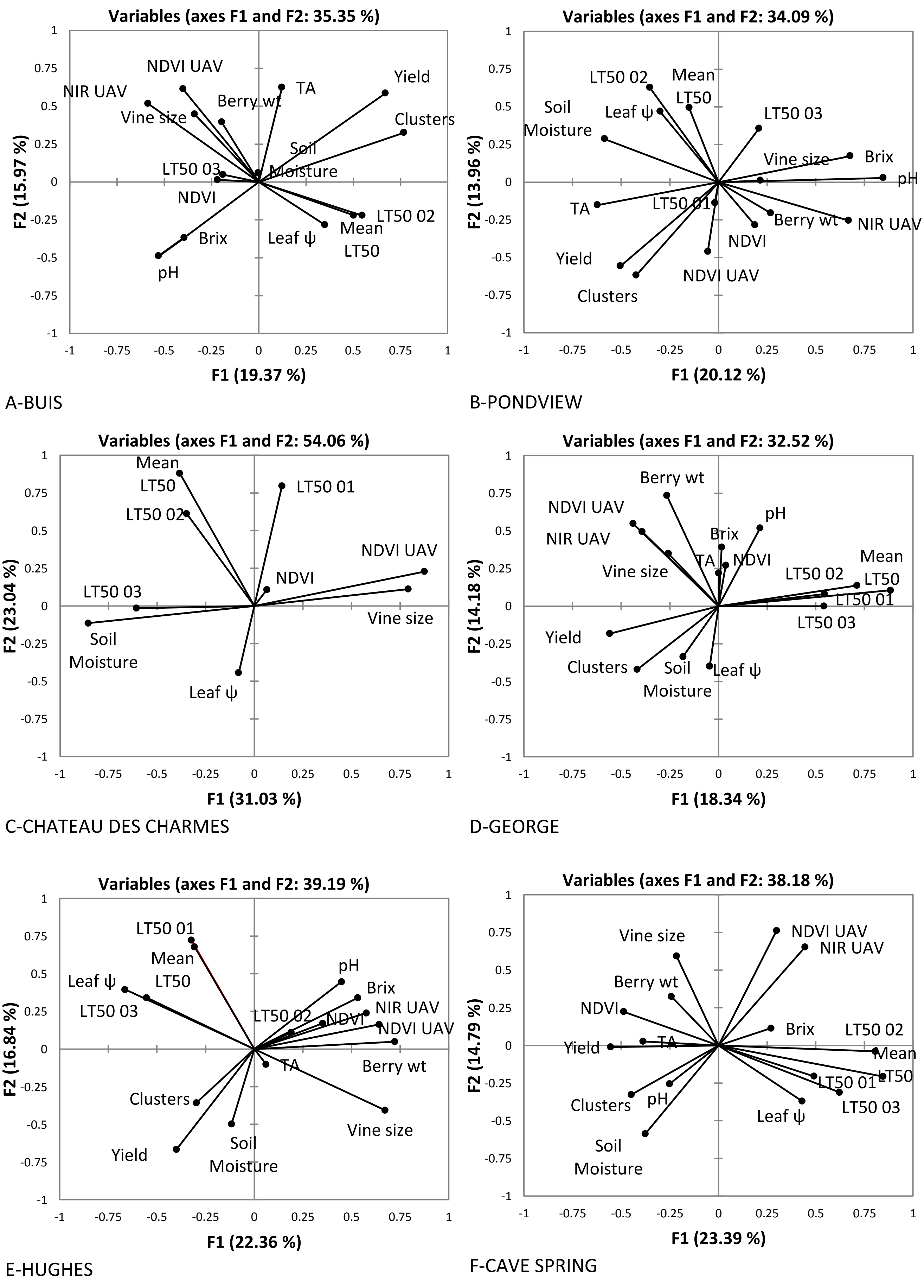

Figure 1. Principal components analysis of six Ontario Riesling vineyards, 2015.

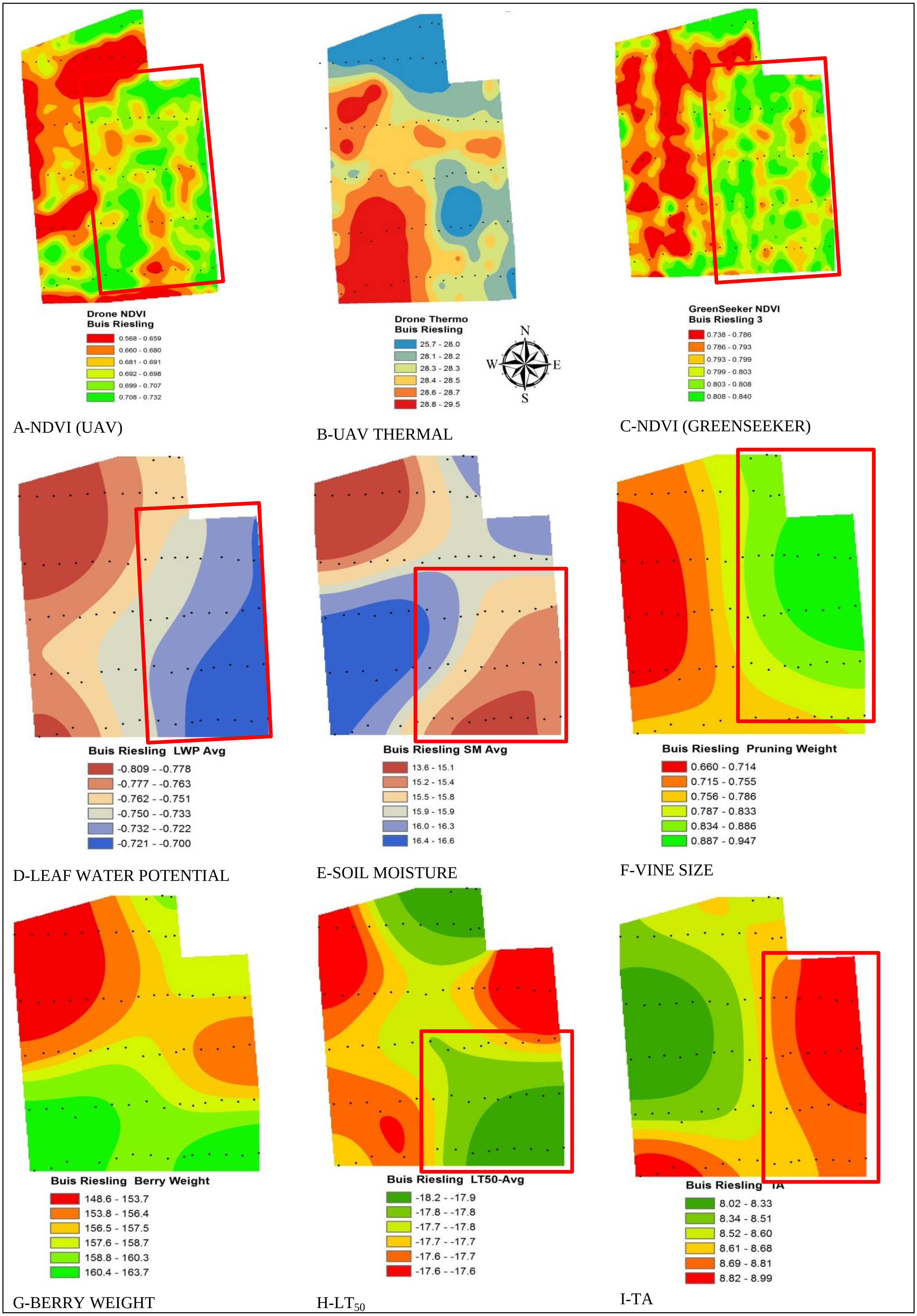

Figure 2. Maps of several related variables, Buis Glenlake Riesling vineyard, Niagara-on-the-Lake, ON, 2015. Scale 1:1812 (UAV maps), 1:2500 (others).