Determining a Robust Indirect Measurement of Leaf Area Index in California Vineyards for Validating Remote Sensing-Based Retrievals

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Abstract

Accurate ground-based measurements of leaf area index (LAI) are needed for validation of remote sensing-based retrievals used in models estimating plant water use, stress, carbon assimilation and other land surface processes. Several methods for indirect LAI estimation with the Plant Canopy Analyzer (PCA, LAI-2200C, LI-COR, Lincoln, NE, USA) were evaluated using destructive (direct) leaf area measurements in 3 split-canopy vineyards and 1 double-vertical vineyard in California, as part of the Grape Remote sensing and Atmospheric Profile and Evapotranspiration eXperiment (GRAPEX). A method with the sensor facing the canopy, and 4 readings occurring evenly across the interrow space, had a coefficient of determination (R^2) of 0.87 and relative root mean square error (RRMSE) of 16%, when compared to direct LAI measurements via destructive sampling. A previously-used method, with the sensor facing down-row, showed lower correlation to direct LAI (R^2 = 0.75, RRMSE = 33%) and underestimation which was mitigated by removing the outer sensor rings from analysis. A PCA method is recommended for rapid and accurate LAI estimation in split-canopy vineyards, though local calibration may be required. The method was tested within small units of ground surface area, which compliments high-resolution datasets such as those acquired by small unmanned aerial vehicles (UAVs). The utility of ground-based LAI measurements to validate remote sensing products is discussed.

Keywords: *leaf area index (LAI), split-canopy vineyard, LAI-2200C*

Introduction

Leaf Area Index (LAI; total one-sided leaf area per unit ground surface area (Watson 1947)) is an important parameter in describing plant canopy processes such as radiation interception, evapotranspiration, and carbon uptake as well as an indicator of crop productivity (Welles and Norman 1991). In grapevines (*Vitis vinifera* L.), methods for accurate and rapid LAI retrieval are needed in plant growth and water use models to determine vine conditions and provide useful information for growers in their decision-making. Reduction of LAI through management practices such as cane pruning has beneficial effects on fruit composition and wine quality (Bergqvist et al. 2001). The relationship between vineyard canopy cover and crop coefficient (Kc) can be used to assess water use, and lead to better irrigation strategies (Williams and Ayars 2005). It is a key input to the thermal-based two-source energy balance (TSEB) model that partitions land surface and associated fluxes between soil/substrate and canopy components and is running at multiple spatial and temporal resolutions using satellite data (Kustas and Anderson, 2009; Semmens et al. 2016; Knipper et al. 2018). In addition, satellite-based LAI predictions have been shown as useful predictors of wine grape yield variability, based on daily retrievals used to obtain optimal ground-satellite correlations (Sun et al. 2017).

LAI is quantified most directly via destructive sampling of leaves. Under this method, plants are defoliated within a given area and the one-sided leaf surface area is measured, typically with an electronic area meter. While highly accurate, this method is very time-consuming and harmful to the crop, and therefore impractical in most situations. Optical ground-based sensors and remote sensing provide non-destructive, or indirect, means for rapid LAI estimation.

Remote sensing-based LAI products are generated using reflectance data and vegetation indices from satellite and aerial platforms. For example, crop/site-specific relationships are frequently used of LAI to Normalized Difference Vegetation Index (NDVI), which combines reflectance in the near infrared (NIR) and red wavebands, to estimate LAI (Myneni et al. 2002; Johnson 2003). The Moderate Resolution Imaging Spectroradiometer (MODIS) satellite produces a global LAI composite every 4 days at 500-meter resolution (MCD15A3H). This product can be disaggregated to field scale using Landsat imagery (30 m resolution) in a reference-based regression tree approach (Gao et al. 2012). More recent satellites, Sentinel-2 and Vegetation and Environmental New micro Spacecraft (VENµS), include red-edge spectral band (700-740 nanometer) sensors at spatial resolutions of 20 meters and 5 meters, respectively. Leaf chlorophyll content is highly correlated to absorption in the red-edge bands, and vegetation indices utilizing these bands may be more suitable than NDVI for LAI prediction (Herrmann et al. 2011; Delegido et al. 2011). The higher spatial resolution (10 m) of the Sentinel-2 visible bands and a near infrared (NIR) band have proven useful as predictors of LAI for precision agriculture applications, when combined in a soil-corrected vegetation index (Clevers et al. 2017). Unmanned aerial vehicles (UAVs) can also be used to create high-resolution LAI maps, at sub-canopy or plant-scale. UAV-derived metrics including NDVI and 3-dimensional canopy structure can be related to spatially-distributed ground-based LAI measurements to produce LAI maps within vineyards (Nieto et al. 2018). Independent of the source, remote sensing-derived LAI data layers which serve as land surface model inputs must be validated with ground-based LAI retrievals.

Ground-based LAI estimation in vineyards can be achieved through a variety of techniques. Hemispherical photography is a popular and relatively inexpensive option (López-Lozano et al. 2009; Fuentes et al. 2014), but requires a considerable amount of processing time (Bréda 2003; Garrigues et al. 2008). Tractor-mounted LiDAR systems have been used to estimate LAI in vineyards, though processing data can be complex (Arnó et al. 2013). Smart phone LAI applications have also begun to be developed and evaluated in vineyards, providing an inexpensive option with instantaneous results, but still require more testing (Orlando et al. 2016). Ceptometers can be used to estimate LAI, from readings of intercepted photosynthetically active radiation, in vineyard canopies but only under a narrow range of optimal illumination conditions (López-Lozano and Casterad 2013). Among the few instruments manufactured specifically for measuring indirect LAI, the Plant Canopy Analyzer (PCA; LAI-2000 and LAI-2200C, LI-COR[1], Lincoln, NE) is well-tested and widely used (Bréda 2003; Weiss et al. 2004).

The PCA is a handheld optical instrument that measures light attenuation through the canopy using a sky-facing fisheye lens, which projects a hemispheric image onto 5 concentric detector rings set at different zenith angles. Actual LAI is linearly proportional to the logarithm of the canopy gap fraction, or the fraction of sky visible through the canopy (Lang and Xiang 1986). The PCA computes foliage density and angle distribution automatically by averaging the logarithms of multiple gap fractions, from readings taken above and below the canopy. The sensor contains a filter to exclude radiation above 490 nm, thus minimizing contribution of scattered light. While it is not optimal to use the PCA under direct sunlight, the PCA model used in this study, the LAI-2200C, includes the ability to measure under a wider range of sky conditions than its predecessor, the LAI-2000, by incorporating scattering correction inputs into the post-processing software.

A few studies have demonstrated the ability of the PCA to estimate LAI in vineyards, though the procedures have varied. LI-COR (2016) recommends facing along-the-row and taking readings across the interrow space, for row crops with a homogenous canopy (no gaps between the rows). In row crops with a heterogeneous canopy, pairs of transects are recommended, with a transect of readings made facing the canopy, followed by a transect facing along-the-row. Sommer and Lang (1994) tested the ability of 2 PCA protocols to estimate actual LAI in minimal and spur-pruned grapevines: (1) facing along the row with 3 readings taken directly beneath the vine (R^2 = 0.92), and (2) facing the canopy with 5 readings taken across half of the interrow space (R^2 = 0.85). Johnson and Pierce (2004) followed the LI-COR two-azimuth protocol in vertical, split, and untrained vineyard canopies, and found that actual LAI correlated significantly (R^2 = 0.78) with PCA measurements, but was substantially underestimated. Döring et al. (2014) found that facing the canopy with 8 readings taken across the interrow space, correlated very highly (R^2 = 0.93) with actual LAI in a vertical-shoot-positioned (VSP) trained vineyard, and minimized underestimation, compared with a protocol facing along-the-row, or the average of both protocols. In each case, local calibration is required.

Validation of satellite-based LAI retrievals with the PCA requires multiple PCA measurements to be combined to represent whole canopies (Anderson et al. 2004; Weiss et al. 2004). Measurements are typically made in grids or transects, e.g. within a 30-m Landsat pixel, and spatially averaged. Several such units are distributed across study areas to capture field variability in LAI. To convert high-resolution multispectral imagery, e.g. from UAVs, to detailed LAI maps, it is necessary to quantify LAI within several smaller units of ground surface area. Techniques such as shoot counting have been used to non-destructively estimate leaf area of single vines (Costanza et al. 2004). However, if a PCA method can accurately estimate LAI in small areas, then a much greater number of locations can be measured

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very efficiently compared to other conventional methods, thus permitting a more accurate and efficient field-scale characterization.

LAI is a key input in modeling vineyard water use and stress and used by the remote sensing-based energy balance models in this issue (Knipper et al. 2018; Nieto et al. 2018). Therefore accurate LAI retrievals will improve the reliability of water use and vine stress monitoring leading to better water management and irrigation scheduling for wine growers and producers. The PCA provides the means to quantify LAI quickly and accurately, if the proper method is employed. The main goal of this study was to recommend a method for rapid and reliable estimation of LAI in California vineyards using the PCA. Measurements came predominately from split-canopy trellis systems, though a double-vertical trellis system vineyard was also tested. This would ensure that the ground-based data being used to validate remote sensing-based LAI retrievals, are trustworthy.

Materials and Methods

Study Sites & Measurement Locations

During the 2016 and 2017 growing seasons (March-October), direct and indirect LAI measurements were acquired at different stages of development, in three vineyards within the Central Valley of California, and one vineyard in the North Coast of California. The study sites were part of the Grape Remote sensing Atmospheric Profiling and Evapotranspiration eXperiment (GRAPEX), an ongoing project started in 2013 which seeks to improve water use efficiency through modeling of evapotranspiration and plant stress (Kustas et al. 2018). The four vineyards represent a north-to-south climate gradient, and a range of vine physiology and canopy structure on which to test models.

Fig. 1 Site photos: **(A)** Borden (June 9, 2016), **(B)** Livingston (July 28, 2016), **(C)** Ripperdan (July 23, 2017), and **(D)** Barrelli (August 7, 2017).

Table 1. Site details.

Site Name	Year Sampled	Cultivar	Trellis System	Row Direction	Row Spacing (meters)	Vine Spacing (meters)	Year Planted
Borden	2016, 2017	Pinot Noir	Split-canopy	E-W	3.35	1.5	2005, 2008
Livingston	2016	Malbec	Split-canopy	E-W	3.35	1.5	2010
Ripperdan	2017	Chardonnay	Double-vertical	E-W	2.74	1.8	2009
Barrelli	2017	Cabernet Sauvignon	Split-canopy	NE-SW	3.35	1.8	2010

Table 1 provides an overview of the four vineyard sites used during the two-year study period. In 2016, LAI was measured in two vineyards: (1) Borden, near Lodi, CA (38.29 N 121.12 W, Fig. 1 A) and (2) Livingston Ranch, near Merced, CA (37.37 N, 120.78 W, Fig. 1 B). In 2017, LAI was measured in three vineyards. Borden was sampled again, along with two additional vineyards: (2) Ripperdan Ranch, near Madera, CA (36.84 N 120.21 W, Fig. 1 C) and (3) Barrelli Creek, near Cloverdale, CA (38.75N 122.98 W, Fig. 1 D).

During both years, indirect LAI measurements were made on a regular basis at several fixed plots throughout each vineyard, and in grids next to eddy covariance flux towers. The plots were established using soil maps and high-resolution NDVI maps, to show the heterogeneity of vineyard blocks. High-resolution imagery was acquired in August 2014 by a UAV flying at 450 m above ground level (agl), resulting in visible and near infrared data at 0.15 m spatial resolution. Around the time of peak vine water stress and coincident with satellite overpasses and UAV flights, a suite of measurements was obtained at these plots, including photosynthesis, temperature, stomatal conductance, hyperspectral reflectance, and indirect LAI. At each plot, LAI was measured with the PCA in a north-south transect consisting of 5 measurements (1 measurement x 5 vine rows), centered around a “data vine” equipped with sap flow and soil moisture sensors. Next to flux towers, LAI grids consisted of 25 measurements (5 north-south transects). Measurements were averaged within transects/grids to produce canopy LAI estimates for remote sensing-based correlations. To avoid damaging the experimental plots, destructive samples were taken outside of these areas, where additional indirect measurements showed LAI values to be in a representative range.

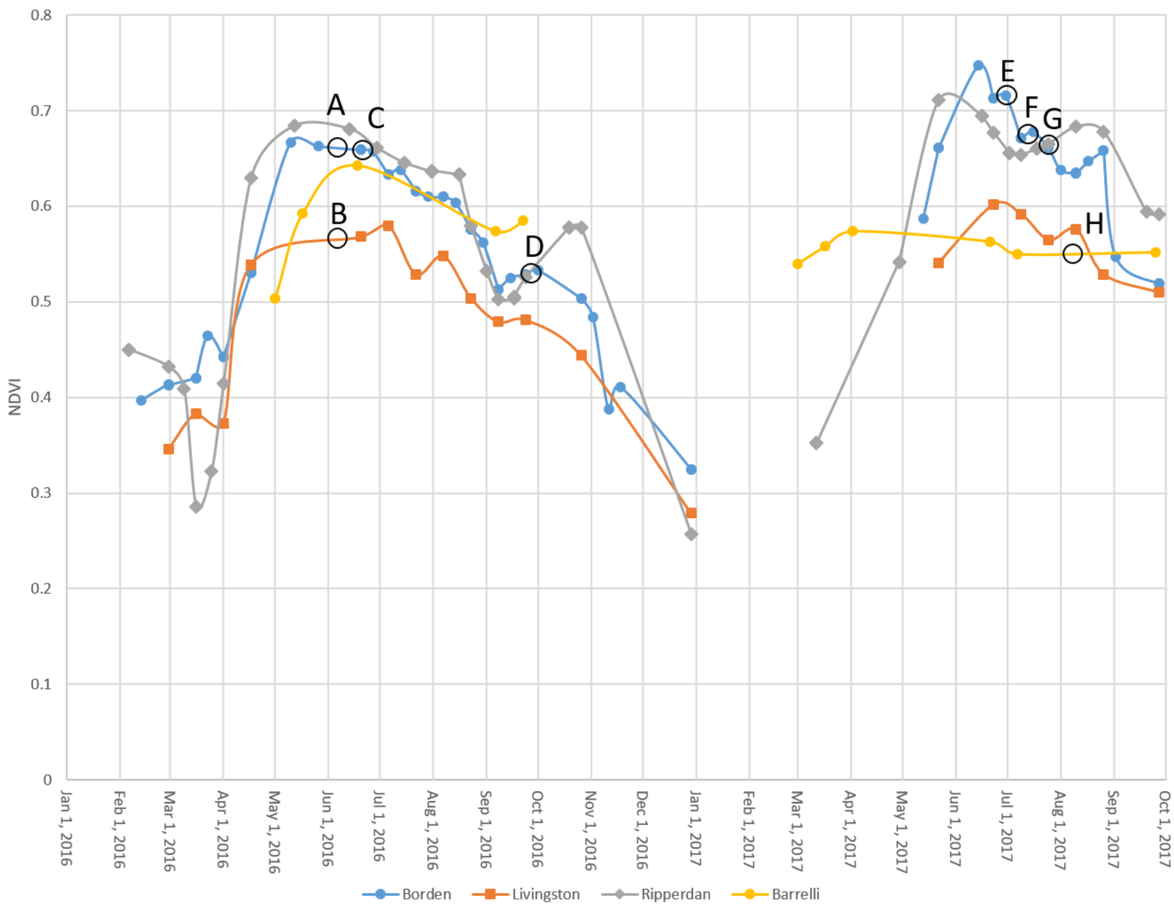

Fig. 2 Landsat 8 NDVI (low cloud-cover scenes) in 4 vineyards, and timing of ground-based LAI measurements, showing relative differences in sampled vine vigor: **(A)** June 6, 2016 at Borden, **(B)** June 8, 2016 at Livingston, **(C)** June 21, 2016 at Borden, and **(D)** September 27, 2016 at Borden, **(E)** June 29 and July 3, 2017 at Borden, **(F)** July 13, 2017 at Borden, **(G)** July 25, 2017 at Ripperdan, and **(H)** August 8, 2017 at Barrelli.

The timing of direct LAI samples was spread across growing seasons, to test indirect methods against a variety of phenological stages and levels of vigor (Fig. 2). In 2016, five samples were acquired in early June (DOY 160) during high biomass at Livingston, along with one sample at Borden. Following pruning in mid-June, three more samples were acquired at Borden (DOY 173). In late September, as vine leaf density was thinning, nine more samples were acquired at Borden (DOY 271). In 2017, measurements were focused mid-season, around veraison. Nine samples were acquired in late June to early July, at Borden (DOYs 180, 184, and 194). Three samples were acquired in late July at Ripperdan (DOY 206), and four samples were acquired in early August at Barrelli (DOY 220).

Indirect LAI

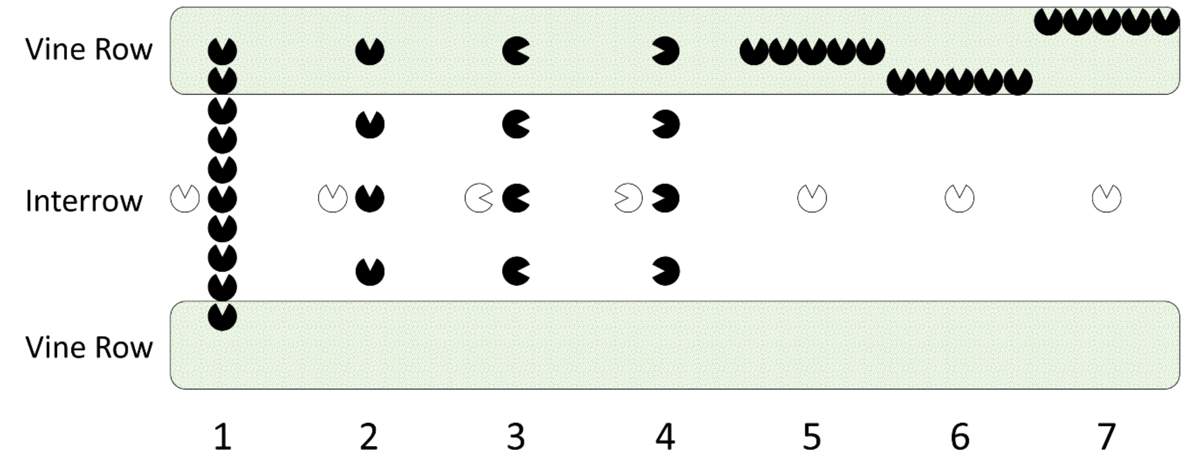

Fig. 3 PCA methods. All readings were performed using a view cap which allowed 45° of the lens to be exposed, as represented by the missing part of the circles. White symbols refer to above-canopy readings; black symbols refer to subsequent below-canopy readings.

Table 2. PCA method descriptions.

Method	No. Readings	Sensor direction	Where evenly-spaced readings occurred
1	10	To the row	Across width of interrow
2	4	To the row	Across width of interrow
3	4	Along the row	Across width of interrow
4	4	Along the row (opposite method 3)	Across width of interrow
5	5	To the row	Across 1 m space under canopy, at row center
6	5	To the row	Across 1 m space under canopy, 30 cm back from row center
7	5	To the row	Across 1 m space under canopy, 30 cm past row center

Prior to defoliation, each direct LAI site was measured with the PCA using seven methods (Fig. 3, Table 2). Each method was intended to capture LAI within a 1-meter section of vine row situated evenly between trellis posts, multiplied by the width of the interrow space. Each method included an above-canopy reading (white symbol) followed immediately by a set of below-canopy readings (black symbols). Below-canopy readings were acquired at 30 cm agl, above any interrow cover crop (present in the early season only), or above the irrigation line in the vine row. The PCA includes lens caps which can be snapped onto the sensor head, to block out a fraction of the azimuthal view. For this study, the cap covering 315° of the lens was used for all readings. The exposed 45° window was pointed away from the user, to ensure the user remained out-of-view. Readings were taken under clear sky, except at Barrelli where overcast conditions prevailed. A two-hour window was avoided around solar noon, and readings were generally taken prior to this, in the morning. Except for two along-row-facing protocols, view direction was to the South, which kept the sun in front of the user but still out-of-view. Therefore, the amount of scattered light being detected was minimized. Nonetheless, extra sky readings were taken per the PCA manual, so that scattering correction could be performed using the FV-2200 software (LI-COR, Lincoln, NE).

In 2016, Method 2 was tested. In 2017, the other six methods were added. Under Methods 1-4, readings were made in a transect perpendicular to the vine row, with one reading between vines at the center of the planted row, and the rest spread evenly across the interrow space. For Methods 2-4, readings occurred at in-row, ¼-row, ½-row, and ¾-row placements. Method 3 was an adaptation of the LI-COR homogenous row crop protocol (LI-COR 2016) used in prior years of the GRAPEX study with a 90° view cap. Under this method, the view direction was due West before solar noon, and due East after, to avoid direct sunlight. Under Methods 5-7, readings were acquired underneath the canopy between vines. Method 5 was directly underneath the center of the planted row. Method 6 required the user to take a step backward, and Method 7 required the user to reach "through" the row.

Terminology

Some investigators (Sommer and Lang 1994; Garrigues et al. 2008; Döring et al. 2014) favor the term "plant area index" (PAI) for indirect LAI estimates made with the PCA. This is because at low ranges of LAI, the PCA tends to overestimate. Non-photosynthetic objects such as trellis posts, vine trunks, cordons, and fruit can block light reaching the sensor when leaf area is low. PAI is then a more literal description, although Döring et al. (2014) observed that estimated PAI did not differ substantially from directly measured LAI in their vineyard study. "Effective LAI" (LAI_{eff}) is another term for indirect estimates, using the Poisson model to describe likelihood of light transmission through the canopy (Weiss et al. 2004). The assumption of random foliage distribution required by gap fraction analysis is tenuous in a structured canopy such as a vineyard, so LAI_{eff} is not an accurate description of these measurements. In lieu of these terms, "indirect LAI" was used in this study, as it remains in accordance with a wide range of vineyard studies, and distinguishes instrument retrievals from actual LAI.

Foliage Clumping

Clumping occurs when foliage is not distributed randomly, as is the case with cordon-trained grapevines. The PCA computes an apparent clumping index (Ω_{app}) for each reading of each sensor ring, and total for each LAI measurement. Ω_{app} is the ratio of two gap fraction averaging methods – the average of the log of gap fractions, and the log of the averages (Ryu at el. 2010). $\Omega_{app} = 1$ means no clumping, and $\Omega_{app} < 1$ means clumping.

Scattering Correction

At present, few studies have made use of the PCA model, LAI-2200C, used here. Its main advantage over the preceding model, LAI-2000, is its ability to take readings under clear sky, and the option to enter scattering correction inputs. The FV-2200 software employs a bidirectional transmission model proposed by Kobayashi et al. (2013) to correct for radiation scattering. This optional step requires taking an extra set of sky readings in the field with different view caps, matching them with the closest below-canopy readings in time, and parameterizing with leaf optical properties. The PCA has a GPS receiver which logs position and time, to provide sun angle information to the model. For this study, input values for leaf optical properties were obtained in the field using a spectroradiometer and an integrating sphere (LI-1800 and LI-1800-12, LI-COR, Lincoln, NE). Spectra were acquired in 1 nm wavebands and resampled to obtain average foliage reflectance and transmittance, and below-canopy surface reflectance, in the blue (350-490 nm) waveband. The FV-2200 software uses these inputs to predict the sensor's view of sunlit and shaded leaves, their fractional irradiances, and the resulting radiation errors in each ring, which get subtracted from the gap fractions, for a final calculation of corrected LAI (LI-COR 2016).

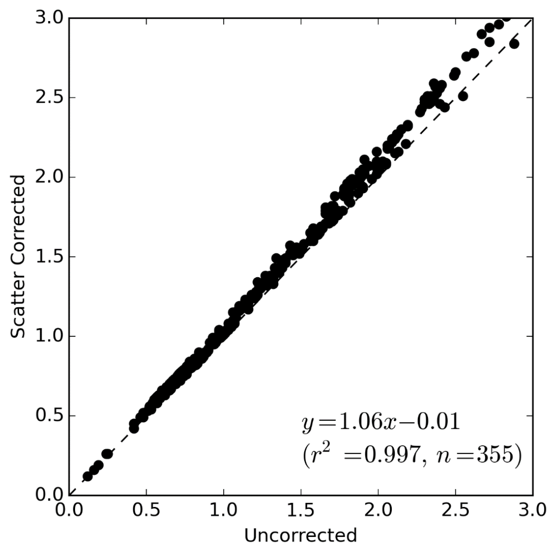

Fig. 4 Comparison of PCA LAI: uncorrected vs. scatter corrected, using measurements acquired 2014-2016 in Borden vineyard.

Comparisons of uncorrected LAI with scattering-corrected LAI, acquired in 2014-2016 in the Borden vineyard, reveal only a slight shift in LAI values (Fig. 4). This shift likely falls within the margin of error introduced by small adjustments in sensor position while taking readings. Under this protocol, measurements were generally taken under optimal light conditions, so scattering correction was less necessary. Nevertheless, additional readings were collected and corrections were applied to the measurements.

Direct LAI

Destructive samples were taken just after indirect measurements were complete. The vine row comprising the South side of the measurement space was sampled. All leaves appearing within a 1 m section between posts were removed at the petiole, and placed into paper bags. Of these, a representative subset containing approximately 25% of the sampled leaves, was collected in a separate sealed plastic bag. This was kept cool until the leaves could be measured on an area meter (LI-3100, LI-COR, Lincoln, NE) the following day. The measured leaves were transferred to a paper bag, which along with the other bags, was dried at 65°C for 2 days. The ratio of leaf area to dry weight was used to obtain the total leaf area (in cm^2) per meter of vine row. This value divided by the plot area (row spacing x 100 cm) was the direct LAI.

Data Analysis

The ability of each PCA method to accurately predict actual LAI was assessed using ordinary least squares regression, coefficient of determination (R^2), root mean square error (RMSE), relative root mean square error (RRMSE), and mean absolute error (MAE). RRMSE is calculated by dividing RMSE by the average of the observed values. RRMSE < 10% connotes excellent model performance, while 10% - 20% is good, 20% - 30% is fair, and > 30% is poor (Despotovic et al. 2016). MAE, the average of the absolute values of error, is less sensitive to the effect of outliers than RMSE as an indicator of model performance (Willmott and Matsuura 2005). The statistical indicators were calculated using the following equations, where n was the number of observations, O_i was observed (direct) LAI, E_i was estimated (indirect) LAI, and $\bar{O}$ was the average of direct LAI values:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - E_i)^2}{n}} \qquad \text{(A)}$$

$$RRMSE = \frac{RMSE}{\bar{O}} \times 100 \qquad \text{(B)}$$

$$MAE = \frac{\sum_{i=1}^{n}|O_i - E_i|}{n} \qquad \text{(C)}$$

Results

Direct LAI ranged from 0.58 to 4.37. One outlying data point (direct LAI = 5.04) acquired at Ripperdan Ranch was excluded from this analysis. For this sample alone, LAI was consistently underestimated by any method, generally to a high degree, in a departure from the statistical population.

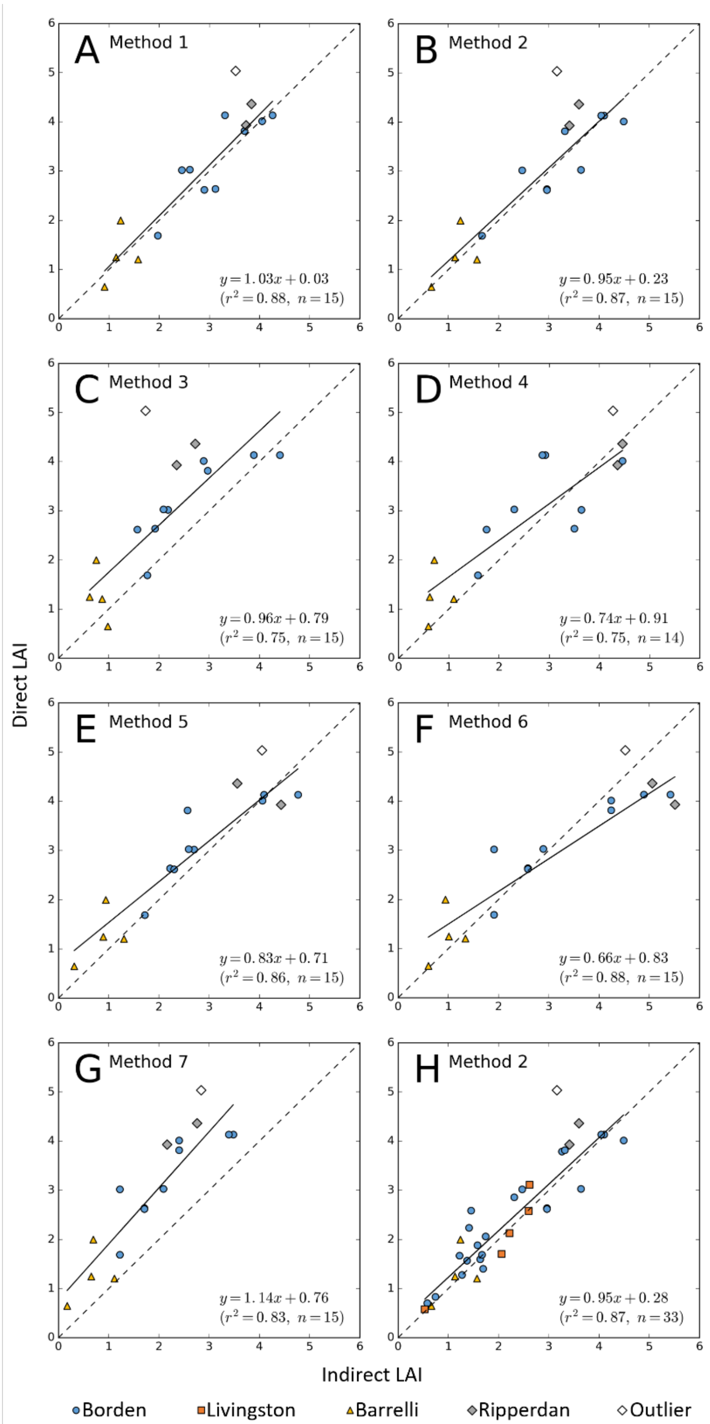

Fig. 5 Comparison of indirect LAI from PCA methods and direct LAI from destructive sampling, in 2017, for **(A)** Method 1 (10 readings facing the canopy), **(B)** Method 2 (4 readings facing the canopy), **(C)** Method 3 (4 readings along the row), **(D)** Method 4 (4 readings along the row facing sun), **(E)** Method 5 (5 readings under canopy), **(F)** Method 6 (5 readings 30cm back from canopy), **(G)** Method 7 (5 readings 30cm through canopy), **(H)** Method 2 including 2016 data. Of the 3 points acquired at Ripperdan (double-vertical trellis system), 1 outlier was excluded, and 2 points were included in the statistical population.

Table 3. Performance of different PCA methods.

Method	R^2	MAE	RRMSE
1	0.88	0.36	15%
2	0.87	0.37	16%
3	0.75	0.79	33%
4	0.75	0.62	27%
5	0.86	0.44	20%
6	0.88	0.53	26%
7	0.84	1.02	40%
2 (2016-2017)	0.87	0.34	19%

Relationships between indirect and direct LAI were evaluated for each PCA method (Fig. 5, Table 3). Methods 1 and 2, in which the sensor faced the canopy and readings were made across the width of the interrow, yielded the most optimal performance metrics and were the best predictors of direct LAI (Fig. 5 A, B, H). Incorporating 18 additional data points from the previous year, Method 2 remained a good predictor of direct LAI (Fig. 5 H). Method 3 had a relatively weak correlation and high underestimation error (y-intercept = 0.79) though the slope of the linear regression was near 1. The underestimation was most likely due to the narrow view cap allowing predominately open sky to be recorded in the interrow, thereby decreasing the average across the sample space. Method 4 allowed the sensor to view more direct sun, which is known to cause errors (LI-COR 2016). While the coefficient of determination and error metrics were similar to Method 3, there was a greater tendency to overestimate high LAI with Method 4. This was likely caused by the greater light intensity differential in above- versus below-canopy readings, and/or an extended canopy shadow (Hicks and Lascano 1995).

Method 5 correlated well with direct LAI, though there was a tendency to underestimate. Method 6 gave similar results, but with a stronger tendency to overestimate high LAI. This may be attributable to a higher concentration of leaves near the sensor at this row position, where branches droop into the interrow. Method 7 probably had a higher proportion of sky in the below-canopy readings, as all values were significantly underestimated.

Discussion

Method Recommendation

A PCA method facing the canopy, with 4 readings across the interrow, proved viable for rapid LAI estimation in 3 split canopy vineyards at several stages of growth. The regression line and performance metrics of a method involving 10 readings nearly matched that of 4 readings. Thus, the time saved by collecting only 4 readings makes this the more practical method. This result is supported by Döring et al. (2014), who found that a method consisting of 8 PCA readings across the interrow, facing the canopy, was the best predictor of LAI in a vertically trained vineyard, but improves upon it by reducing the required number of readings. Methods consisting of along-row readings led to underestimation, consistent with vineyard studies by Grantz and Williams (1993), Sommer and Lang (1994), and Johnson and Pierce (2004). In a discontinuous canopy, gaps may be overemphasized with an along-row orientation. Especially in the outer (more horizontal) sensor rings, the field-of-view becomes dominated by the interrow space when viewing down-row (Grantz and Williams 1993). Sommer and Lang (1994) found that a PCA method using three readings taken directly under the vine row at 30 cm intervals yielded better predictions than a method spanning half of the interrow using an along-row sensor direction. However, our results showed significant errors when only measuring under the vine, highlighting the importance of interrow canopy gaps in overall LAI predictions. Vine-only measurements can be used to determine foliage density or LAI of an isolated plant per the PCA manual; however multiple additional measurements must be made of its shape (LI-COR 2016). The canopy dimensions must be input into the FV-2200 software to compute the individual plant’s LAI, making such measurements impractical for regular use.

Table 4. Average apparent clumping index per site and method.

Method	Borden	Ripperdan	Barrelli	All Sites
1	0.73	0.70	0.74	0.73
2	0.79	0.69	0.72	0.74
3	0.74	0.52	0.88	0.72
4	0.72	0.46	0.87	0.70
5	0.93	0.94	0.97	0.94
6	0.92	0.94	0.97	0.94
7	0.91	0.94	0.98	0.94

By viewing the vine row incrementally with readings across the interrow, the heterogenous structure of the canopy can be better inferred. Average Ω_{app} per study site is given in Table 4. Methods under the vine row resulted in Ω_{app} of nearly 1, suggesting no clumping, while methods spanning the interrow resulted in lower Ω_{app}, confirming clumping. Methods 1 and 2 showed the most consistent high degree of clumping across sites, and resembled the grape Ω_{app} = 0.8 reported by Ryu et al. (2010). Methods using readings only under the vine row cannot account for the heterogeneous canopy structure that typically exists in vineyards, and are therefore inappropriate for rapid LAI estimation.

Scattering correction is an optional step in processing PCA data. It is unnecessary under diffuse lighting conditions, e.g. uniformly overcast skies. In sunny conditions, as are typical in Central Valley vineyards, efforts can be made to minimize error from scattered light. Measurements should be made in the morning or late afternoon, when the sun is low enough to be in front of the user but not directly overhead, and a view cap should be used. Simple comparisons can be made of uncorrected to scattering-corrected measurements. If they reveal little change in estimated LAI, e.g. Fig. 4, scattering correction steps can be skipped or performed less often in subsequent samplings, to improve efficiency.

The effectiveness of the PCA method relies on careful execution. For each reading the user should be cognizant of what the sensor is seeing. Holding the sensor too close to leaves during a reading can drastically inflate LAI estimates. The PCA manual advises that the distance between the sensor and the nearest leaf above it should be at least four times the width of the leaf, and this distance should be even greater when a view cap is used (LI-COR 2016). The distance can be decreased by increasing the number of below-canopy readings, but at the expense of efficiency. For the vineyards tested in this study, by keeping the sensor just above the irrigation line height (approximately 30 cm agl) for all readings, sufficient distance from sensor to leaf was maintained.

Direct LAI values obtained in the Ripperdan site were the most severely underestimated by PCA methods. Only 3 samples were available from this vineyard, and they were acquired during a high biomass period. It is possible that errors were made in data collection, leaf sample processing, or reporting. However, it is notable that Ripperdan differs from the other vineyards in having a double-vertical trellis system and relatively narrow rows. The vine training system may lend itself to higher degrees of foliage clumping, which were not fully accounted-for by the instrument. Destructive LAI values here were in a higher range (LAI = 3.93-5.04) than the other sites and the highest value was the least predictable, possibly due to gap fraction saturation. LAI values obtained by gap fraction analysis with the PCA have been found to plateau around 5-6, resulting in greater underestimation at higher ranges of LAI (Gower et al. 1999). More direct and indirect LAI data are needed from this vineyard, particularly at earlier stages of growth, to determine broader applicability of the recommended method.

While certain studies have highlighted the importance of plantation geometry and training system in developing PCA protocols (Ollat et al. 1998), others have found that vine training does not seem to influence LAI estimation bias (Johnson and Pierce 2004). For split canopy vineyards, PCA method 2 (Fig. 3, Table 2) is recommended for indirect LAI estimation within an area of 1 meter of vine, multiplied by the row width. The proposed PCA method should be confirmed under different planting geometries, and local calibration may be needed.

Remote Sensing Validation

Validation of remote sensing-based LAI retrievals is possible using the recommended PCA method at multiple locations. Since LAI is highly spatially variable, multiple grids and/or transects should be employed within study areas. For validation of coarse-resolution remote sensing data, e.g. Landsat, grids of PCA measurements can be positioned within pixels, chosen to represent different levels of vine vigor. Several such grids allow relationships between ground-based data and satellite-based indices to be established. The effectiveness of the recommended PCA method was demonstrated for small units of ground area, which supports the use of high-resolution UAV data for precision LAI mapping in vineyards. Groups of sub-meter resolution pixels can be aggregated over the space of single PCA measurements or PCA transects, to correlate remote sensing data to ground based measurements.

During the first three years of the GRAPEX study, indirect LAI was measured in the Borden vineyard using Method 3. It was adapted from a homogenous row crop protocol (LI-COR 2016) known to be successful in row crops such as corn. LAI estimates acquired with this old method have been combined with UAV imagery to create high-resolution vineyard LAI maps for TSEB model input (Nieto et al. 2018). To improve these maps, a preliminary empirical calibration equation like that given in Fig. 5 C can be applied to the old LAI estimates. This equation will be improved following more comparisons of the old method to direct LAI observations.

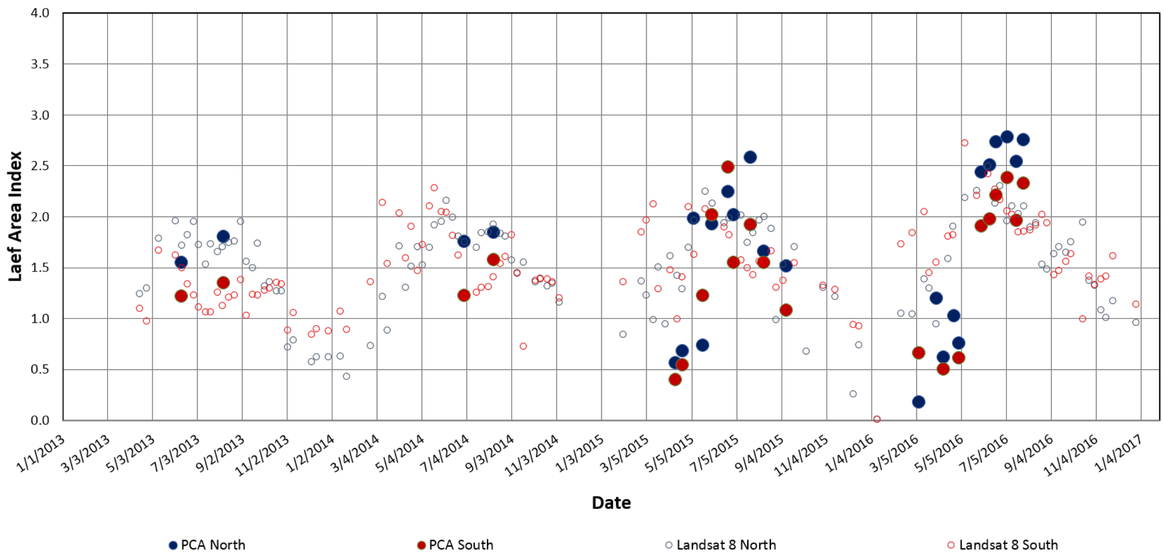

Fig. 6 LAI retrieved from Landsat 8 and PCA method 3, at flux tower sites in Borden vineyard blocks – North (older) and South (younger) – in 2013-2016.

PCA measurements made using Method 3 show underestimation during the early part of the growing season, compared to Landsat-derived LAI during years 2013-2016 (Fig. 6). Sun et al. (2017) observed that satellite-based estimates tend to be higher than ground-based retrievals when the signal is dominated by a dense cover crop, which typically undergoes senescence in early June. While the cover crop signal likely contributed to Landsat-derived LAI values in the Spring, the difference between Landsat and ground-based observations was possibly made even greater due to the underestimation by PCA Method 3. This effect would be more pronounced at earlier stages of growth, since vine shoots have not yet extended into the interrow space, and readings taken there contain little-to-no vegetation when facing along the row.

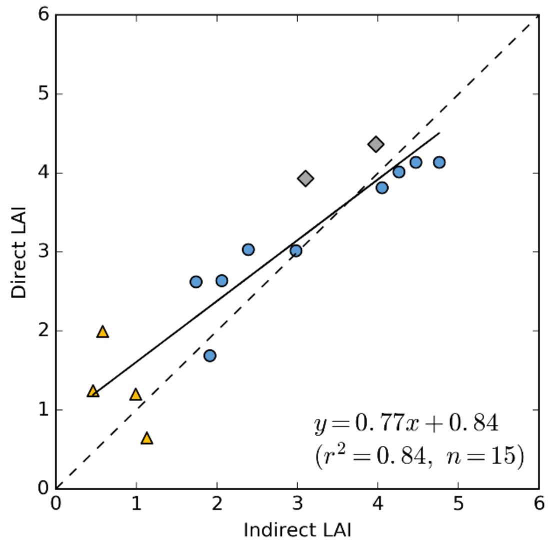

Fig. 7 Comparison of indirect LAI from PCA method 3 after masking the 2 outermost rings, and direct LAI from destructive sampling. Sites are symbolized as in Fig. 5.

Other studies which found high degrees of underestimation following a similar PCA protocol in grapevines have advocated excluding data from the outer 3 rings of the sensor (Grantz and Williams 1993; Johnson and Pierce 2004), or the outermost ring only (Döring et al. 2014). This limits the diffuse radiation caused by scattering at higher zenith angles when viewing along-the-row. For the 15 samples used in this study, omitting data from rings 4 and 5 (zenith angle > 53°), and recomputing with the FV-2200 software, resulted in the most improvement in the correlation and error metrics (R^2 = 0.84, MAE = 0.53, RRMSE = 22%, Fig. 7), compared with using all 5 rings (Fig. 5 C). Underestimation, particularly at the high end of LAI, was reduced. Therefore, old data can be reprocessed masking the outer rings to improve estimates, and pending more trials, an empirical calibration equation can be applied.

Conclusion

For the split canopy vineyards analyzed in this study, a PCA method facing the canopy, with 4 readings across the interrow, was sufficient to estimate LAI. Using more readings did not significantly improve PCA-derived estimates. Protocols facing along the row resulted in weaker relationships, especially when the sun was too much in-view. Multiple readings within the planted row led to inconsistent predictions, and would require additional canopy measurements and processing steps to obtain reliable LAI estimates. For validation of remote sensing-based LAI retrievals, PCA estimates obtained with an old method (with the sensor facing down the row, as in previous years of GRAPEX), were improved by masking the sensor's 2 outermost rings.

The ability of a PCA method to rapidly and accurately predict LAI in a split-canopy vineyard was demonstrated, though different vineyard conditions may require a local calibration. The recommended PCA method enables improved validation of leaf area retrievals using remote sensing. This will lead to more reliable water use and vine stress monitoring with the remote sensing-based energy balance models, leading to better water management and irrigation scheduling for wine growers and producers.

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