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Abstract: Background and Aims: Knowledge of the spatial variability of grapevine canopy density is useful in managing the variability of grape composition and yield. Rapid assessment of the characteristics of vineyards by remote sensing offers distinct advantages over ground-based measurements. In an effort to capture such advantages, this study aimed to assess the relative contribution to LAI of grapevine canopy density and grapevine canopy area derived from high-spatial-resolution airborne digital imagery.Methods and Results: High-spatial-resolution airborne NDVI imagery of minimally pruned, unconfined (i.e. not confined by trellising) grapevines was used to partition image pixels into grapevine-only and non-grapevine groupings. An evaluation of the relative contributions of grapevine planimetric area (number of grapevine pixels across a single row) and leaf layers (NDVI of grapevine-only pixels) found that the variability observed across the vineyard was dominated by changes in canopy area rather than grapevine-only NDVI.Conclusion: The primary predictive variable of grapevine LAI is canopy area. Low-spatial-resolution NDVI imagery of minimally pruned, unconfined vineyards is therefore effective in mapping spatial variability in planimetric canopy area, rather than LAI.Significance of the Study: The process of estimating grapevine LAI from mixed pixels has incorrectly assumed that both components of LAI within a pixel's footprint, namely the number of leaf layers and planimetric canopy area, produce a consistent response in NDVI. Correlations between NDVI and LAI reported in previous studies based on low-resolution imagery most likely relied on the proxy relationship between NDVI and canopy area.

Low resolution remotely sensed images of winegrape vineyards map spatial variability in planimetric canopy area instead of LAI

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Abbreviations and Definitions: ADAR Airborne Data Acquisition and Registration, *Area* grapevine canopy area, c_v coefficient of variation, CD (remotely sensed) canopy descriptors, LAI leaf area index, NDVI normalised difference vegetation index, PAB photosynthetically active biomass, r^2 coefficient of determination

Abridged Title: Remote sensing of grapevine LAI

Abstract

Remotely sensed normalised difference vegetation index (NDVI) images of winegrape vineyards at spatial resolutions that yield mixed pixels containing grapevine and inter-row (non-grapevine) spectral signatures are often used to map grapevine leaf area index (LAI, the ratio of total single sided leaf area to the planimetric canopy area). However, the process of estimating grapevine LAI from mixed pixels incorrectly assumes that both components of LAI within the pixel's footprint, namely the number of leaf layers and planimetric canopy area, produce a consistent response in NDVI. In this paper, high-spatial resolution airborne digital imagery of minimally-pruned, unconfined (i.e. not confined by trellising) grapevines were used to partition image pixels into grapevine-only and non-grapevine groupings. An evaluation of the relative contributions of grapevine planimetric area (number of grapevine pixels across a single row) and leaf layers (grapevine pixel-only NDVI) has found that the variability observed across the vineyard was dominated by changes in canopy area rather than grapevine-only NDVI. It is concluded that low resolution NDVI imagery of minimally-pruned, unconfined vineyards are effectively mapping spatial variability in planimetric canopy area, rather than LAI.

Introduction

High levels of spatial variability in fruit composition and yield are common to many vineyard blocks, presenting management challenges to viticulturists (Bramley and

Proffitt 1999, Bramley 2001). Due to modification of light and temperature microclimate in the fruiting zone, canopy density is a major variable influencing grape composition and yield (e.g. Smart 1985, Smart 1987, Smart et al. 1988, Dry 2000, Bergqvist et al. 2001, Spayd et al. 2002, Ristic et al. 2007). Maps of vineyard canopy density are therefore valuable tools in the practice of precision viticulture, allowing viticulturists to segment harvests based on grape composition or to apply spatially specific grapevine management. However, measuring grapevine canopy characteristics on the ground is time consuming and expensive. Remote sensing, on the other hand, offers rapid assessment of vegetative characteristics of large vineyard areas (Lamb et al. 2001, Hall et al. 2002, Johnson et al. 2003), providing a less expensive opportunity to infer maps of predicted grape quality than from ground-based observation. The key to enabling such inferences is developing an understanding of the links between remotely sensed imagery of vineyards and grapevine canopy characteristics.

Vegetation indices are common measures of photosynthetically active biomass (PAB) based upon a function of the reflectance in specific wavebands of the electromagnetic spectrum. Recent work (Johnson et al. 2003, Lamb et al. 2004) has shown that differences in grapevine performance can be identified from remotely sensed data using the normalised difference vegetation index (NDVI). The NDVI is calculated as

$$NDVI = \frac{NIR - red}{NIR + red} \tag{1}$$

(Rouse et al. 1974), where NIR (near infrared) and red are the reflectance values in those respective bands of the electromagnetic spectrum. The NDVI is a convenient and commonly used index of PAB since it can be calculated for scenes that have been acquired with relatively low cost and widely available multispectral imaging systems; it requires the collection of reflectance data in only two bands. Several studies have shown that vineyard NDVI values correlate with leaf area index (LAI, the ratio of total single sided leaf area to the planimetric canopy area). For example, values taken from NDVI images have been negatively correlated with levels of the highly damaging grapevine aphid, phylloxera (Baldy et al. 1996), a common symptom of which is a reduction in canopy growth. The potential of determining prospective wine quality for vineyard regions based on relationships between grapevine canopy (described by NDVI imagery) and fruit composition has been demonstrated by Johnson et al. (1998, 2001) and Lamb et al. (2004). The relationship between NDVI imagery and measures of canopy density such as LAI is therefore of particular interest. The relationship between NDVI and vineyard LAI is well founded, because NDVI is strongly related to the gross amount of chlorophyll, and greater leaf area results in a greater gross amount of chlorophyll per unit area of the vineyard.

Reported relationships between NDVI and various viticultural parameters have been derived using imagery with spatial resolutions of the order of metres. Imagery is therefore comprised of predominantly mixed pixels, containing reflectance information from both the grapevine canopy and the inter-row space. Using 4-metre resolution (here we refer to a pixel size of 4 m × 4 m on the ground) IKONOS satellite imagery, significant correlations have been achieved between NDVI data and both LAI and leaf area per grapevine (m^2 per grapevine) in multiple vineyards (Johnson et al. 2001, 2003, Johnson 2003). Dobrowski et al. (2003) used 0.6 m resolution imagery acquired by an airborne imaging system (ADAR) to estimate dormant pruning weights over consecutive growing seasons. Lamb et al. (2004) used imagery, initially 0.6 m resolution, to estimate phenolics and colour levels in red winegrapes. Interestingly, Lamb et al. (2004) found that the NDVI imagery explained most of the variance observed in the total phenolics and colour levels of the minimally-pruned Cabernet Sauvignon grapevines when the imagery was sub-sampled to 3 m resolution (i.e. imagery converted to lower resolution equal to the vineyard trellis row spacing). The reason for choosing a low resolution pixel size equal to the inter-row spacing, or an integer multiple of this value, is that in a uniform vineyard the proportion of canopy to inter-row space within a pixel is independent of pixel location relative to the grapevines and inter-row (Figure 1). When the inter-row is itself uniform (for example senesced cover crop or bare soil), this spacing subsequently connects NDVI and planimetric canopy size, as was found by Lamb et al. (2004). The fact that grape attributes like phenolics and colour were linked to NDVI implies a hidden (and assumed) connection between planimetric canopy size and canopy LAI. However, this connection has never been tested.

In the context of winegrape vineyards, remotely sensed imagery can be grouped into two classes of spatial resolution: *low* spatial resolution imagery of vineyards can be defined as a resolution for which the majority of pixels contain reflectance information from both the grapevines and the inter-row space, whereas *high* spatial resolution imagery of vineyards can be defined as a resolution for which the majority of pixels contain information on reflectance from either grapevines or inter-row space only. High spatial resolution NDVI images of vineyards provide a means of distinguishing between grapevine pixels and inter-row space pixels. Histograms of the NDVI values for vineyard imagery typically exhibit bimodal distributions. In a situation of a senesced inter-row crop or bare soil, the lower value NDVI mode represents the inter-row space and the higher value NDVI mode represents the grapevine canopy (Hall et al. 2002). However, higher NDVI values can exist in the inter-row due to vigorous weeds or covercrop (e.g., Frazier et al. 2004). Nevertheless, in many cases an NDVI threshold is sufficient to distinguish between inter-row space and grapevine canopy. Once grapevine canopy pixels have been classified, a distinction can be made between canopy LAI and canopy area (Figure 2). Canopy area can be estimated simply as a count of pixels that are classified as "grapevine". Canopy LAI can be estimated by calculating the mean NDVI of each of the pixels classified as "grapevine".

Vegetation indices, such as the NDVI, often have non-linear relationships with LAI (Barrett and Curtis 1999). Specifically, when NDVI is plotted as a function of LAI, an asymptotic relationship at high LAI levels is apparent (Nemani et al. 2001). The key point is that for pixels with a large LAI, differences in LAI will not be apparent via corresponding differences in their NDVI. In high spatial resolution vineyard imagery, canopy-only pixels tend to have very high NDVI values, commonly ranging between 0.75 and 0.95 (Hall et al. 2002, 2003). Therefore, small variations in high magnitude NDVI values may correspond with large changes in corresponding LAI, relative to changes that would occur for variation in smaller magnitude NDVI values.

The objective of this paper is to use a high spatial resolution image of a trial vineyard to determine the relative contributions of planimetric canopy size and canopy LAI to NDVI values in a low resolution image of the same vineyard.

Material and Methods

The study site was a mechanically-pruned block (c. 1 ha) of *Vitis vinifera* L. cv. Cabernet Sauvignon located at Charles Sturt University, Wagga Wagga, New South Wales (latitude 37º 6’ S, longitude 147º 28’ E). The grapevines were planted in 1977 and have since been subject to spatially homogeneous management. The inter-row space is 3.6 m and individual grapevines are separated, along the rows by 1.8 m. The block is situated on a gentle (<10º) incline sloping towards the east, with straight rows planted north-south, perpendicular to the slope. This field site was chosen on the basis that it contained mechanically-pruned grapevines that are not subjected to mid-season pruning, resulting in a significant amount of free growth out into the inter-row space; in many cases the canopy was observed to extend out to 1 metre either side of the cordon wire.

A total of 48 sample grapevines were randomly selected from the block. The locations of the sample grapevines were recorded as [*grapevine*, *row*] coordinates, where *grapevine* is the sequential grapevine number (1 being the most northerly) and *row* is the sequential vineyard row number (1 being the most westerly). Each sample ‘grapevine’ was defined as the canopy between the trunk of the nominated grapevine and the trunk of the adjacent grapevine to the south; in effect being the composite of two half-grapevines. This produced sample grapevines with easily recognisable boundaries, i.e. two adjacent grapevine trunks (Figure 3).

Multispectral airborne images of the target vineyard site were acquired using Charles Sturt University’s airborne video system (ABVS) (Louis et al. 1995). The ABVS comprised 4 digital video cameras, in a 2 by 2 array, fitted with 12 mm focal length lenses and a computer containing a 4-channel framegrabber board. Each camera captured a static 740 by 576 pixel image in a separate waveband governed by an interchangeable filter with a 25 nm spectral width. In addition to blue (band 1; 450 nm), the standard vegetation wavebands of green (band 2; 550 nm), red (band 3; 650 nm) and near-infrared (band 4; 770 nm) were used. Images of the vineyard site were acquired as close as practicable to solar noon at an altitude of 305 m (±10 m) above ground level, resulting in a spatial resolution of ca. 0.25 m and image coverage of approximately 2 ha. Three imaging missions were completed in the summer of 2001-2002. The dates of image overflights, and associated growth stages, were: 29 October 2001 during rapid canopy development (4 weeks after budburst), 4 December 2001 (4 weeks after flowering) and 30 January 2002 when the canopy was fully developed (at veraison).

High and low reflectance targets of known spectral characteristics, measuring 2 m by 2 m, were included in each image. The reflectance targets were used to calibrate image pixels from raw digital numbers to reflectance values following the procedure of Spackman et al. (2000). Images were also corrected for radiometric and geometric distortion (Louis et al. 1995, Spackman et al. 2000). All vegetation growing between and under the grapevines was sprayed with herbicide in the weeks prior to imaging overflights, thereby reducing the inter-row space to bare soil/senesced vegetation.

Sixteen ground control points (GCPs) were accurately located in the vineyard block using a differential global positioning system (4000SSE Geodetic Surveyor, Trimble Navigation Limited, Sunnyvale, California). The GCPs were identified in the imagery and used to georectify the images using a first-order polynomial function. To avoid the resampling of image pixels and the concomitant degrading of spectral integrity of each pixel, the map coordinates were warped to image pixels rather than warping images to a map grid. The infrared and red bands of the images were converted to normalised difference vegetation index (NDVI) values (Equation 1). NDVI images were then classified into inter-row and grapevine pixels using the observed bimodal distribution of NDVI values and the *Vinecrawler* algorithm (Hall et al. 2003) applied to extract *MeanNDVI* for the descriptor of canopy LAI and *Size* for the descriptor of canopy area.

The LAI of selected grapevine canopies was estimated on the ground using an LAI-2000 plant canopy analyser (LI-COR Inc., Lincoln, Nebraska, USA) within 48 hours of each over flight. Fieldwork was conducted at dusk or dawn in order to minimise effects from scattering of direct sunlight through the leaf canopy in accordance with recommendations of Lang et al. (1985). The method used to collect LAI data with the canopy analyser followed that described as *Method 1* by Sommer and Lang (1994), that is in the direction of the row, directly under the centre of the grapevine and using a 315º view restrictor with the opening pointing in the direction of the row. One measurement above the canopy was taken as a calibration and three measurements, equally spaced along the cordon below the canopy, were averaged for each sample grapevine.

Due to the high NDVI values expected in the vineyard, and the associated likelihood of a non-linear NDVI-LAI relationship, linear, logarithmic and exponential models were fitted to each pairing of the remotely sensed canopy descriptors and LAI. The models of the canopy descriptors *(CD)* used were -

$$CD = a \times LAI + b, \tag{2}$$

$$CD = a \times \ln LAI + b, \tag{3}$$

$$CD = a \times e^{LAI} + b, \tag{4}$$

where *a* and *b* are the fitted parameters for each model.

Results and Discussion

Frequency distribution diagrams of values for NDVI of pixels at three stages of vineyard phenology are given in Figure 4. At stages corresponding to post-budburst and post-flowering, the NDVI histograms are distinctly bimodal (top and middle charts in Figure 4). An inspection of true and false colour images classified on the basis of each distribution peak confirms that pixels with values close to peak 1 (left peak) always represented the inter-row regions whilst pixels close to peak 2 (right peak) represent grapevine regions of the vineyard. An NDVI value of 0.6, based on the value between the two peaks for the phenological stages corresponding to post-budburst and post-flowering was subsequently used as the threshold value to classify inter-row and grapevine pixels. An example of a masked image based on the 0.6 threshold is given in Figure 5.

Of the proposed models (Equations 2, 3 and 4), the logarithmic model (Equation 3) best described the relationships between LAI and the remotely-sensed canopy descriptors. Less response was observed in the NDVI values for grapevines that had high LAIs, which is consistent with the established theory (Barrett and Curtis 1999) relating NDVI to LAI. However, the plots of the models (Figure 6) revealed any deviation from linearity to be minor, perhaps due to the level of noise in the data being too high to enable recognition of any non-linearity. A subsequent test to examine the differences between the coefficients of determination based on comparing the Fisher *Z*-transform values for each model showed no significant differences between any best fitting model and its corresponding linear model. Subsequent analyses of the relationships between the LAI and the canopy descriptors were therefore conducted using calculations of the coefficient of determination using a linear model (Equation 2).

Scatter plots, with lines representing the associated linear models, for the relationships between LAI and the grapevine canopy descriptors, *NDVI* and *Area*, using combined data of all three phenological stages are presented in Figure 7. The coefficients of determination (r^2) show highly significant relationships between each of the variables for all of the time periods combined. A feature of the data collected for this study was that sets of data were collected at different phenological stages of the grapevines. Therefore, canopy characteristics changed each time data was collected. Separating the data on the basis of the three phenological stages produced strikingly different results. It is important to make a distinction between combined data and data collected at a single phenological stage, because in practice interpretation about spatial variability in the vineyard will be based on one phenological stage only, providing a data set with a much smaller range. Coefficients of determination (r^2) for the relationships of NDVI and *Area* with LAI and also of NDVI with *Area* for the data separated into phenological stages are presented in Table 1.

When data from all phenological stages are combined, *Area* had the stronger relationship with LAI (r^2 = 0.831), compared to NDVI (r^2 = 0.743). However, there was no significant difference in the level of correlation between each descriptor. In essence, *Area* and NDVI provided no significant advantage over each other in terms of predicting LAI. However, when separated into individual phenological stages (Figure 6 and Table 1) there were reductions in the strength of correlations between the remotely sensed variables and LAI. The reductions in the level of significance of correlations were not consistent for each of the variables, but for imagery collected at a single phenological stage, *Area* was a stronger predictor of LAI than NDVI. A multiple regression analysis of the combined LAI data that included *Area*, NDVI and phenological time (days since budburst) confirms *Area* as the primary predictor of LAI, with NDVI a significant secondary predictor variable (Table 2). Phenological time had no explanatory power in the multiple regression models once the primary predictor of *Area* had been accounted for.

Low spatial resolution imagery using NDVI as a measure of grapevine canopy has been variously shown to be successful at correlating NDVI values to viticultural parameters that are known to be dependent upon canopy area and density (e.g. Johnson et al. 2001, 2003, Johnson 2003, Dobrowski et al. 2003). These results appear to contradict the results of this study for which it was shown that NDVI values of pixels that were identified as canopy only did not correlate strongly to LAI. However, there exists a significant difference between the type of imagery used in this study and the types of imagery used in the previous studies. Low spatial resolution imagery (compared to high spatial resolution imagery) as outlined in the introduction, contains mostly mixed pixels and, therefore, for vineyard scenes, most, if not all, pixels comprise reflectance information for two surface types, namely inter-row space and grapevine canopy. Therefore, the variability of NDVI values in low resolution vineyard imagery can be mostly attributed to variation in the proportion of the two surface types included in each pixel rather than any variation in the NDVI due to differences in canopy density.

In addition to showing the relative contributions of canopy area and canopy density to correlations with LAI of grapevines, this study revealed that the high spatial resolution imagery exhibited very high NDVI values for the canopy only pixels (typically above 0.8 and often above 0.9, see Figure 4). It has been established that for very high LAI, the NDVI saturates (Wang et al. 2005). With little detectable difference for very high LAI, it may be inferred that the NDVI is not an effective measure of grapevine canopy density. Consideration of other vegetation indices should be developed if differences in grapevine canopy LAI are to be detected using remote sensing techniques. For example, the enhanced vegetation index (EVI) (Huete et al. 1997) has been shown to be more sensitive to changes in vegetation density at high LAIs (Huete et al. 2002) and is therefore likely to be a more appropriate vegetation index for the measurement of differences in dense grapevine canopy vegetation.

Recent studies have shown that the NDVI may be a poor choice of vegetation index when measuring vineyard canopy characteristics. In a study involving the examination of 36 different vegetation indices derived from hyperspectral data correlations with grapevine leaf pigments, NDVI was one of the most poorly performing indices (Zarco-Tejada et al. 2005). In addition to investigations into hyperspectral indices by Zarco-Tejada et al. (2005), effect on grapevines of environmental stresses such as excessive heat has been investigated by collecting grapevine canopy spectra with a spectrometer under controlled conditions (Dobrowski et al. 2005). The result of the Dobrowski et al. (2005) study demonstrated that simple fluorescence ratio indices, calculated in the red-edge spectral region showed superior results in comparison to the NDVI for assessing grapevine stress and photosynthetic status. Although the NDVI was shown to be inferior to other remotely sensed measures of some canopy aspects, there is an important distinction between these two studies employing hyperspectral data (Zarco-Tejada et al. 2005, Dobrowski et al. 2005) and studies involving the NDVI. Those using the NDVI are concerned with estimating grapevine canopy density or LAI directly, which is useful for examining effects of canopy architecture on fruit composition and yield, using the knowledge of the effect of light interactions with fruit. The hyperspectral studies, on the other hand, were concerned with determining specific physiological conditions of the grapevines such as chlorosis or heat and water stress. The usefulness of hyperspectal imagery in the estimation of LAI or other grapevine canopy descriptors is yet to be reported.

As well as the consistent and strong correlations that were found in this study to be present between *Area* and LAI, there was also a significant correlation between NDVI and LAI (r^2 = 0.133) when canopy maturity was reached at veraison. Also at veraison there was a corresponding correlation between *Area* and NDVI (r^2 = 0.289), which was not significant at post-budburst or post-flowering. At veraison there is more variation in the NDVI set (coefficient of variation (c_v) = 0.0257) than at post-flowering (c_v = 0.0103), which increased the probability of a significant correlation.

The strong relationship between *Area* and NDVI at veraison shows that NDVI may be a useful indicator of LAI at canopy maturity (at around veraison). Although in this case *Area* had the stronger correlation with LAI, *Area* may not have strong correlations for vineyards where there is little observable variation in the canopy area. Where there is little variation in canopy area (e.g., vineyards where grapevines are trained along wire trellises and/or subject to mid-season trimming), the NDVI values for low resolution imagery would mostly contain information on the canopy density. If it is assumed that the NDVI-LAI correlation is strongest at canopy maturity for these vineyards, as was shown in this study, then imaging at veraison will yield the strongest correlations between NDVI values for low resolution imagery and LAI, an assertion indirectly supported by the results of Lamb et al. (2004).

Conclusion

This work has considered the relationships that exist between LAI, and remotely sensed descriptors of grapevine canopy area and canopy density (as expressed by the NDVI of grapevine canopy pixels). High spatial resolution imagery allowed for the differentiation of canopy area and canopy density for individual grapevines. The quantitative descriptor for canopy area was calculated as the number of pixels above a threshold NDVI, and the canopy density was calculated as the mean value of the NDVI values of the pixels that made up the canopy area measure. The remotely sensed descriptors of canopy area (rather than descriptors of canopy density) were found to have strong relationships with ground based measurements of LAI, whereas little to no significant relationship was present between NDVI and LAI.

This study has demonstrated that when the relationships between LAI and both canopy density and canopy area are examined using high spatial resolution NDVI imagery, the primary predictive variable is canopy area. The results support the premise that the correlations between NDVI and LAI reported in previous studies based on low resolution imagery most likely rely on the proxy relationship between NDVI and canopy area.

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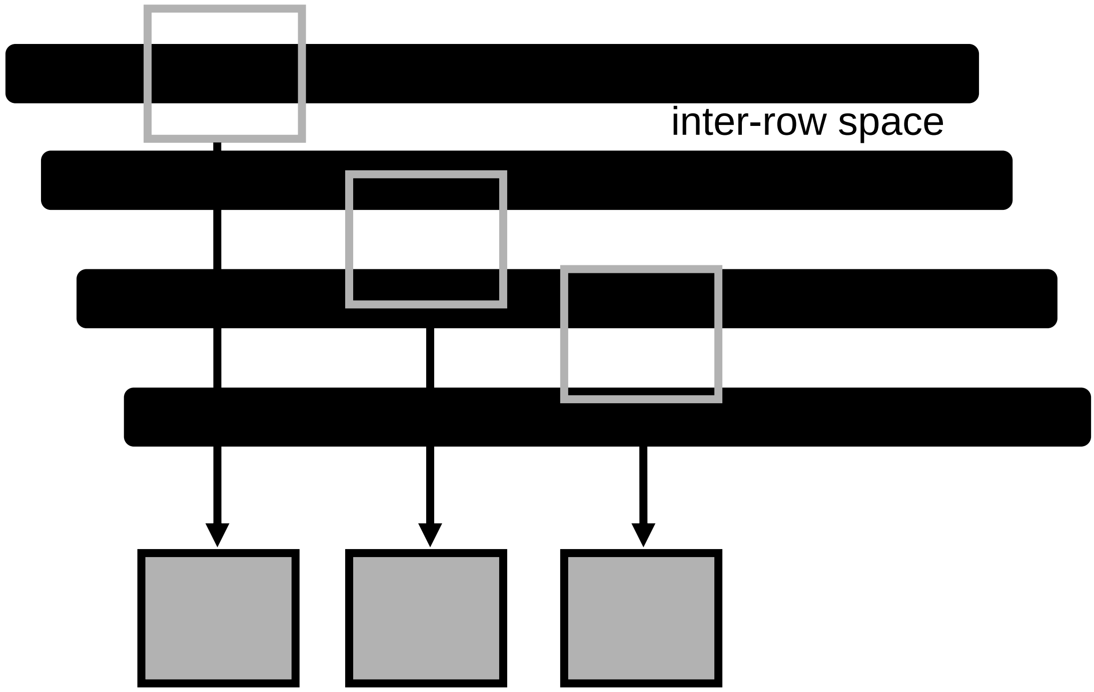
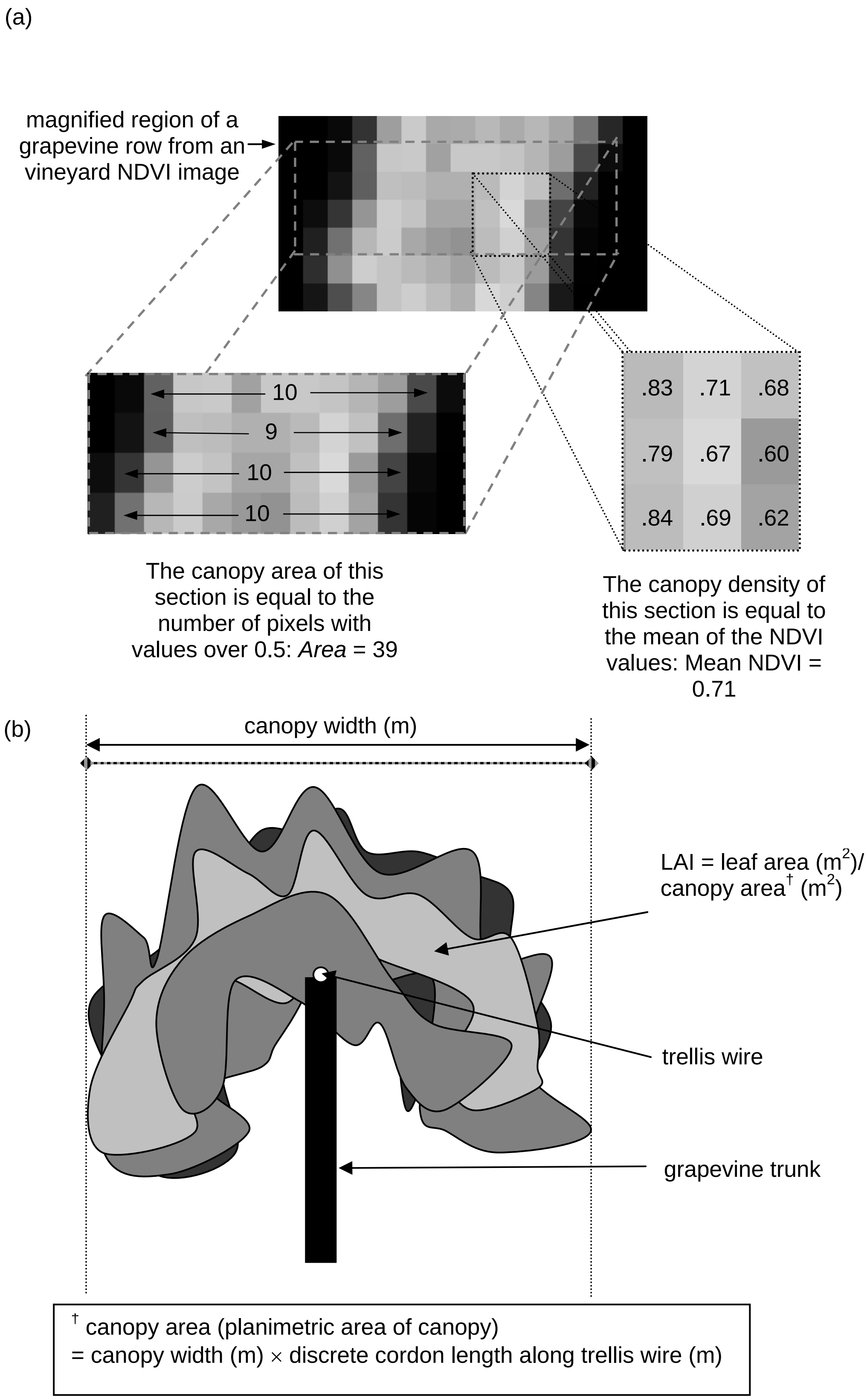
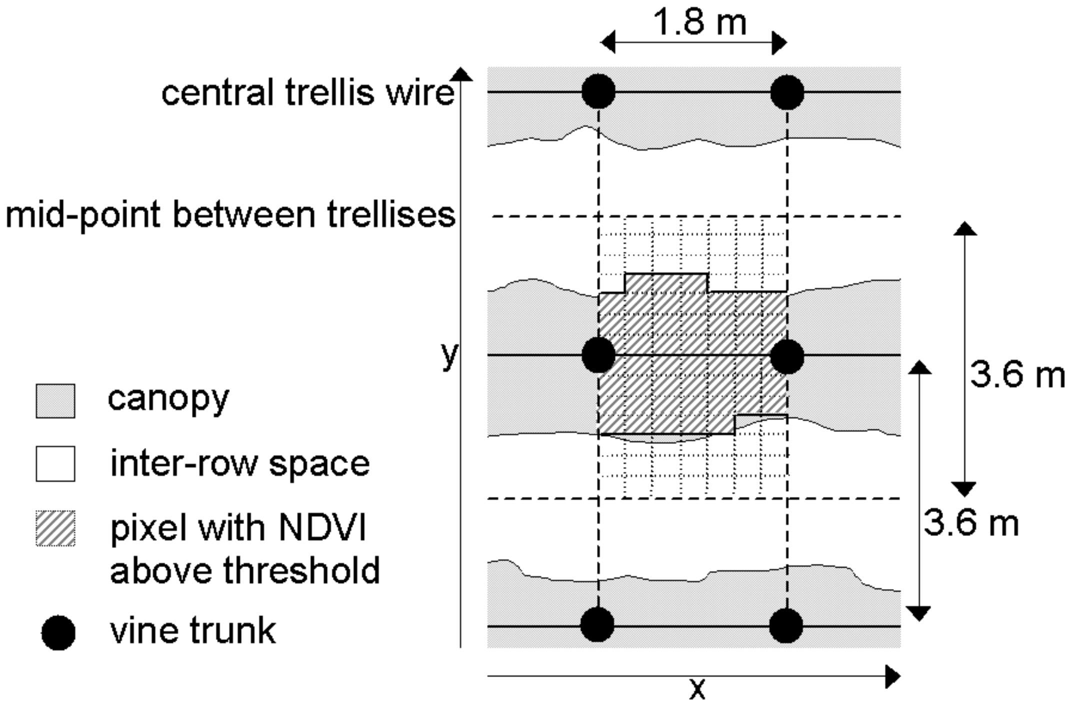
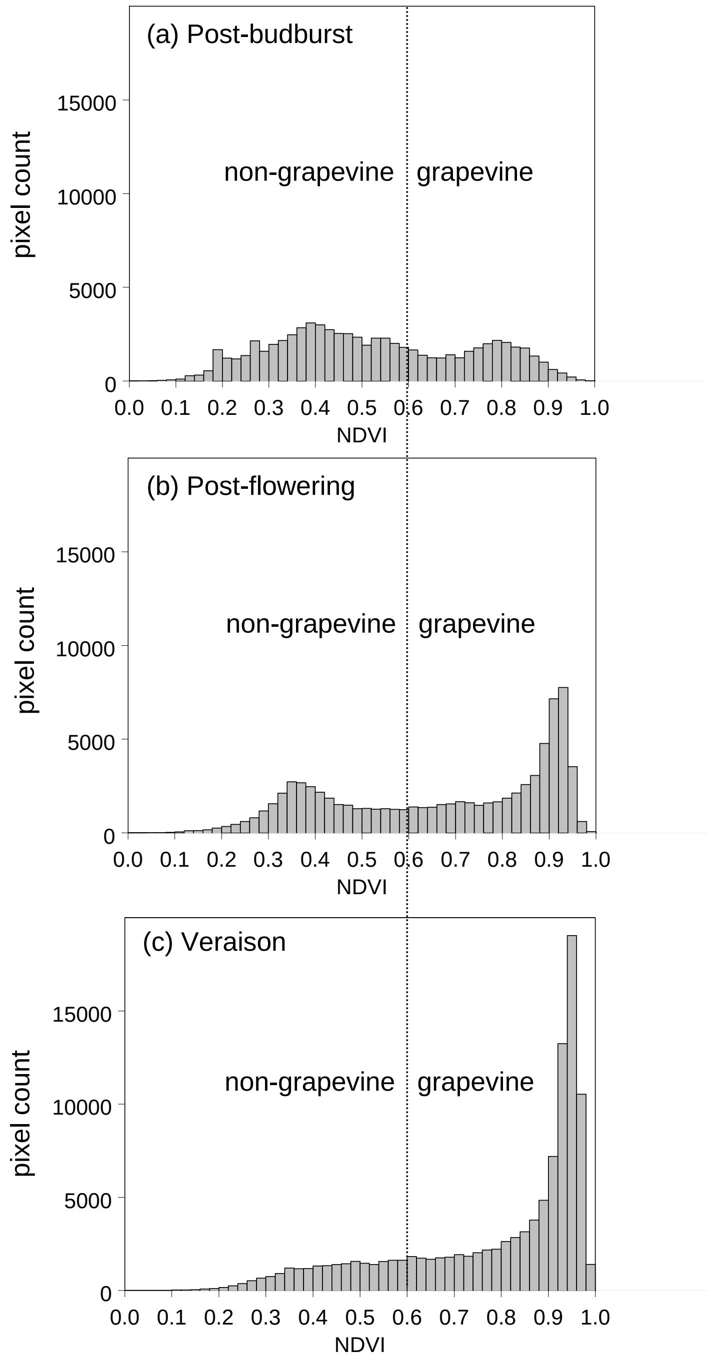

inter-row space

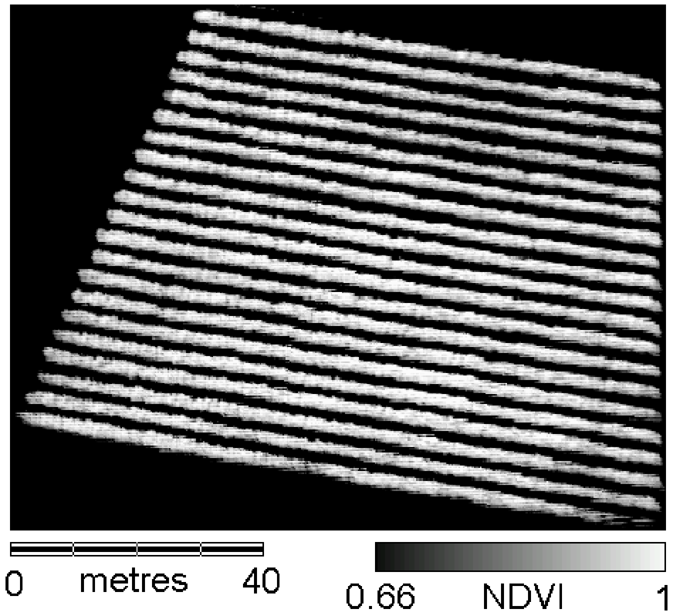
(a)

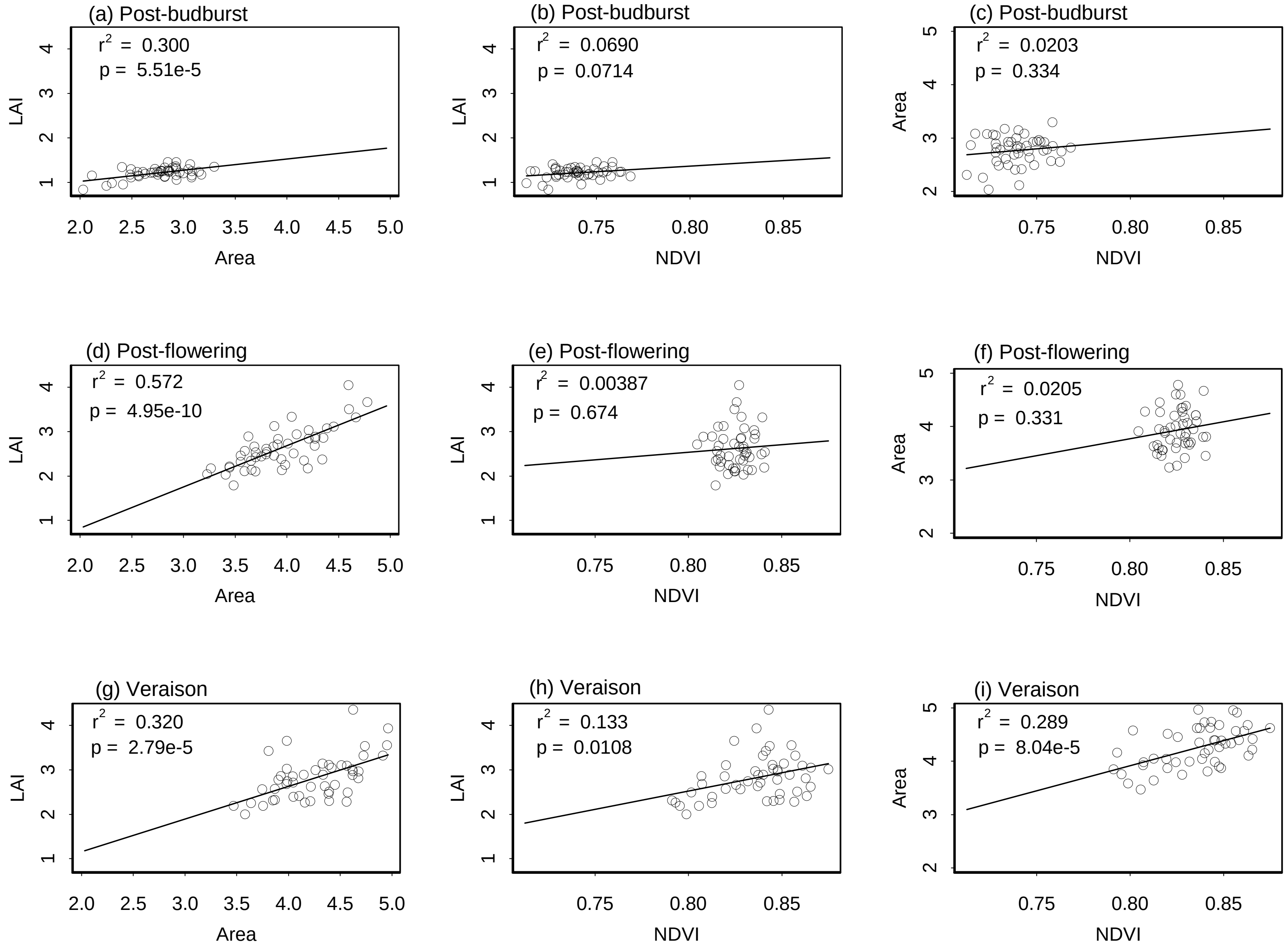


magnified region of a grapevine row from an vineyard NDVI image
10
9
10
10
.83
.71
.68
.79
.67
.60
.84
.69
.62
The canopy area of this section is equal to the number of pixels with values over 0.5: *Area* = 39
The canopy density of this section is equal to the mean of the NDVI values: Mean NDVI = 0.71
(b)
canopy width (m)
LAI = leaf area (m2)/ canopy area† (m2)
trellis wire
grapevine trunk
† canopy area (planimetric area of canopy)
= canopy width (m) × discrete cordon length along trellis wire (m)

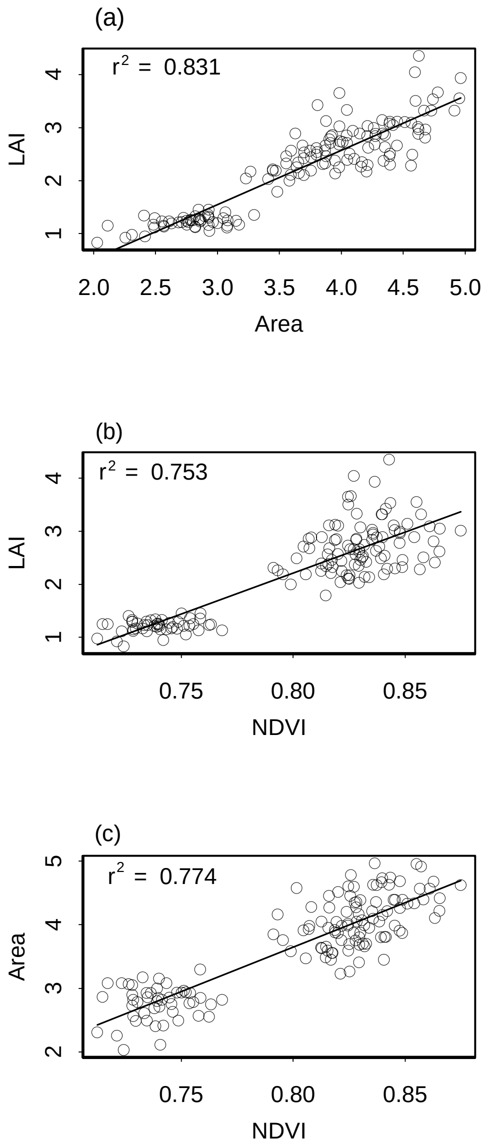

1.8 m
central trellis wire
mid-point between trellises
y
canopy
inter-row space
pixel with NDVI above threshold
vine trunk
3.6 m
3.6 m
x


(a) Post-budburst
pixel count
15000
10000
5000
0
non-grapevine
grapevine
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
NDVI
(b) Post-flowering
pixel count
15000
10000
5000
0
non-grapevine
grapevine
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
NDVI
(c) Veraison
pixel count
15000
10000
5000
0
non-grapevine
grapevine
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
NDVI


0 metres 40
0.66 NDVI 1



(a) Post-budburst
r2 = 0.300
p = 5.51e-5
LAI
Area
(b) Post-budburst
r2 = 0.0690
p = 0.0714
LAI
NDVI
(c) Post-budburst
r2 = 0.0203
p = 0.334
Area
NDVI
(d) Post-flowering
r2 = 0.572
p = 4.95e-10
LAI
Area
(e) Post-flowering
r2 = 0.00387
p = 0.674
LAI
NDVI
(f) Post-flowering
r2 = 0.0205
p = 0.331
Area
NDVI
(g) Veraison
r2 = 0.320
p = 2.79e-5
LAI
Area
(h) Veraison
r2 = 0.133
p = 0.0108
LAI
NDVI
(i) Veraison
r2 = 0.289
p = 8.04e-5
Area
NDVI


(a)
r² = 0.831
LAI
Area
2.0 2.5 3.0 3.5 4.0 4.5 5.0
1 2 3 4
(b)
r² = 0.753
LAI
NDVI
0.75 0.80 0.85
1 2 3 4
(c)
r² = 0.774
Area
NDVI
0.75 0.80 0.85
2 3 4 5

List of Figure Captions

Figure 1 Simulated NDVI image of a block of grapevines with row showing similar individual spatial characteristics and vigour. Pixels with dimensions equal to the grapevine-row spacing will have the same values regardless of where they lie relative to the inter-row gap. Adapted from Lamb et al. (2001).

Figure 2 (a) Canopy area and canopy density defined in terms of NDVI imagery and (b) a canopy cross-section demonstrating canopy dimensions in terms of canopy density and extent.

Figure 3 Area taken up by one overlapping canopy in a vineyard is within a rectangle bounded by the heavy dashed line. Area is split into squares to illustrate pixels either above or below the threshold NDVI.

Figure 4 Histograms of NDVI values extracted from the study site at (a) post-budburst, (b) post-flowering and (c) veraison. The dashed vertical line situated midway between the two peaks in (a) and (b) separates two classes of pixels. Pixels considered grapevine canopy pixels are those to the right of the line (in this case 0.60).

Figure 5 Enhanced Grey-scale NDVI image of the study site acquired on 4/12/01 (subsequent to flowering).

Figure 6 Scatter plots illustrating relationships between the three canopy measures at each phenological stage: (a), (d), and (g) LAI versus *Area*; (b), (e) and (h) LAI versus NDVI; (c), (f) and (i) *Area* versus NDVI; at (a), (b) and (c) post-budburst; (d), (e) and (f) post-flowering; and (g), (h) and (i) veraison. Lines in plots represent linear models of best fit, with their coefficients of determination (r^2) and associated p-values displayed in each chart.

Figure 7 Scatter plots illustrating relationships between the three canopy measures for data from all phenological stages combined: (a) LAI versus *Area*; (b) LAI versus NDVI; (c) *Area* versus NDVI. Lines in plots represent linear models of best fit, with their coefficients of determination (r^2) displayed in each chart.

	Dependent variable	*Independent variable*	r^2
Post budburst	LAI LAI *Area*	*Area* NDVI NDVI	0.300** 0.0690 0.0203
Post flowering	LAI LAI *Area*	*Area* NDVI NDVI	0.572** 0.00387 0.0205
Veraison	LAI LAI *Area*	*Area* NDVI NDVI	0.320** 0.133* 0.289**

	Degrees of Freedom	*Sum of Squares*	*Mean Square*	F-*Statistic*	p-*values*
Area	1	80.8	80.8	508	$<1.00\times10^{-6}$
NDVI	1	2.16	2.16	13.6	3.09×10^{-4}
Time	1	0.232	0.232	1.46	0.229
Residuals	160	25.4	0.159		

List of Table Captions

Table 1 Coefficients of determination (r^2) for each combination of linear models between the NDVI, *Area* and LAI variables collected at each of the three phenological stages. Levels of significance for r^2 are indicated by: * for $p < 0.05$ and ** for $p < 0.001$.

Table 2 Analysis of variance (ANOVA) table for the multivariate regression model of LAI using the predictor variables of *Area*, NDVI and phenological time. The magnitude of the *F*-Statistic indicates the proportion of the variance in LAI explained by each of the predictor variables with larger *F*-Statistics indicating higher levels of explanation. The associated *p*-values indicate the probability of the level of variance being explained by chance.