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ORIGINAL RESEARCH ARTICLE

Utilization of unmanned aerial vehicles for zonal winemaking in cool-climate Riesling vineyards

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ABSTRACT

Individual vineyards can vary spatially for several viticultural attributes, including water stress, nutrient status, growth/vigour and disease—which can, in turn, impact berry composition and resulting wine products. The goal of this study was to determine if vineyard variability detected by remote sensing using an unmanned aerial vehicle (UAV) could be used to zonally harvest vineyard blocks and produce wines that are sensorially differentiable. The specific hypothesis was that remote sensing would detect vineyard variation in viticultural variables and associate this variation with differences in wine sensory attributes based upon zonal harvesting. In six commercial Riesling vineyards across the Niagara Peninsula in Ontario, Canada, a UAV collected multispectral data, which were used to calculate the normalized difference vegetation index (NDVI). Grapevines (≈ 80) in a grid pattern were geo-located within each block and vineyard UAV NDVI maps were used for zonal harvesting of geo-located vines in areas corresponding to high *vs.* low NDVI. Wines made from these zones were then compared chemically and sensorially. Overall, wines created from high *vs.* low NDVI zones differed inconsistently in their basic wine composition. Sensorially, for certain sites and vintages, panellists distinguished between wines made from high *vs.* low NDVI zones using a sorting task. UAV NDVI demonstrated the ability to determine areas within a vineyard block that could produce wines that were sensorially distinguishable from one another.

KEYWORDS: remote sensing, precision viticulture, cool climate, Riesling, sensory

INTRODUCTION

The term *terroir* refers to the complete grape-growing environment and surrounding factors, including climate, soils, topography, and the vine, which impart characteristics to the resulting wine (van Leeuwen, 2010). It is possible that the *terroir* of wines can be influenced by differences in the grape-growing environment within small geographic areas (e.g., individual vineyard blocks), which can influence corresponding viticultural variables (Bramley and Hamilton, 2007; van Leeuwen, 2010). Significant variation in berry composition and yield components can occur within individual vineyard blocks, which can then impact the resulting wines. Vineyard variation has been demonstrated for total yield (Tardáguila *et al.,* 2011), berry weight (Cortell *et al.,* 2007a; Reynolds *et al.,* 2007), soluble solids or Brix (Baluja *et al.,* 2013; Cortell *et al.,* 2007a; Reynolds *et al.,* 2007), titratable acidity (TA) (Baluja *et al.,* 2013; Cortell *et al.,* 2007a,), pH (Baluja *et al.,* 2013), potentially volatile terpenes (PVT) (Reynolds *et al.,* 2007), anthocyanins (Cortell *et al.,* 2007a), and phenolics (Baluja *et al.,* 2013), as well as the general ripening and maturation of berries (Pagay and Cheng, 2010) and indices of wine-grape quality (Bramley, 2005; Urretavizcaya *et al.,* 2014). Variation within individual vineyard blocks opposes the common winemaker requirement of uniform batches of fruit in terms of composition, quality, and yield thresholds (Bramley, 2005). Thus, growers can choose to alter vineyard management in an attempt to homogenize the resulting crop or harvest grapes at the sub-block level according to variation in berry and yield variables.

The second option, termed selective or zonal harvesting, can enable the production of multiple wine products from a singular vineyard block which has demonstrated economic benefits (Proffitt and Pearse, 2004). The concept of zonal harvesting has been increasingly studied over recent years as the adoption of geospatial technologies has enabled a deeper understanding of the spatial distribution and patterns within vineyard blocks (Cox, 2002) and the capacity for differential mechanical harvesting (Sethuramasamyraja *et al*., 2010). However, determining vineyard variation and the identification of zones for harvesting can be costly and time-consuming. Recent developments in remote-sensing technologies have enabled their application in precision viticulture - a differentiated management approach in response to vineyard spatial variability, including the monitoring and management of differences in water and nutrient status, plant health and pathogens, and soil conditions (Matese and Di Gennaro, 2015). More recently, studies have aimed to determine the efficacy of using remotely sensed vineyard zones for selective harvesting and winemaking. Remote sensing technologies can include aircraft, satellites, unmanned aerial vehicles (UAV) and ground-based sensors; the latter is often referred to as proximal sensing, each with associated advantages and disadvantages (Matese and Di Gennaro, 2015). UAVs are particularly useful for remote sensing in small vineyard blocks due to their lower costs and the collection of high spatial resolution data while often limited by their operating times. A commonly used remotely sensed measurement is the normalized difference vegetation index (NDVI) which can provide a quantitative measure of vegetation vigour in a variety of vegetated environments, including vineyards. NDVI is calculated from a ratio of spectral reflectance values measured in the red and near-infrared regions of the electromagnetic spectrum or EMS (Rouse *et al*., 1974). Values for this index range from –1 (non-vegetated surfaces) to +1 (healthy vegetation). NDVI has been correlated with measures of vine canopy structure and vigour (Drissi *et al*., 2009) and with grapevine yield and quality (Fountas *et al*., 2014).

Zonally harvested wines have been attributed to multiple grape-growing factors. Wines made from zones of differing water status were sensorially distinguishable and had different intensity ratings for several aromas, tastes and mouthfeel descriptors (Ledderhof *et al.,* 2014). Furthermore, wines made from water-stressed vines were rated with a higher global appreciation note compared to wines from low water-stressed vines (Koundouras *et al.,* 2006). Zonal wines from differing vine vigour areas also showed differences in their anthocyanin and pigmented polymer composition (Cortell *et al.,* 2007b) and different sensory intensity ratings for several attributes such as astringency, earthy, chemical, and heat/ethanol attributes (Cortell *et al.,* 2008). Harvesting and vinification based on different vine sizes and soil textures revealed wine sensory differences such as decreased mineral and citrus aroma and increased apple aroma from wines from higher vine vigour vines and higher mineral and citrus aroma and less apple aroma from wines from clay soil vines (Reynolds *et al.,* 2007). The impact of vine vigour, as detected by NDVI, on resulting wines has been demonstrated in various studies. The direction of this impact, whether higher or lower NDVI vines will produce higher or lower quality wines, likely depends on a variety of factors, including viticultural attributes, vineyard management, and vintage/season. Wines made from aerial maps separated into zones of low, medium and high NDVI were distinguishable in sensory difference testing and both low and medium NDVI wines were deemed of higher quality than the high NDVI zonal wine as judged by the chief winemaker (Johnson *et al.,* 2001). Furthermore, wines made from zones pertaining to differences in remotely sensed NDVI and proximally sensed soil electrical conductivity differed in their chemical analyses of colour intensity, dry extract and anthocyanin concentration, and their sensory ratings for colour intensity, structure and total score (Priori *et al.,* 2013). Wines also differed when made from zones of differing vigour and yield as measured by multispectral remote-sensing imagery of plant cell density index (near-infrared/red) and yield measured by a mechanical harvester equipped with a yield monitor (Bramley and Hamilton, 2007, Bramley *et al.,* 2011a). Difference sensory testing demonstrated that the zonal wines from low vigour/low yield and high vigour/high yield areas were notably different from each other in each year of the study, while descriptive analysis demonstrated that low yield/low vigour wines were fruitier with higher intensity red berry aromas, floral aromas,

fresh berry, and dried fruit flavours. The high vigour/high yield wines had more green attributes, such as stalky flavour and olive and meaty aromas. Chemical analysis [solid phase microextraction-gas chromatography-mass spectrometry; SPME-GC-MS] of these wines further demonstrated them to be different for 21 compounds, of which 10 of the differences were stable across the three vintages. Lastly, when zonal harvesting of remotely sensed low vigour and high vigour zones was implemented for commercial scale vinification, commercial-scale zonal wines were distinguishable by untrained panellists, however, only from certain areas within the vineyard (Bramley *et al.,* 2011b).

Research to date has demonstrated that not only do individual vineyard blocks demonstrate significant variability in their berry and yield attributes but that the harvesting of sub-block zones for vinification leads to wines that differ in their chemical and sensory attributes. However, of the studies documenting remote sensing capabilities for sub-block harvesting and wine production, most have occurred in red grape cultivars for red wine production and thus, more research is needed for white grape varieties. Furthermore, most of these studies have occurred in vineyard blocks > 3 ha; thus, more research is needed to determine the efficacy of zonal harvesting and detection by remote sensing in smaller vineyard blocks, such as those often seen in Ontario, Canada. Lastly, the majority of these studies have occurred in warmer climatic regions and more research is needed in cool-climate wine regions to understand the potential for remote sensing technologies to be used in zonal wine production across different grape growing environments. This research aimed to determine the efficacy of remote sensing technologies, namely NDVI measured with a UAV, for zonal harvesting and vinification in Ontario Riesling vineyards. By comparing the chemical and sensory attributes of wines produced from remotely sensed zones, a greater understanding of the breadth and scope of this technology for winemaking opportunities will be developed.

MATERIALS AND METHODS

1. Study Sites

This research was conducted on six commercial Riesling vineyards across the Niagara Peninsula located in southern Ontario, Canada (Figure 1, Supplementary Table 1). Within the Niagara Peninsula exists several sub-appellations of viticultural importance determined by the wine and grape regulatory body of Ontario—the Vintners Quality Alliance (VQA). These sub-appellations vary slightly from one another in several variables, such as growing degree days, average precipitation, frost-free days, soil type, and physical geography/topography (VQA Ontario, n.d.). The six vineyards chosen for this study represented five of these sub-appellations: Buis Vineyards (Niagara Lakeshore sub-appellation), Pondview Estates Winery (Four Mile Creek sub-appellation), Château des Charmes (CDC; St. David's Bench sub-appellation), George Vineyards (Lincoln Lakeshore sub-appellation), Hughes Vineyards (Lincoln Lakeshore sub-appellation), and Cave Spring Cellars vineyards (Beamsville Bench sub-appellation).

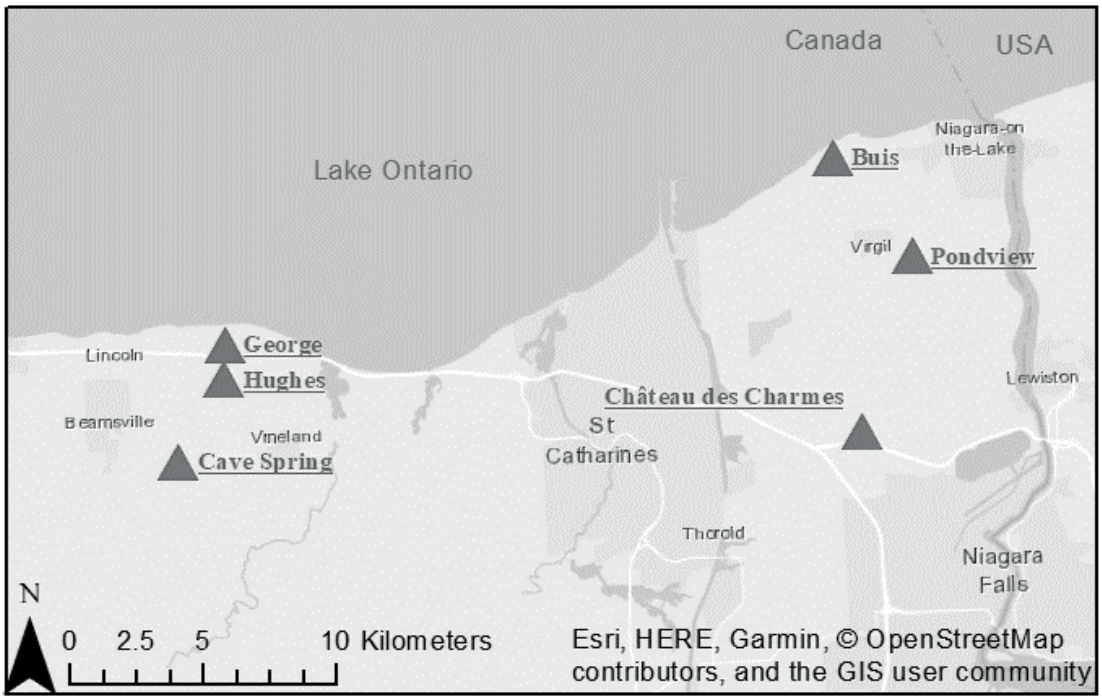


FIGURE 1. Locations of six Riesling vineyard study sites in the Niagara Peninsula in Ontario as indicated by triangles.

Map created in ArcMap 10.6.1 (ESRI 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute) with the World Light Grey Canvas base-map and the World Light Gray Reference layer © Esri Canada. Source: Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community.

2. UAV NDVI data collection and map making

Flights were performed in 2016 near veraison, on August 17 for Pondview, Château des Charmes, and Buis and on August 18 for Hughes, George, and Cave Spring, using the eBee Classic (senseFly, The Parrot Group, Switzerland). The UAV was flown at an altitude of 90 m with a 60 km/h maximum speed. The Parrot Sequoia multispectral sensor with four 1.2 Mpx monochrome sensors with a global shutter (The Parrot Group, Switzerland) operated in the visible and near-infrared portions of the EMS using four spectral bands (green: 530–570 nm, red: 640–680 nm, red edge: 730–740 nm, and the near-infrared: 770–810 nm). Data acquisition resulted in a spatial resolution of 8.47 mm at an altitude of 90 m. Equipment onboard also consisted of a GPS unit, an incident light sensor measuring incoming radiation, and an inertial station to correct anomalies in flight attitude (i.e., yaw, pitch, and roll), ensuring the verticality and orientation of imaging. This equipment was complemented by a ground control station that provided real-time feedback on the position of the aircraft and its imaging. Image acquisition and corrections were performed over each vineyard block by AirTech UAV Solutions Inc., Inverary, ON. A geometric correction was performed to correct the image geometry and bidirectional reflectance. Geometric distortions caused by changes in UAV attitude and altitude were corrected using the information provided by the inertial station. A radiometric correction was performed to correct the effects of vignetting. Data were also adjusted for the input of the incident light sensor.

The series of images acquired during each flight were assembled into mosaics by selecting the overlapping areas near the nadir to limit the viewing angle and the problems of directional effects. Once assembled and corrected, the NDVI was calculated on mosaics from the reflectance in the near-infrared (NIR) and red wavebands as NDVI = (NIR-R)/(NIR+R). NDVI maps were created in ArcMap 10.5–10.6 (ESRI 2011. ArcGIS Desktop: Release 10. Environmental Systems Research Institute, Redlands, CA) to determine areas of low and high NDVI for zonal harvesting. The UAV NDVI data were interpolated to create a smooth contour map for later visual delineation of NDVI zones using the Diffusion Interpolation with Barriers tool in ArcMap and six quantile breaks were used to separate these data so that each class contained an equal number of features to avoid empty classes or disproportionate class sizes.

3. Harvesting and winemaking

The 2016 UAV NDVI interpolated maps created for each vineyard site were used to create zones of high and low NDVI by visual delineation, with each zone separated into three field replicates (Figure 2). The same maps were used (2016 UAV NDVI maps) for the harvesting template in both years (2016 and 2017) to maintain temporal consistency, as vineyard NDVI spatial patterns have demonstrated strong interannual temporal stability (Acevedo-Opazo *et al.,* 2008; Kazmierski *et al*., 2011). Harvest dates were based on the timing of the commercial harvest for each site. Harvest was taken from sample grapevines (n = 70–88, depending on the site) throughout each vineyard block occurring in an ~ 8 m × 8 m grid pattern. These grapevines were flagged and geo-located using an Invicta 115 GPS Receiver (Raven Industries, Sioux Falls, SD) and a post-differential correction providing a final positional accuracy of ~ 0.30–0.50 m. Each of these geo-located vines were hand-harvested (all bunches on the vine) into individual harvest bins, which were later combined based on their NDVI zone (high *vs.* low) and their field replicates (1–3) according to the UAV NDVI maps (~10–16 vines were harvested per replicate, depending on the site). Combined harvest bins were labelled and transported back to the Brock University pilot winery for immediate crushing/destemming using an electric crusher/destemmer (Criveller, Niagara Falls, ON). Crushed/destemmed products were stored at 7 °C overnight with the addition of 5 g/hL of β-split Endozyme (AEB Group, Lodi, CA) and 40 ppm sulphur dioxide (SO_2) using potassium metabisulfite. The following day, grapes were pressed with a small water bladder press to a maximum of 200 kPA. The juice was then allowed to settle at room temperature for 24–48 h and subsequently racked into 20-L and 11-L glass carboys.

Settled and racked juice was inoculated with *Saccharomyces cerevisiae* v. *cerevisiae* Fermol Arôme Plus (AEB Group, Lodi, CA) at a dosage of 30 g/hL following the manufacturer's recommended rehydration procedure with FermoPlus Energy GLU (AEB Group, Lodi, CA) yeast nutrition for rehydration at a ratio of 1:4 nutrition:yeast. Yeast nutrition for fermentation Fermoplus Integrateur (AEB Group, Lodi, CA) was added to each carboy at a rate of 45 g/hL. Carboys were then transferred to a temperature-controlled fermentation chamber set to 16 °C until dryness. The wines were then removed, racked, 40 ppm SO_2 added, and transferred to –2 °C to undergo cold stabilization and lees contact for ~3 months. Due to the high acidity and subsequent sensory implications, sucrose was added to wines in 2016 based on a bench trial tasting of each site as follows: 10 g/L for Cave Spring, Château des Charmes (CDC), Pondview, Hughes and 15 g/L for Buis and George. In 2017, sugar additions were added at a standard rate of 10 g/L per site. Additionally, 150 mg/L potassium sorbate and 30 ppm of SO_2 were also added. Wines were then sterile filtered using EK 0.45 µm filter pads (Scott Laboratories Ltd., Petaluma, CA). Filtered wines were bottled using a hand-held bottle-filler with tubing and subsequently closed with an automated corker (model ETSILON-R, Bertolaso; San Vito, Italy) using DIAM© 5 closure (DIAM Bouchage, Paarl, South Africa). During bottling, 250 mL wine samples were taken for subsequent wine chemical analyses. Bottled wines were stored in the Brock University Cool Climate Oenology and Viticulture Institute (CCOVI) controlled cellar at 17.5 °C and 74.5 % relative humidity for 12 months for 2016 wines and 3 months for 2017 wines prior to sensory analysis.

4. Basic wine composition

Wine pH was measured using an Accumet pH/ion meter (model 25; Denver Instrument Company, Denver, CO) and titratable acidity (TA) using a ManTech PC-Titrate auto-titrator (Man-Tech Associates, Guelph, ON) titrated to a pH 8.2 endpoint with 0.1 N NaOH.

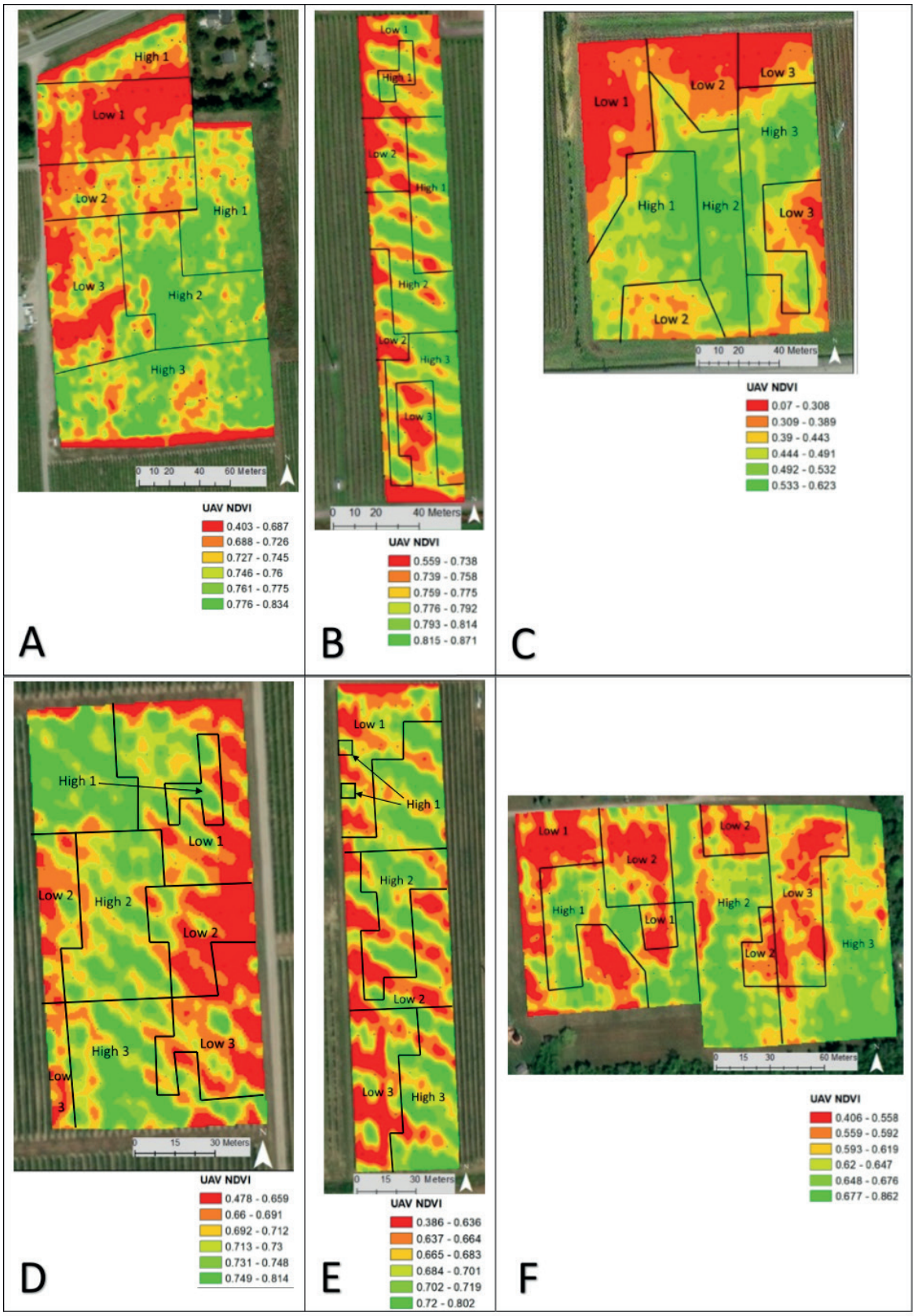


FIGURE 2. UAV NDVI zonal maps used for the harvesting of Riesling wines of High *vs.* Low NDVI and associated three field replicates.

NDVI legends are equal area quantiles. Vineyard sites from top left to bottom right are A) Buis; B) Pondview; C) Château des Charmes; D) George; E) Hughes; F) Cave Spring. Maps were made in ArcMap 10.6.1 with the World Imagery basemap Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community (ESRI 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute).

Three samples of distilled water and three samples of tartaric acid (4, 7, 9 g/L) were placed at the start and end of the titration run to ensure the reliability of the titration. The titrator was calibrated using pH 4 and 7 standards. Ethanol measurements were performed using a GC (Hewlett-Packard 6890 series, Agilent Technologies, Santa Clara, CA) equipped with a flame ionization detector (FID), split/split-less injector, and Chem Station software (version E.02.00.493). A Carbowax - DB®-WAX (30 m, 0.25 mm, 0.25 µm) column (122-7032 model; Agilent Technologies, Santa Clara, CA) was used for separation with helium as the carrier gas (flow rate of 1.5 mL/min). Two 0.5 µL wine samples were injected for each wine replicate, spaced at the beginning and end of the run to account for possible variation across the run. A 5 % CV between both samples was considered acceptable; if above this level of variation, samples were re-run. A six-point calibration curve was used, and 1-Butanol (2 %) was used as an internal standard.

5. Sensory evaluation

Sensory sorting tests are a well-documented form of sensory analysis used across a variety of food and beverage products, such as beer and wine (Ballester *et al.,* 2005; Chollet *et al.,* 2014; Parr *et al.,* 2007). A sorting task was the preferred method as it produces similar results to other profiling techniques without the associated training requirements (Cartier *et al.,* 2006, Chollet *et al.,* 2014). A labelled sorting task was conducted in September 2018 to determine if sensory differences could be detected between wines from high *vs.* low NDVI vineyard zones. Both 2016 and 2017 wines were analysed within the same week to provide panellists with young wines (2017; < 6 months bottle age) and aged wines (2016; > 1 yr bottle age). A total of 19 untrained panellists, seven males and 12 females, were recruited from CCOVI staff and students as well as vineyard growers and management. Panellists were given no training prior to wine sorting; however, all participants were directly involved in the wine industry and thus were considered highly educated wine consumers. Each vintage represented a separate sensory session and the same panellists were used for both 2016 and 2017 wines to minimize any influence of differences in panel composition when comparing vintage results. Panellists were informed that they would be participating in a wine sorting study and had no knowledge of the study design, including the nature of and the number of zones and replicates. They were only informed that the study was assessing the impacts of remote sensing on Riesling wine sensory attributes. Sensory sessions were carried out in CCOVI's sensory laboratory using computers equipped with Compusense® Cloud (Compusense Inc., Guelph, ON). The Compusense sorting template was used and each separate sorting task consisted of six wines per site, with six sites total. Each site consisted of the two zonal wines (high and low NDVI) and their associated three field replicates. Wines were presented in a randomized incomplete block design, ensuring each panellist experienced the wines in a different order. International Standards Organization (ISO) clear wine glasses were coded with three-digit numbers containing 40 mL samples, served at room temperature, and covered with plastic Petri dishes to prevent the loss of aromatic intensity.

Panellists were each assigned a private booth equipped with an individual computer using the Compusense Cloud program. Each booth was prepared with the first three flights of wines and panellists were prompted by Compusense to start with the first flight and were asked to sample the wines left to right and subsequently sort them based on similarities and differences using any attributes of the wines. There were no specifications as to the attributes they could use and no list of attributes was provided; however, red ambient lighting was used, which restricted the use of visual factors in the sorting task. The only specification of the sorting task was that a minimum of two groups and a maximum of five groups needed to be made, ensuring all wines were not put into one group (all the same) or each in its own group (all different). Once wines were sorted into groups, panellists were instructed that each wine group required labelling with descriptor(s) based on their sorting criteria. The labels could be as long or short as needed by individual panellists. Between each of the first three flights, a mandatory 2-minute break was incorporated, in which panellists were provided water and plain crackers to cleanse their palettes. After the sorting of the first three flights was completed, a mandatory 20-minute break was included to both minimize mental fatigue associated with sorting and to provide researchers time to prepare the next three flights of wines. The presentation design of the first three flights was repeated for the last three flights. Each session lasted ≈ 1–2 hours for each panellist. The same sensory session design was then repeated for the 2017 wines after a 2–4-day gap per panellist.

6. Data analyses

6.1. NDVI zones and basic wine composition

NDVI values of the harvested and geo-located vines corresponding to the NDVI zones and field replicates were extracted from NDVI imagery in ArcMap 10.5–10.6 (ESRI 2011. ArcGIS Desktop: Release 10. Environmental Systems Research Institute, Redlands, CA). For each site, NDVI values were compared across NDVI zones (high *vs.* low NDVI) using a two independent sample two-tailed t-test in XLSTAT (version 2019, Addinsoft, New York, NY). NDVI values were further compared across NDVI zones (high *vs.* low) and their associated three field replicates (a total of six categories) using a one-way ANOVA and a post-hoc Tukey HSD (honestly significant difference) in XLSTAT. Lastly, two independent sample two-tailed *t*-tests were run on the basic wine composition data (pH, TA, ethanol), comparing the high and low NDVI wines per site and per vintage in XLSTAT.

6.2. Sorting group data

Sorting data were analysed following Chollet *et al.* (2014) and Alegre *et al.* (2017) analysing each site and vintage separately. Co-occurrence matrices were created for each panellist, using a wines × wines matrix with each cell encoded by a binary representation of whether two wines belonged

to the same group or different groups (1 = same group, 0 = different groups). These individual panellist co-occurrence matrices were then summed, giving a total similarity matrix where wines that were grouped together more often were considered more similar than wines less frequently grouped together. This final similarity matrix was then used as input into a multi-dimensional scaling (MDS) using XLSTAT (Addinsoft, New York, NY) to create a visual representation of the wines in a 2-D space. A metric MDS was used as the similarity matrix is equivalent to a squared Euclidean metric (Abdi, 2007). Acceptability of the resulting MDS was based on Kruskal's Stress Value, and a commonly used acceptable stress value is < 0.2 (Chollet *et al.,* 2014, Alegre *et al.,* 2017).

The resulting configuration of each MDS was further analysed by adding the MDS coordinates into an agglomerative hierarchical clustering (AHC) algorithm in XLSTAT (Addinsoft, New York, NY) using Ward's criterion. AHC is an iterative classification method that calculates the dissimilarity between all objects (wines) and then creates classes based on two objects (wines) which, when clustered together, minimize the agglomeration criteria (Ward's method). Ward's method aims to minimize the total within-group dispersion based on a classical sum-of-squares criterion (Murtagh and Legendre, 2014). This results in a dendrogram, which is a clustering tree rooted in the class that contains all objects and then the successive hierarchal separation of classes.

6.3. Sorting descriptor data

Descriptor data were analysed separately from sorting data following Chollet *et al.* (2014). To begin, a contingency table was made of the frequency in which each descriptor was designated to each wine (panellist frequency). When multiple descriptors were used for a group of wines by an individual panellist, each descriptor was weighted by 1/N, where N is the number of descriptors used in that group; therefore, the weight for each participant was equal to 1. Due to the panellist's freedom to use any descriptors during their sorting tasks, a large variation in descriptors was used across the panellists. Therefore, to reduce the size of the contingency table, the descriptors that were only used by one panellist were removed and descriptors with similar meanings were combined using white wine aroma and mouthfeel wheels as guides (Noble *et al.,* 1987; Pickering and Demiglio, 2008). The contingency table was then used in a correspondence analysis (CA) (Picard *et al.,* 2003; Chollet *et al.,* 2014), creating a symmetric plot that displays the wines and their descriptors on a descriptor-based space. Confidence ellipses (95 %) were not included in symmetric plots as they overlapped for all wines and were thus not different.

RESULTS

1. NDVI zones and basic wine composition

While NDVI values from geo-located vines significantly differed when comparing high *vs.* low NDVI zones for each site (Supplementary Table 2), the comparison of NDVI values across the two zones and their three field replicates demonstrated less clear zonal differences (Table 1). The ANOVA and post-hoc Tukey HSD demonstrated that for four sites, Pondview, Château des Charmes, Hughes, and Cave Spring, the NDVI values for the three field replicates per NDVI zone did not differ from one another, while the NDVI values across the two NDVI zones did significantly differ (i.e., there was a clear grouping by NDVI values of the three high NDVI replicates *vs.* the three low NDVI replicates). However, for Buis and George, the grouping of zones and replicates by NDVI values did not produce a clear separation of high *vs.* low NDVI zones. For these two sites, there were significant differences in NDVI values for replicates within the same zone and similarities in NDVI values between replicates across zones.

When comparing the basic wine chemistry of wines made from sample grapevines that corresponded to the two NDVI zones and three field replicates, the basic wine composition did not differ between NDVI zones except for pH, which differed between high and low NDVI wines in multiple sites in both years.

TABLE 1. Mean NDVI of sample vines from High *vs.* Low NDVI zones and their associated three field replicates for six Riesling vineyards in Niagara, Ontario.

	Mean NDVI					
NDVI zone and replicate	Buis	Pondview	Château des Charmes	George	Hughes	Cave Spring
High 1	0.761 a	0.794 a	0.493 a	0.752 a	0.718 a	0.662 a
High 2	0.774 a	0.795 a	0.514 a	0.738 a	0.711 a	0.646 a
High 3	0.758 a	0.806 a	0.520 a	0.733 ab	0.714 a	0.645 a
Low 1	0.659 c	0.752 b	0.307 b	0.690 bc	0.666 b	0.549 b
Low 2	0.732 ab	0.733 b	0.351 b	0.667 c	0.634 b	0.559 b
Low 3	0.709 b	0.750 b	0.341 b	0.668 c	0.642 b	0.581 b
Pr > F(Model)	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Sample vines (n = 10–16 per replicate, depending on the site) in a grid-pattern were geo-located and NDVI values were extracted from UAV imagery. One-way ANOVA significance ($p < 0.05$) is shown along the bottom row and represented by different letters according to a Tukey HSD post-hoc test.

TABLE 2. Mean wine pH, titratable acidity, and ethanol for wines made from Low and High NDVI zones in six Riesling vineyards over two vintages in Niagara, Ontario.

Site	Year	pH			Titratable acidity (g/L)			Ethanol (% v/v)		
		Low NDVI	High NDVI	p-value	Low NDVI	High NDVI	p-value	Low NDVI	High NDVI	p-value
Buis	2016	2.87	2.81	**0.03**	9.18	9.62	0.05	10.04	9.75	0.14
	2017	2.82	2.86	**0.01**	10.59	10.72	0.49	9.31	9.16	0.55
Pondview	2016	3.00	2.92	**0.04**	8.60	8.51	0.75	11.72	11.21	0.06
	2017	3.07	3.15	**0.02**	6.94	6.80	0.68	12.06	11.48	0.21
Château des Charmes	2016	2.94	2.99	0.12	7.49	7.91	0.14	11.02	11.08	0.96
	2017	2.97	3.11	**0.003**	7.93	8.05	0.69	11.52	11.66	0.57
Hughes	2016	2.89	2.91	0.54	8.57	8.84	0.40	10.68	10.36	0.15
	2017	2.98	2.98	0.84	8.56	8.39	0.49	10.40	10.24	0.70
George	2016	2.86	2.97	0.07	9.88	10.22	0.09	9.70	9.84	0.53
	2017	2.98	2.98	1.00	9.12	9.01	0.60	8.94	9.18	0.22
Cave Spring	2016	2.97	2.95	0.40	8.53	8.83	0.14	12.50	12.61	0.44
	2017	3.00	3.04	**0.05**	9.58	9.53	0.90	10.35	10.56	0.31

Significant p-values (95 % confidence) from a two-sample t-test are in bold (n = 3 field replicates per NDVI zone).

In 2016, pH differed between NDVI zonal wines in two sites and in 2017 in four sites; however, the nature of the differences varied between years. In 2016, both Buis and Pondview had a higher pH in low NDVI wines compared to high NDVI wines (Table 2). In 2017, both Buis and Pondview again, as well as CDC and Cave Spring, had different pH values across zones; however, with a higher pH in high NDVI wines compared to low NDVI wines (Table 2). TA differed in Buis 2016, with a higher TA in the high NDVI wines (Table 2). Ethanol did not differ between wines in any site or year (Table 2).

2. Sensory sorting results

2.1. Sensory grouping data multidimensional scaling (MDS) and agglomerative hierarchal clustering (AHC)

All MDS Kruskal Stress Values were below the acceptable value of 0.2 (Figure 3). Kruskal Stress Values tended to be slightly lower (better fit of data) for 2016 wines compared to 2017, except for Pondview, which did not differ between years (2016 = 0.160, 2017 = 0.158), and George, which was slightly higher in 2016 (2016 = 0.198, 2017 = 0.184). For Buis, the 2016 wines were not sorted based on NDVI zone (Figure 3A, Figure 4A); however, in 2017, two replicates of each NDVI zone were sorted together: low(L)1 and L2 *vs.* high(H)1 and H2 (Figure 3B, Figure 4B). In Pondview, for 2016 wines, panellists again did not sort wines based on NDVI zones (Figure 3C, Figure 4C); however, for 2017 wines, panellists sorted L1 and L2 together and, to a lesser extent, sorted H1 and H3 together (Figure 3D, Figure 4D). CDC was the most consistently sorted site in both years (Figure 3E, Figure 3F), with panellists sorting two replicates per NDVI zone together for 2016 wines: H2 and H3 *vs.* L2 and L3 (Figure 3E, Figure 4E). For 2017 wines, panellists sorted all three replicates of each NDVI zone together, with L1 and L2 *vs.* H1 and H3 being the most similar within each zone according to the AHC (Figure 3F, Figure 4F). George 2016 NDVI zonal wines were not sorted separately; however, wines were sorted based on field replicates instead (L1 and H1, L2 and H2, L3 and H3) (Figure 3G, Figure 4G). Here, field replicates were located on an N-S gradient, with replicate 1 being the most southerly and replicate 3 being the most northerly (Figure 2). For George 2017 wines, two replicates per NDVI zone were slightly sorted together, with L2 and L3 *vs.* H1 and H3 being sorted together after the 1st AHC node (Figure 3H, Figure 4H). In Hughes, 2016 wines were fully separated based on the two NDVI zones, with replicates 1 and 2 for both low and high NDVI zones being the most similar within each zone according to the AHC (Figure 3I, Figure 4I). However, for 2017 wines, NDVI zones were not sorted separately (Figure 3J, Figure 4J). For Cave Spring, for the 2016 wines, panellists were unable to sort the NDVI zones (Figure 3K, Figure 4K); however, for the 2017 wines, panellists sorted two replicates of each NDVI zone together; L3 and L1 *vs.* H3 and H2 (Figure 3L, Figure 4L). Overall, panellists were able to sort at least two replicates per NDVI zone in 2017 wines for four of six sites; however, in 2016, this occurred in only two sites. Perfect sorting of all replicates and NDVI zones were seen in CDC 2017 and Hughes 2016, where all three replicates per NDVI zone were sorted together and separated from one another.

2.2. Sensory descriptor data and correspondence analysis (CA)

The results of each correspondence analysis varied from representing 62.7 % to 85.5 % of the data depending on the site and vintage (Supplementary Figure 1). No wines were significantly different from one another in the CA maps as the 95 % confidence ellipses overlapped for all wines, i.e., there was no significant grouping of wine NDVI zones or replicates based solely on the descriptor frequencies.

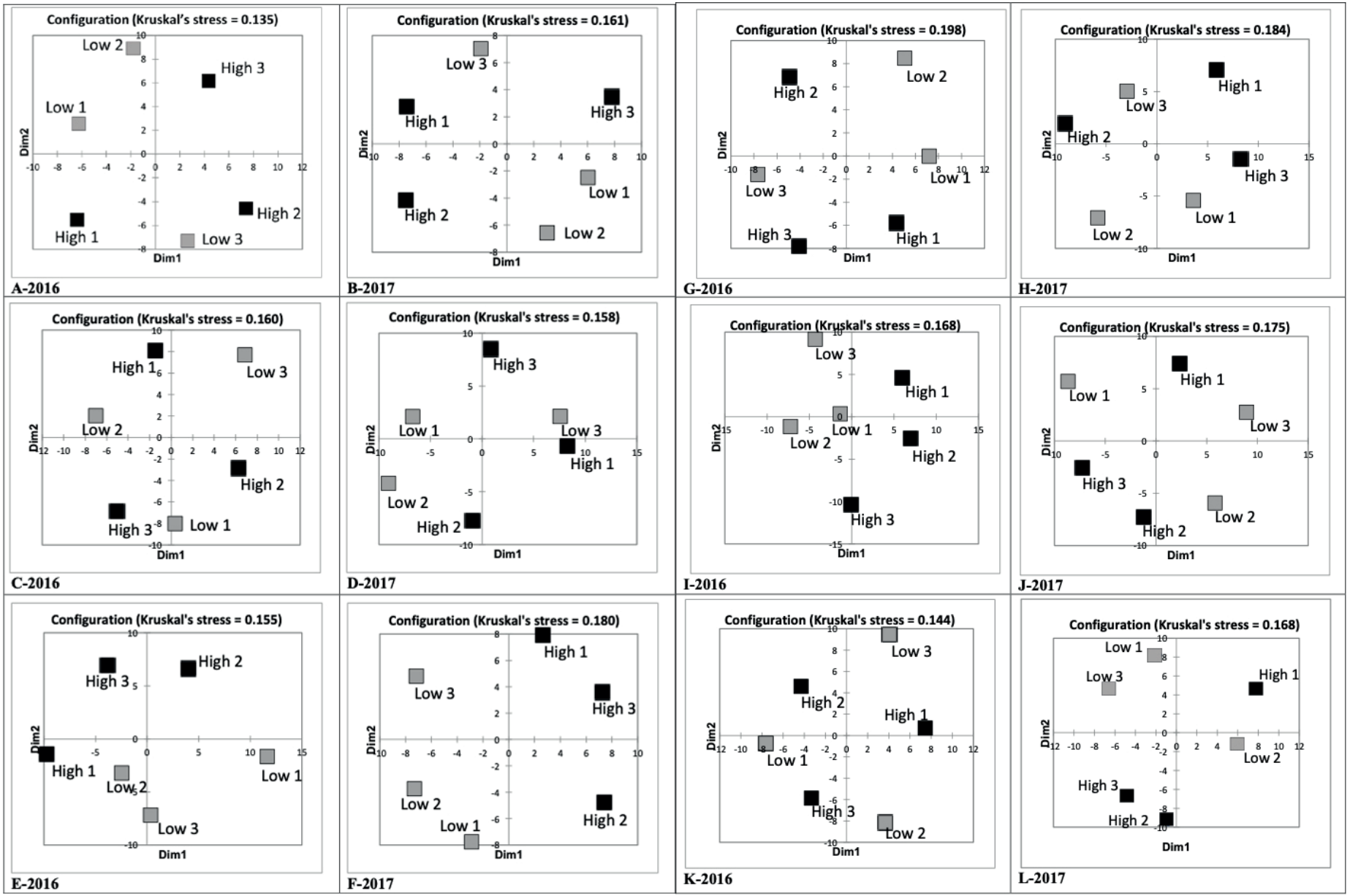


FIGURE 3. Multi-dimensional scaling two-dimensional configuration of the sensory sorting (n = 19) of High *vs.* Low NDVI wines from six Niagara, Ontario Riesling vineyards.

Wines were made from High *vs.* Low NDVI vineyard zones delineated by unmanned aerial vehicle and each zone had three field replicates. From top left to bottom right are; Buis (A, B), Pondview (C, D), Château des Charmes (E, F), George (G, H), Hughes (I, J), Cave Spring (K, L).

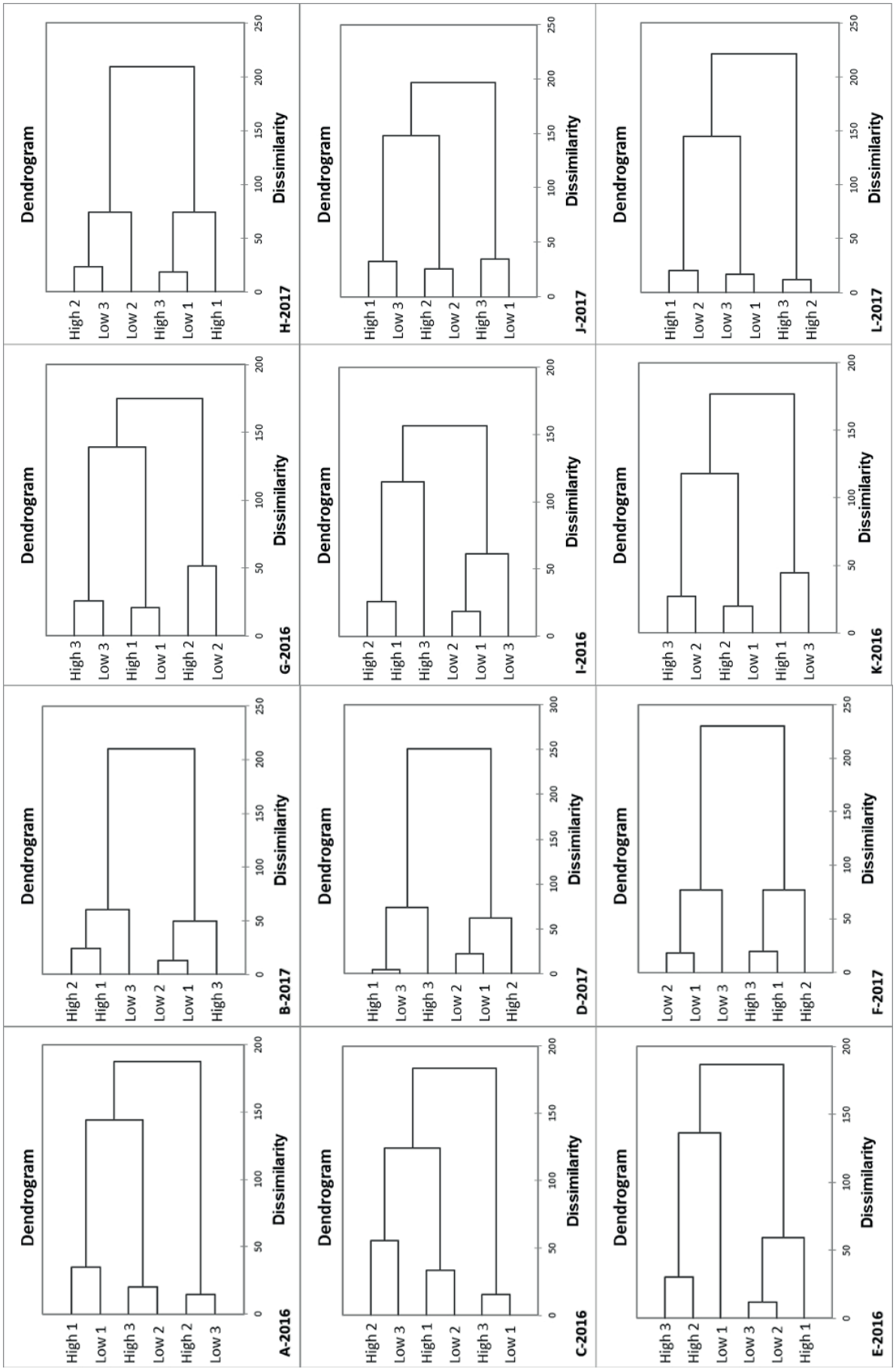


FIGURE 4. Agglomerative hierarchical clustering dendrogram of the coordinates from the multi-dimensional scaling 2-dimensional configuration of the sensory sorting (n = 19) of High *vs.* Low NDVI wines from six Niagara, Ontario Riesling vineyards.

High *vs.* Low NDVI vineyard zones were delineated by unmanned aerial vehicle and each zone had three field replicates. From top left to bottom right are; Buis (A, B), Pondview (C, D), Château des Charmes (E, F), George (G, H), Hughes (I, J), Cave Spring (K, L).

Furthermore, chi-square tests for each site and vintage were not significant (p-value > 0.05); therefore, the descriptors and wines were not significantly associated with one another. These CA maps, though not significant, may still provide insights into the attributes associated with wine products for the sites and vintages where panellists were able to sort at least two replicates per NDVI zone together in the AHC and MDS results—highlighting descriptors that may have contributed to this sorting. In the Buis 2017 CA, similar to the sorting AHC results, L1 and L2 were grouped together with the descriptor of citrus, while H1 and H2 were grouped together near the floral descriptor (Supplementary Figure 1B). In Pondview 2017, the AHC had sorted L2 and L1 together, and in the descriptor-based CA, L2 and L1 were not as close together but were the only wines near descriptors of vegetal, petrol, and citrus (Supplementary Figure 1D). In the CDC 2016 CA projection, similar to the AHC sorting results, H3 and H2 were grouped together and near descriptors of honey/caramel, citrus, vegetative, and soft, while L3 and L2, which were grouped together in the AHC sorting results, were not as clearly grouped together and were near opposing descriptors with L2 near neutral/muted and acidic and L3 near aromatic and sweet (Supplementary Figure 1E). In CDC 2017, similar to the AHC sorting results, NDVI zonal wines were grouped separately on the CA map with all three high NDVI replicates near descriptors of tropical fruit, fruity, floral, and acidic, and all three low NDVI replicates near vegetative, lower acidity, sweet, unpleasant, and citrus (Supplementary Figure 1F). In Hughes 2016, although the AHC sorting results fully separated the two NDVI zones, only two replicates per zone were located together in the CA map, with H3 and H2 near stone fruit and L1 and L2 grouped together, along with H1 near apple (Supplementary Figure 1I). In Cave Spring 2017, where the AHC sorting results grouped two replicates per NDVI zone together, in the CA map, the NDVI zones were separated with high NDVI wines near descriptors of vegetal, fruity, tree fruit, and acidic and low NDVI wines near citrus and lower acidity (Supplementary Figure 1L).

Due to the freedom of panellists to use any descriptors, there was low consistency in the descriptors used for describing high *vs*. low NDVI wines across sites. However, a few common descriptors were seen in the groupings of at least two replicates per NDVI zone. Overall, there was a trend for groupings of low NDVI wine replicates being described as citrus (Buis 2017, Pondview 2017, CDC 2017, Cave Spring 2017) and groupings of high NDVI wines being described as fruity/stone fruit/tropical fruit (CDC 2017; Hughes 2016, Cave Spring 2017) and floral (Buis 2017, CDC 2017).

DISCUSSION

This study tested the hypothesis that wines produced from different NDVI zones in cool-climate Riesling vineyards would differ in both chemical and sensory attributes. Grapevines with higher NDVI have been associated with larger leaf area index (Johnson, 2003), canopy size (Acevedo-Opazo *et al.,* 2008), higher yield (Debuisson *et al.,* 2010), and higher water status (Acevedo-Opazo *et al.,* 2008) - variables which may impact berry composition and resulting wines. Vines with higher vine vigour and less exposed clusters can have lower Brix and aroma compounds and higher TA (Cortell *et al.,* 2007a; Reynolds and Wardle, 1989). Furthermore, the benefits of deficit irrigation and low water status on grapevine berry composition and wine products are commonly seen (Balint and Reynolds, 2017; Chapman *et al.,* 2005; Koundouras *et al.,* 2006). Lastly, higher-yielding vines have been associated with decreased berry quality (Matthews and Nuzzo, 2005), although factors like crop load, the ratio of vine size to yield are more important than total yield alone (Kliewer and Dokoozlian, 2005).

Overall, it was predicted that remotely-sensed NDVI zones would be associated with vines of differing viticultural attributes, such as vine size, local soil conditions, vine water status and yield, and thus would have differences in their berry composition, ultimately leading to differences in NDVI-based zonal wines. Relationships in the viticultural data collected from these same vineyards for both seasons (2016 and 2017) suggested that there were indeed direct correlations between NDVI and soil moisture, leaf water potential (ψ), vine size, yield, and berry weight, and inverse correlations between NDVI and Brix, pH, potentially volatile terpenes (PVT) in these sites (Reynolds *et al.,* 2019). Therefore, the hypothesis was based on the assumption that NDVI zones would produce different wines, primarily because of these relationships. However, correlations between NDVI and other predictors of wine quality are by no means absolute, and this must be heeded whenever precision viticulture is an intended objective.

A comparison of wine TA, pH and ethanol between low and high NDVI wines demonstrated that pH differed between NDVI zones. However, in 2016, wine pH was higher in low NDVI wines compared to high NDVI wines in two sites, yet in 2017 wine pH was lower in low NDVI wines compared to high NDVI wines in four sites. These differing results are consistent with Reynolds *et al.* (2007), who found that Riesling wine pH only differed between vines of differing vine sizes and soil texture in certain years. Although differences in wine pH, TA and ethanol are of significance in winemaking and can strongly influence wine sensory attributes, sensory differences between zonal wines have been associated primarily with volatile aroma compounds rather than differences in basic wine chemical attributes (Bramley *et al*., 2011a; Koundouras *et al.,* 2006). Furthermore, differences in basic berry composition, which influence the resulting basic wine composition, can be minimized upon implementation of temporal zonal harvesting, where the harvest can occur on different dates based on differences in Brix and TA, the often-used determinants of harvest maturity. For example, temporally variable zonal harvesting of remotely sensed vineyard zones was implemented where the low vigour/low yield zones were harvested one week earlier than the high yield/high vigour zones based on their decided harvest maturity of 24 °Brix (Bramley and Hamilton, 2007).

Sorting task results may have also been attributable in part to vintage variation. Correct sensory sorting of wines between

high and low NDVI zones also demonstrated interannual variation - the sorting of NDVI zonal wines was much stronger in 2017 *vs.* 2016. In 2016 wines, only two sites demonstrated sorting based on NDVI zones, with one site, Hughes, sorting all three replicates per NDVI zone together and CDC sorting two replicates per NDVI zone together. However, in 2017 three sites sorted two replicates per NDVI zone together, Buis, Pondview, and Cave Spring, and one site, CDC, sorted all three replicates per NDVI zone together. Differences in sorting task success could be attributed to the often-strong vintage variations that have been demonstrated regarding the aroma potential of wines (Araujo *et al.,* 2004). Glycoconjugates of aroma compounds in Agiorgitiko wines were higher in 1998 *vs.* 1997 (Koundouras *et al.,* 2006), particularly for the glycosides of volatile phenols, monoterpenes, and norisoprenoids, which increased by more than 50 % in 1998, influencing the sensory properties of the wines. Reynolds *et al*. (2007) demonstrated that vintage and wine age had stronger impacts on wine sensory attributes than vine size and soil texture. The difference in sorting task success between years could be further explained due to variations in growing seasons, as the 2016 growing season had below average precipitation and higher than average GDD accumulation, while 2017 consisted of average to above average growing season precipitation and GDD accumulation (Grape Growers of Ontario, 2017; Grape Growers of Ontario, 2018). Wines made from zones of different vine water statuses have demonstrated differences in their wine sensory attributes (Ledderhof *et al.,* 2014). However, in 2016, NDVI and leaf ψ were not consistently spatially associated (Reynolds *et al.,* 2019), and differences in high *vs.* low NDVI wines may not be associated with water stress this year.

Another possible reason for the difference in results between vintages could be due to the differences in wine bottle ageing before sensory analysis. González-Viñas *et al.* (1998) demonstrated the impact of bottle ageing on the organoleptic properties of a white variety, Airén, after storage for 6, 18, 30 and 42 months in bottle. The descriptive analysis described younger wines with fresh-citric, floral, and apple aromas, while wines stored longer in the bottle had sweet-raisin and spicy-green pepper aromas. Wines from different storage ages were also sensorially distinguishable from one another due to the loss of the fresh-citric aroma and the appearance of a spicy-green pepper flavour (González-Viñas *et al.,* 1998). One of the most common descriptors used in the sorting of these Riesling wines by panellists was citrus, which was used in each site and vintage. Thus, any loss in the aroma compounds responsible for the citrus descriptors over time could strongly impact the ability to distinguish between wines.

Yet another mitigating factor that may have impacted sorting success is simply the location of replicates within the vineyard. An interesting result was that of George 2016, which displayed the sorting of wines based on field replicates rather than sorting by high *vs.* low NDVI zones. Panellists sorted H1-L1, H2-L2 and H3-L3 together. The field replicates for this site were located within the vineyard on a north-south gradient, with replicate 1 being the most northern and replicate 3 being the most southern. This replicate-based sorting of the wines, which was not seen in any other site or vintage, could be due to the direct proximity to Lake Ontario in this site, where even minor differences in distance from the lake could greatly impact the microclimate conditions in the vineyard. This variation may not have been accounted for by remotely sensed NDVI.

The descriptor-based wine CA results were not strong, as 95 % confidence ellipses for all wines overlapped in each site and each year. However, the descriptor-based CA results demonstrated a trend for low NDVI wines being described as citrus and high NDVI wines as fruity, stone fruit, and floral. Reynolds *et al.* (2007) found that Riesling wines from higher vine size zones had higher intensity of apple aroma and lower intensity of citrus aroma in certain years. Due to the strong correlations (linear and spatial) between NDVI and vine size in this study (Reynolds *et al.,* 2019), previous findings of large vine size zonal wines being higher in apple and lower in citrus intensity were consistent with the general trend for high NDVI wines being rated as fruity and low NDVI as citrus. Though labelled sorting can provide an indication of the different descriptors associated with sorted products (Chollet *et al.,* 2014), multiple factors can influence the usefulness of descriptor results. Inconsistencies were seen between the grouping of wines based on the sorting task co-occurrence matrix and the grouping of wines based on the descriptor frequency data. Though free sorting tasks have become common in sensory profiling of food and beverage items, their use in complex products, such as beer (Lelièvre *et al.,* 2008), has demonstrated discrepancies in the descriptors generated between trained and untrained panellists, despite the similarities in the grouping of beers performed by each group. Thus, the sorting/grouping results of this research should be considered more readily than those of the descriptor data. The inclusion of a list of descriptors for panellists to choose from may have enabled more uniform results across panellists; however, Lelièvre *et al.* (2008) demonstrated that providing panellists with a list of descriptors for beer products did not assist in the accuracy of descriptors used. Conventional profiling/descriptive analysis could have been used, though this has been shown to produce similar product configuration maps compared to sorting data (Cartier *et al.,* 2006).

Implementing selective harvesting in vineyard blocks of this size (≈ 1–3 ha) may only be economically beneficial with zoning above a certain geographic area threshold, though this will likely be linked to local production systems and final wine product objectives. Previous research demonstrating the economic benefits from zonal harvesting and wine production have occurred in larger blocks in total areas, such as producing multiple wine products from a vineyard block of 12 ha in size (Bramley *et al.,* 2011b) and an 8.47 ha block using two zones; one 2.47 ha and one 6 ha (Proffitt and Pearse, 2004). Smaller geographic zones, as seen in this study, as well as the use of multiple zonal categories

(in this case, field replicates), which further decreases the considered area used to produce each individual wine, can possibly lead to less distinct differences between zonal wines. For example, Johnson *et al.* (2001) separated a vineyard into three zones of low, medium, and high NDVI for selective harvesting and winemaking. Wines from the low and high NDVI zones were sensorially distinguishable from one another, although they were not consistently considered different from the medium NDVI wine. Furthermore, in duo-trio tests of commercial scale vinification of wines produced from two high vigour and yield zones and one low vigour and yield zone, panellists could only distinguish one of the high zone wines from the low zone wine (Bramley *et al.,* 2011b). Similar zonal overlap may have occurred in this study as the mean NDVI of geo-located vines differed significantly when comparing high *vs*. low NDVI zones in every site; however, when comparing mean NDVI across zones and their field replicates, there was some overlap in NDVI values across certain replicates from the two zones in two out of six sites. These results could demonstrate potential challenges in zoning by NDVI within small geographic areas, though more research is needed to determine if field and zone size is a contributing factor. However, these results could also indicate that a more robust and systematic method to determine NDVI zones and replicates is preferred over the visual delineation of zones that were used in this study. Interestingly, the one site with the most consistent sorting of wines by NDVI zone, CDC, also had the largest difference in the mean NDVI of sample vines from high *vs*. low NDVI zones (0.332 *vs*. 0.509). While NDVI values and ranges are very context-specific, this could demonstrate that the efficacy of remotely sensed NDVI zonation for winemaking is related to the magnitude of NDVI variability present in the vineyard – such that vineyards with larger variation in vine vigour and other remotely sensed vine attributes would produce more sensorially differentiable wines when zonally harvested. Pringle *et al*. (2003) discuss the importance of considering the magnitude of variability when deciding to implement spatially variable management of crops. Overall, more research is required to determine at which spatial scales and at which magnitude of NDVI variability selective harvesting and zonal winemaking are economically feasible and sensorially detectable. This study indicated that zonal wines could be distinguishable from one another in very small geographic areas (< 1 ha in area), and by including field replicates in this study, the strength of sensory differences between low and high NDVI wines was further highlighted.

CONCLUSION

UAV-based remote sensing was used to successfully determine within-field zones that produced significantly different wine products in small (1–3 ha) Niagara, ON Riesling vineyards. Basic wine composition between NDVI zonal wines demonstrated differences in wine pH; however, vintage and site variations were seen in the pH differences between zones. Sensory differences between zonal wines were clearer, as high and low NDVI wines were sorted separately in multiple sites in both years, though only one site showed temporally consistent success in the sorting of high and low wines across both years. Descriptors produced from the wine sorting task did not differ across the wines. However, a trend was seen across sites and years where high NDVI wines were described as floral and fruity and low NDVI wines as citrus. These results indicated that remote sensing has the potential to be used for the selective harvesting and the production of zonal wine products that are sensorially distinguishable from one another, though more research is required to understand differences observed across sites and years.

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