Viticultural Mapping by UAVs, Part 2

Applying unmanned aerial vehicles in viticulture

By Andrew G. Reynolds, Ralph Brown, Marilyne Jollineau, Adam Shemrock, Hyun-Suk Lee, Briann Dorin, Mehdi Shabanian, Baozhong Meng

Attempts have been made, with limited success, to identify unique zones using remote sensing and to associate regions with variables such as vine water status, soil moisture, vine vigor, yield and berry composition.

Although less laborious than manual data collection and production of a multitude of maps, use of conventional aircraft can be costly, and remote sensing in agricultural systems is often imprecise.[30] Data must be converted to variables, e.g., normalized difference vegetative index (NDVI) data through environmental software such as Environment for Visualizing Images (ENVI).[9] Moreover, validation of data acquired by remote sensing is still necessary to determine whether ostensibly unique zones are relevant from a standpoint of physiology, yield, and berry composition. One particular challenge involved masking of cover crop NDVI from all images to assess the vine canopy-specific NDVI.[15, 16]

In viticultural applications, remote sensing has been used in modelling vegetative growth, and to infer grape composition from those measurements. Remotely sensed multispectral data was used to delineate a Chardonnay vineyard into small-lot production zones.[12] Vine size (weight of cane prunings; an estimate of vigor) was related to vigor zones identified by airborne images. Vigor zones also were 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.

Relationships between vegetation indices (VIs) and vegetative growth were explored by Dobrowski et al.[7] There were strong, positive correlations between extracted VIs and vine size over two years. Additionally, relationships established in the first season were able to predict the vine size in the second season.

Remote sensing can be used to predict grape composition variables.[14] 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. The strongest negative correlations between NDVI and color and phenols occurred around *veraison*.

In Languedoc (France), Acevedo-Opazo et al.[1] investigated remotely sensed VIs, vine water status, and grape composition on a number of wine grape varieties in non-irrigated vineyards. Temporally stable relationships occurred between zones based on the NDVI and vegetative growth, vine water status and yield. These zones also were consistent with soil type.

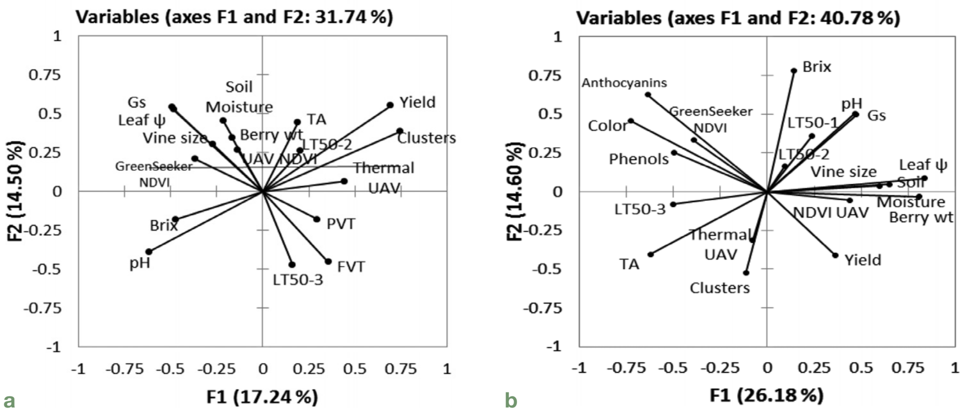

Figure 1: The principal components analysis for two vineyards in 2015. Figure 1a (left): the Buis Riesling vineyard in Niagara-on-the-Lake, Ont. and Figure 1b (right): the George Cabernet Franc vineyard in Vineland, Ont.

EDITOR'S NOTE

This is the second installment of a two-part series on using unmanned aerial vehicles (UAV) to obtain data to help vineyards implement precision viticulture. In the first article, the authors looked at the different UAV platforms, hardware, sensors and image processing. Here, the authors discuss the use of UAVs in viticulture and include the results of a study done in Ontario vineyards.

KEY POINTS

Remote sensing by unmanned aerial vehicles (UAVs) has been useful in monitoring vineyard vegetative growth and to make inferences about grape composition.

A study in Ontario used UAVs to examine correlative relationships between vegetation indices and vineyard variables including vine size, yield, berry weight, berry composition and winter hardiness.

UAVs have significant potential to identify zones of superior fruit composition and potential wine quality.

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.

Remote sensing has proved to be 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.[16] Similar applications were made in Pinot Noir vineyards, and proved to be a good tool to determine color and phenolic potential of grapes, in addition to water status, yield and vine size.[15] These studies were unique in their employment of remote sensing in cover-cropped vineyards and thereafter using protocols for excluding the spectral reflectance contributed by inter-row cover crops.

UAV-based remote sensing likewise has been used for making inferences about grape composition from multispectral measurements.[23] However, use of UAVs for remote sensing in vineyards is a relatively new area of research, thus far untested in Canada, and capable of acquiring high-resolution spatial data without the high cost of conventional aircraft. As with proximal sensing, there has been little published, and most of that has confirmed an ability to acquire NDVI and related images. Relationships were found between photosynthesis and chlorophyll fluorescence by hyperspectral imagery captured via UAVs, as well as between both photosynthesis and chlorophyll fluorescence vs. remote measurements.[35] Other relationships were demonstrated between both chlorophyll a/b and leaf carotenoids vs. several VIs based on multispectral images acquired by UAVs.[38]

UAVs were used for assessment of vineyard water status by correlation of stem Ψ with NDVI.[2] Further relationships were observed between several Vis, including NDVI vs. vine water status [leaf water potential (Ψ) and stomatal conductance].[38] Addition-

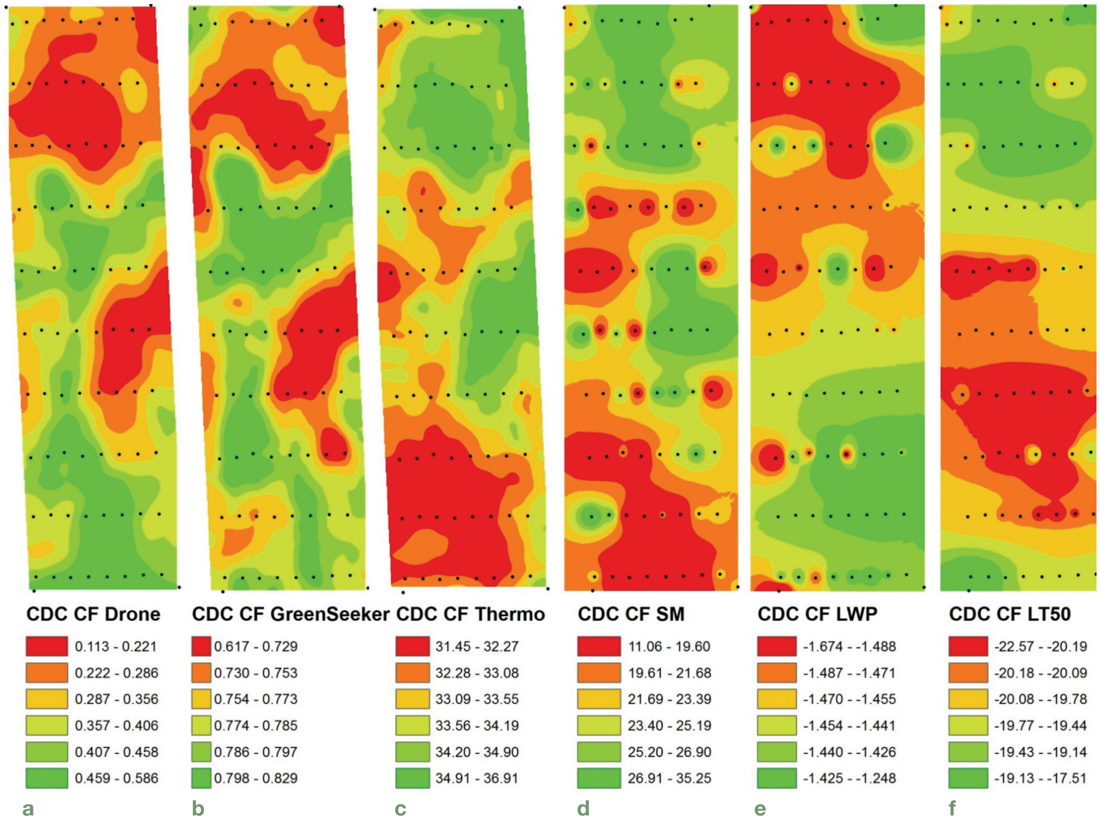

Figure 2: Spatial maps of the Cabernet Franc vineyard at Chateau des Charmes (CDC), St. Davids, Ont. in 2016. 2a: UAV-based NDVI; 2b: GreenSeeker-based NDVI; 2c: UAV-based thermal image; 2d: Soil moisture; 2e: Leaf water potential; 2f: LT^{50} (winter hardiness). Scale 1 =2167.

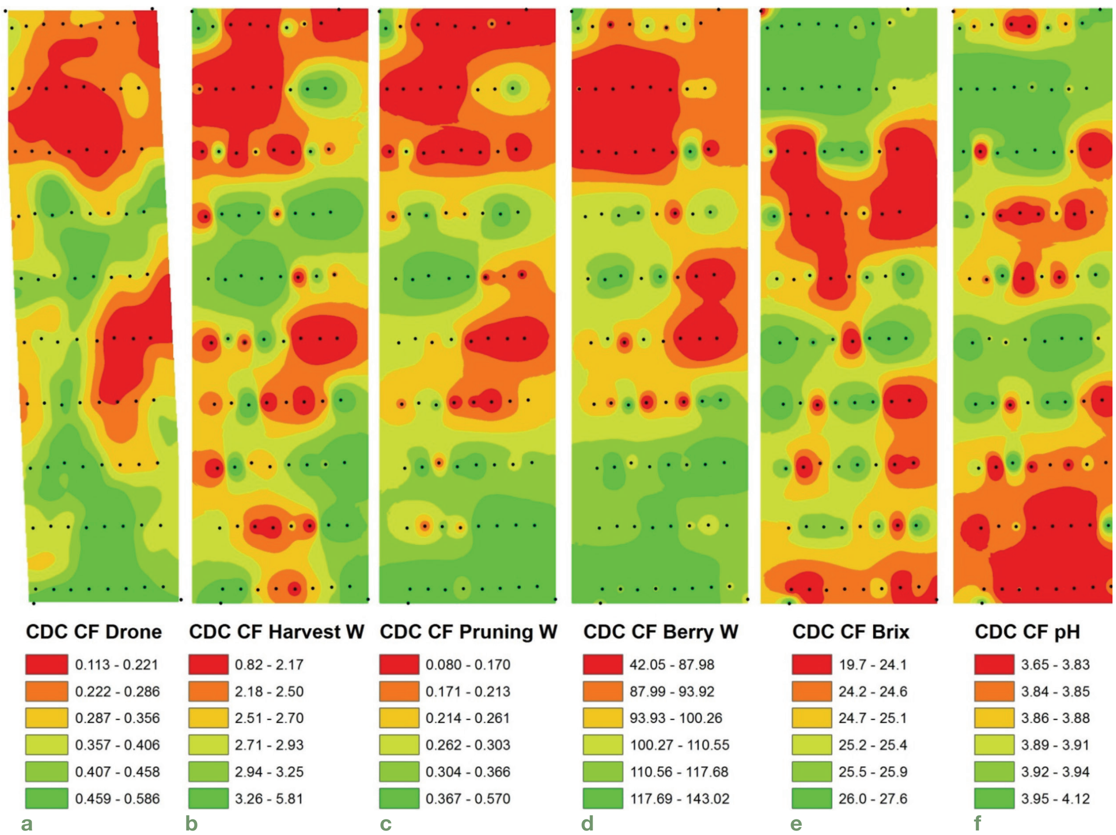

Figure 3: Spatial maps of the Cabernet Franc vineyard at Chateau des Charmes, St. Davids, Ont. in 2016. 3a: UAV-based NDVI; 3b: Yield per vine (kg); 3c: Weight of cane prunings per vine (kg); 3d: Berry weight (g): 3e: Berry soluble solids (Brix): 3f: Berry pH. Scale 1 = 2167.

ally, several other VIs were correlated to water-status variables.[37] Nutritional deficiencies also have been detected by UAVs; e.g., NDVI was correlated with levels of iron chlorosis, carotenoid pigments in leaves, and anthocyanins in leaves and grape berries.[21] More recently a crop water-stress index was calculated based upon a combination of leaf Ψ and stomatal conductance and was associated with UAV-derived thermal images.[29] UAVs have been successfully linked to wireless sensor networks to assess correlations between VIs and thermal zones in vineyards.[6]

Recently in Ontario, UAVs were used to examine correlative relationships between VIs and several vineyard variables.[25] Vine size, LT_{50} (winter hardiness), 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 apparent from examination of the maps. Multivariate statistical analysis (e.g., principal components analysis; PCA) confirmed these relationships.

Spatial analysis also was performed (e.g., Moran's *I* and k-means clustering) to verify the existence of actual discrete zones in the study vineyards. The NDVI values were considerably higher in GreenSeeker maps vs. those from UAV flights, primarily because reflectance data were acquired from the sides of the canopies with GreenSeeker and from the tops of the canopies with UAVs. Vine water status and several fruit-composition variables were correlated with UAV-derived NDVI. This suggests that UAVs have significant potential to identify zones of superior fruit composition and potential wine quality.

Case study in Ontario

We used this technology in a case study of vineyards in Ontario to create maps illustrating spatial variability in both ground-based variables and UAV data, and its usefulness in understanding and improving potential wine quality.

The Ontario wine industry produces about 65,000 tons of grapes and consists of cultivars such as Riesling, Chardonnay, and Cabernet Franc, with lesser quantities of Merlot, Cabernet Sauvignon, Sauvignon Blanc, Pinot Gris, and Pinot Noir (grapegrowersofontario.com). Soils are characterized as variable, a result of widespread glacial activity more than 10,000 years ago, and consequently many vineyards are situated on several soil series that can range widely in texture, depth and water-holding capacity.[13] This variability 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 to 15 years this interest has expanded to include identification of unique portions of vineyard blocks, some less than 1 hectare, that might be capable of producing extremely high-value wines based upon yield, vine size or water-status-based quality levels.

Researchers chose six vineyards each of Cabernet Franc and Riesling (1 to 2 ha in area) in different Niagara sub-appellations. The sites included the following sub-appellations: Niagara Lakeshore, Creek Shores, St. Davids Bench, Lincoln Lakeshore north, Lincoln Lakeshore south, and Beamsville Bench.

Soil types[13] 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). This array of soil types provided a significant range of water-holding capacities that affected vine water status.

Vineyard blocks were GPS-delineated to determine shape, and 80 to 100 sentinel vines were identified within each vineyard and geo-located by GPS. Post-collection differential correction was performed to sub-meter accuracy (about 30 to 50 centimeters). Field measurements and berry samples were taken on these vines over two years, and we are completing our third year of data collection.

Vineyard soil moisture was measured by time domain reflectometry. Measurements took place at berry set, lag phase and *veraison* on all sentinel vines. Vine water status was mea-

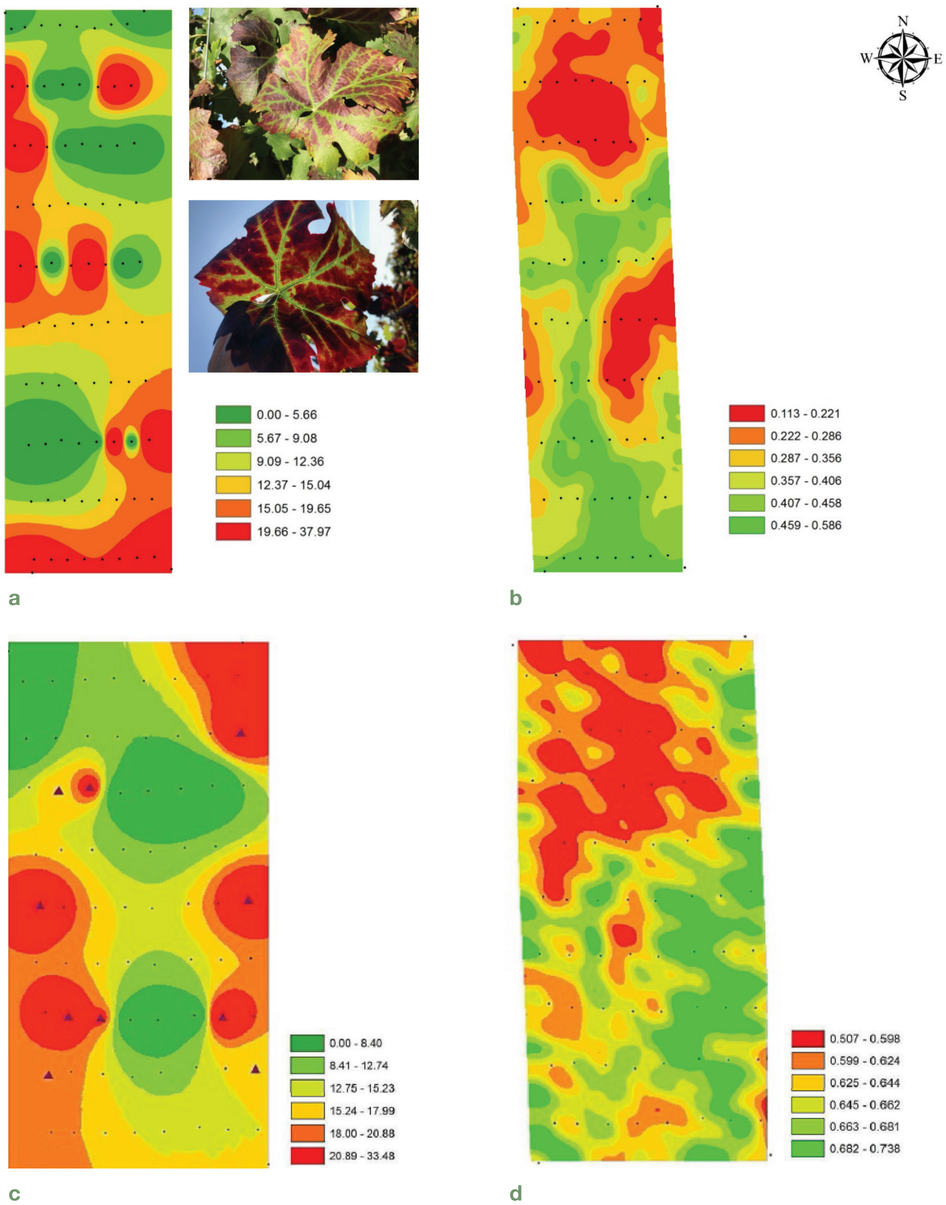

Figure 4: Maps of two Ontario Cabernet Franc vineyards in 2016 showing GLRaV3 titer [quantification cycle (Cq) value] (a, c) vs. their respective corresponding UAV-based NDVI (b, d). Scale (a, b): 1 = 2167; (c, d): 1 = 1240.

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sured using midday leaf Ψ by pressure bomb. Measurements were made only at designated leaf Ψ vines (about 15 per vineyard block), on the same days as SWC measurements, from 1000h to 1400h (ca. solar noon), under full sun. Leaf *gs* was measured by a hand-held porometer on those vines used for leaf Ψ.

Fruit from each sentinel vine was harvested, cluster number determined, and fruit weighed. Cane prunings were weighed to determine vine size. A 100-berry sample was taken from each sentinel vine, weighed to determine mean berry weight, and thereafter soluble solids were measured using a refractometer, pH by a pH/ion meter and titratable acidity by autotitrator.

Monoterpene aroma compounds [free volatile terpenes (FVT) and potentially-volatile terpenes (PVT)] were analyzed on Riesling samples taken from leaf Ψ vines based on a distillation method. Cabernet Franc juice sample absorbance was measured using a spectrophotometric method at 420 nm and 520 nm, with color intensity calculated as $A_{420}+A_{520}$, and hue as A_{420}/A_{520}. Total anthocyanins were quantified using the pH shift method, while total phenols were quantified using the Folin-Ciocalteu method.

All vines designated for leaf Ψ and gs measurements were sampled September 2016 to determine grapevine leafroll-associated virus (GLRaV) titer. Total RNAs were isolated from leaf samples using a method recently developed in the Meng lab. 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 identify virus presence. To determine virus titer for comparison and correlation to the UAV and GreenSeeker data, quantitative qPCR was conducted by Power SYBR Green PCR Master Mix and StepOnePlus qPCR (Applied Biosystems).

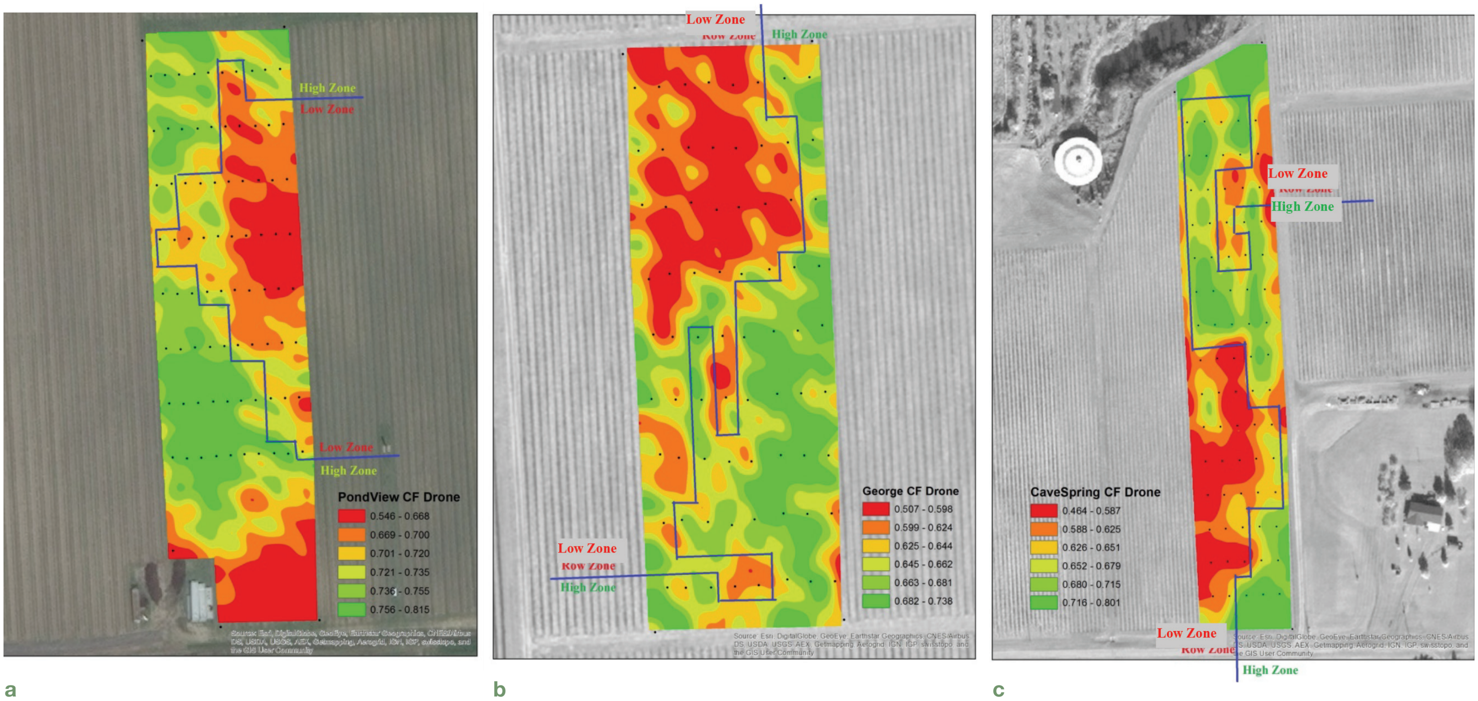
GPS coordinates from vineyard blocks and sentinel vines were imported into a GIS environment (ArcGIS) and linked to all point data collected from sentinel vines. Spatial interpolation techniques (i.e., kriging) applied to these data were used to estimate the value of vineyard variables at unsampled locations.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

A GreenSeeker unit (Trimble Navigation) mounted on a four-wheel-drive vehicle was used to collect NDVI data on dates close to soil moisture and leaf Ψ data collection. An additional reading was collected in mid-September. Data were imported into Farmworks software and spatial maps created. Shapefiles were thereafter imported into the ArcGIS database. GPS coordinates identical to the sentinel vines were identified, and NDVI data corresponding to these coordinates were extracted for statistical analyses.

The UAV flights corresponded to the *veraison* soil moisture, leaf Ψ, and GreenSeeker data collection. Image acquisition was performed using the SenseFly eBee UAV (see Figure 2A) supplied by Air-Tech Solutions, Inverary, ON. The UAV had 30 minutes of endurance, a 9-kg payload, and was equipped with an autopilot system allowing a 1000-m visual range and 5-km radio line of sight. The UAV was flown at both 90 and 120 m elevations in separate flights and a maximum speed of 60 km/h.

Two sensors were used for image acquisition. The first operated in the visible and near-infrared portions of the electromagnetic spectrum (EMS) utilizing five spectral bands (blue, green, red, red edge, near-infrared) equipped with an incident light sensor. The second sensor operated in the thermal–infrared (IR) portion of the EMS. It ensured acquisition of imagery in the thermal-IR range covering 750 to 1350 μm. 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 was performed over each



a b c

Figure 5: These maps were derived from UAV data and are examples of NDVI-based zones in three Ontario Cabernet Franc vineyards. 5a is Pondview in Virgil, Ont.; 5b is George in Vineland, Ont.; and 5c is Cave Spring in Beamsville, Ont. Scales are 5a: 1 = 1039; 5b: 1 = 1240; and 5c: 1 = 1581.

vineyard block. Data were stored onboard and retrieved after the flight mission. Geometric correction was performed to correct the image geometry. Georeferencing was achieved by identifying control points (targets) on the ground. Geometric distortions caused by changes in UAV attitude and altitude were corrected using the information provided by the inertial station.

The series of images acquired during each flight was assembled into mosaics by selecting the overlapping areas to limit the viewing angle and the problems of directional effects. Once assembled and corrected, NDVI was calculated on mosaics. The NDVI pixel values corresponding to the field points were extracted and compiled into a geodatabase that included all field-based variables (e.g., leaf Ψ).

An example of UAV correlations with other variables is shown in Figure 1 (page 60). It should be noted that mathematical relationships between NDVI and other variables of importance never will be exactly the same for every vineyard. There is substantial variability between vineyards, varieties and years. That is the nature of making biological measurements and attempting to correlate those to a physical measurement such as leaf reflectance.

The UAV NDVI and thermal indices were correlated with vine size in all Riesling vineyards in 2015, including that of the Buis vineyard in Niagara-on-the-Lake depicted in Figure 1a. The application of PCA provides a pictorial method of portraying correlations between multiple variables in a large data set. The variables represented by lines (eigenvectors) are considered correlated if the eigenvectors are parallel to each other, and inversely correlated if they are roughly 180° from each other.

In Figure 1a, NDVI acquired by UAV was correlated with GreenSeeker NDVI, soil moisture, leaf Ψ, gs, and berry weight, and inversely correlated to thermal data, FVT and PVT in Riesling. This suggests that zones of low NDVI might be linked to fruit with higher terpenes, and by inference higher-quality wine.

Noteworthy associations in other Riesling vineyards included UAV indices and berry weight (five sites), TA (two sites—Buis, George), FVT/PVT (three sites), and GreenSeeker NDVI (four sites). Inverse correlations of note with UAV data included soil moisture and leaf Ψ (five sites). Direct correlations also were noted for NDVI and at least one LT_{50} measurement for four sites: LT_{50} measured in March (Buis), January LT_{50} (Pondview), February LT_{50} (Hughes, Cave Spring). This suggests that high NDVI was associated with low winter hardiness, since LT_{50} is a negative value. Yield was not consistently related to NDVI; yield and NDVI were inversely correlated in three sites (Buis, Hughes, Pondview) but unrelated in two others. For the most part we found similar patterns in all Riesling vineyards in 2016.

In Cabernet Franc, UAV NDVI was associated with soil moisture, leaf Ψ, gs, yield, and berry weight, and inversely correlated to color, anthocyanins and phenols in the George vineyard in Vineland in 2015 (Figure 1b). UAV NDVI was correlated with vine size in all other Cabernet Franc vineyards. 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 GreenSeeker NDVI (four sites). NDVI was inversely correlated with anthocyanins, A_{520} and total phenols in four of five Cabernet Franc vineyards in 2015. This suggests that zones of low NDVI might be associated with grapes of higher color and phenols, and possibly higher wine quality than high-NDVI zones. Application of PCA of 2016 data revealed similar relationships.

This project has produced literally hundreds of maps! With 12 vineyards under study, three seaons of data collection, and a minimum of 14 variables, that means more than 500 maps. Maps for Chateau des Charmes Cabernet Franc vineyard 2016 are depicted in Figure 2 (page 61). The UAV NDVI map showed a low NDVI zone in the north end of the vineyard (Figure 2a). This corresponded closely with maps produced using GreenSeeker (Figure 2b), highest regions from the thermal camera (Figure 2c) and soil moisture (Figure 2d), and lowest regions of leaf Ψ (Figure 2e), and higher LT_{50} (i.e. less winter hardy; Figure 2f).

Zones of low UAV NDVI (Figure 3a) (page 61) were associated with low yield (Figure 3b), vine size (Figure 3c), berry weight (Figure 3d), higher Brix (Figure 3e) and higher pH (Figure 3f), once again suggesting enhanced fruit maturity in low NDVI zones. Conversely, those high-NDVI zones identified by the UAV were typically low in thermal camera data and high in GreenSeeker NDVI, leaf Ψ, soil moisture, vine size, berry weight and TA, and lower in LT_{50} (i.e., more winter hardy).

Other Cabernet Franc vineyards showed associations in the UAV data between low NDVI and high thermal zones. These corresponded to low GreenSeeker NDVI, soil moisture, leaf Ψ, vine size and berry weight, and higher LT_{50} zones. There was some spatial correlation with high-TA and low-Brix areas, but pH and overall yield usually were not strongly related spatially.

In most vineyard blocks the UAV NDVI maps were comparable to GreenSeeker NDVI maps. In general, there were good direct spatial correlations between UAV and GreenSeeker NDVI vs. leaf Ψ, leaf g_s, soil moisture, vine size, LT_{50} and TA, and inverse ones with Brix and pH. There were also many situations in which maps from thermal data were inversely correlated spatially with NDVI.

Most frequent spatial correlations in Riesling with UAV and GreenSeeker NDVI zones were leaf Ψ, gs, soil moisture, vine size, berry weight, yield and TA. Noteworthy inverse spatial correlations included Brix, pH, FVT and PVT. The 2016 patterns in leaf Ψ, soil moisture, yield components and berry composition were for the most part consistent with those observed in 2015 for both Riesling and Cabernet Franc.

GVLRaV3 titer was determined in 2016 in all vineyards for all vines used for leaf Ψ. Zones of low GLRaV titer corresponded spatially with zones of low NDVI in two Cabernet Franc vineyards (Figure 4) (page 62). The same trend was apparent for three Riesling vineyards. However, low NDVI zones also corresponded in some cases with low leaf Ψ, low soil moisture and high concentrations of anthocyanins and phenols. This is a major challenge, because we need to identify unique spectral signatures that designate virus-affected areas that do not correlate spatially with other variables such as leaf Ψ; otherwise there is a strong possibility of misdiagnosis. Consequently, more research is needed to identify other vegetation indices that are unique and specific to zones of varying virus status. This work is ongoing.

Maps also identify management zones within vineyards that might correspond to fruit of different potential wine quality. This is, in essence, the raison d'être of precision viticulture. Figure 5 depicts three Ontario vineyards that show clear zones of high and low NDVI determined by UAV. During harvest, it was clear that the high NDVI zones had larger clusters, larger berries, generally higher yields per vine and, in the case of Riesling, more bunch rot than low NDVI zones.

Conclusions

Unmanned Aerial Vehicles (UAVs) are a valuable tool to acquire high-resolution aerial images of vineyards. The data within the high-resolution aerial images can be used to determine the spatial distribution of a variety of canopy variables within a vineyard block and between different vineyard blocks. In this way UAVs can be used to measure the spatial distribution of vigor, water stress, nutrient status, disease, yield components and berry composition. One of the major challenges is the massive amount of data that are collected, the time required for post-flight data processing and the need to derive useful vegetation indices that are specific to variables of interest.

Andrew G. Reynolds is professor of biological sciences/viticulture at the Cool Climate Oenology and Viticulture Institute, Brock University, St. Catharines, Ontario, Canada; Hyun-Suk Lee and Briann Dorin are graduate students at CCOVI, Brock University. Marilyne Jollineau is associate professor in the department of geography at Brock University. Ralph Brown is professor of engineering at the School of Engineering, University of Guelph, Guelph, Ontario. Mehdi Shabanian is assistant professor and Baozhong Meng is associate professor at the University of Guelph. Adam Shemrock is with Air-Tech Solutions, Inverary, Ontario.

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