

# A Method For Extracting Detailed Information From High Resolution Multispectral Images Of Vineyards

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**Abstract.** Airborne digital images of vineyards have great potential for yielding valuable information for viticulturists and vineyard managers. Regions of poorly performing vines can be identified based on vegetative vigour (normalised difference vegetation index, NDVI) and targeted for specific management practices. This paper outlines a computer-assisted method to analyse high-resolution images of vineyards that is able to generate information down to the individual vine scale. The method exploits typical vineyard spatial characteristics to extract information on spatial variation in vegetative growth – valuable information in assessing vineyard performance. Most commercial vineyards are set out as rows of vines with distinct empty spaces in between. This allows vineyard images to be analysed in terms of not only actual canopy spectra, but also in terms of local canopy shape, size and texture. An algorithm has been developed to extract numerous vine descriptors including width, vigour and shape for quasi-regular discrete distances (approximately one pixel length) along vine rows. These data are then used in conjunction with measured on-ground biophysical data (e.g. grape yield and quality indicators) to generate calibration algorithms for mapping vine parameters over entire vineyards.

## 1. INTRODUCTION

Grapevine (*Vitis vinifera* L.) health and productivity are influenced by numerous physical, biological and chemical factors, including spatial variations in topography, physical and chemical characteristics of soils and the incidence of pests and diseases. The spatial variation in these factors effects a spatial variation in grape quality and yield within vineyards, leading to a reduction in average wine quality and productivity. With an increasing differentiation in pricing between grapes based on measured quality attributes becoming inevitable (Winemakers Federation, 1996), increasingly intelligent management decisions are required to mitigate vineyard variability to produce a higher-quality higher-value product. However, these decisions rely upon the availability of accurate and reliable data to describe the variability exhibited by the vines. Presently, this data is time consuming and expensive to generate.

The emergence of global positioning systems (GPS) technology means traditional on-site measurements of physical, chemical and biological parameters associated with vine productivity can now be linked to specific locations within vineyards. This information, when used in conjunction with computer-based geographical information systems (GIS), provides viticulturists with the capability to process and map spatial relationships between attributes and make management decisions based on numerous layers of information (Taylor, 2000). In recent years, yield maps produced by grape-yield monitors in Australia have shown up to eight-fold differences in yield can occur within a single vineyard block (Bramley and Proffitt, 1999). Furthermore, there are considerable spatial variations in quality indicators

such as colour and baume (Bramley and Proffitt, 2000). Relationships between yield and quality indicators are often inferred. However, these relationships do vary significantly between vineyards (Holzapfel et al., 1999; Holzapfel et al., 2000; Lamb and Bramley, 2001). Moreover, preliminary data suggest regions of high and low-yielding vines in a vineyard tend to remain stable in time, inferring that soils play a significant role in such variability (Bramley et al., 2000). The accurate characterisation of spatial variations in those parameters that influence vineyard productivity requires a considerable amount of data. Traditional methods of generating such data are generally time consuming and expensive. For example, measuring basic fruit quality and yield parameters of sixty sample sites in a one-hectare block requires more than thirty work-hours. The move toward on-the-go sensing of yield and quality parameters by combining the latest sensor technology with GPS-equipped vehicles is slow and currently limited to grape yield, although the measurement of baume, effectively the sugar content of grapes, using near infrared spectroscopy is currently under development (Williams, 2000). The use of electromagnetic induction or EM-survey techniques to accurately characterise soil structure is also becoming more widely used in the grape and wine industry (Lamb and Bramley, 2001).

The use of airborne remote sensing as a means of monitoring crop growth and development is attracting interest from researchers and commercial organisations, primarily because of the opportunities for cost-effective generation of spatial data amenable to support precision agriculture activities (Lamb, 2000). To date, limited use is being made of this technology in the grape and wine industry, either for research support or as a commercial monitoring tool, and is now the subject

of a major research project conducted by the Cooperative Research Centre for Viticulture. This paper presents some of the recent research undertaken in order to find the most useful information that can be extracted from multispectral remotely sensed images of vineyards. Specifically, a method of processing vineyard image data to extract quantitative information about physical vine attributes specifically relating to vine vigour is described.

Vine vigour is often reported to have a considerable effect on fruit yield and quality (for example Dry, 2000; Haselgrove et al., 2000; Petrie et al., 2000; Tisseyre et al., 1999; Iland et al., 1994). In a case involving consideration of vine vigour variability, data showed that yields of vigorous vines were nearly double that of stressed vines in the same block of Cabernet Sauvignon (Clingleffer and Sommer, 1995). This study implies that levels of vigour can be used in order to forecast yields. In the same study, considerable delays in fruit maturation were associated with vigorous higher yielding vines. Three levels of vine vigour used in the study produced large differences in juice and wine parameters and therefore a loss in average quality. As well as overall vigour, links between canopy shape and vine characteristics have been reported by several studies. For example, Intrieri et al. (1997) describe significant differences in total vine assimilation of CO<sub>2</sub> by vines before and after various canopy shape and thickness manipulations. Similarly, Smithyman et al. (1997) report on the influence of three different canopy configurations on vegetative development, yield and composition of grapevines.

Current remote sensing products in the viticultural industry rely on a mostly qualitative assessment of derived images. Quantitative relationships between spectral and on-ground biophysical data are mostly used only within specific research projects (Lamb, 2000). However, quantitative analyses performed within the industry could greatly increase the value of information that can be obtained from the images and hence greatly improve on-ground management resulting in higher quality products. Two problems need to be solved in order to achieve this. These are to (1) increase precision location to allow individual vine identification and (2) measure and map vine vigour. Similar problems were described as research goals by Tisseyre et al. (1999). The aims for quantifying remotely sensed imagery are similar. These two aims have provided the focus points of the research for this project to date.

## 2. DATA COLLECTION

### 2.1 Airborne Multispectral Imaging of the Vineyard

Airborne multispectral images of two vineyards have been collected for this project. Each has been imaged at key phenological stages in the annual growth cycle: budburst, anthesis (flowering), veraison (onset of berry

ripening) and immediately prior to harvest. The two vineyards are very different in character; one site is being manipulated by differing nitrogen application regimes and irrigation systems and the other is subject to standard uniform management. For the purposes of this paper, only the site subject to uniform management is considered. This vineyard site is part of Charles Sturt University's commercial vineyard situated at Wagga Wagga, New South Wales. It is a well-established hedge-pruned block (1 ha) of Cabernet Sauvignon with a row spacing of 3.6 m. Individual vines are separated by 1.8 m along the rows. The block is on a small (<10°) east-west incline with the rows planted perpendicular to the slope.

The multispectral airborne imaging system used to acquire vineyard images consists of 4 CCD video cameras, each having a 740 by 576 pixel array and fitted with 12 mm focal length lenses. Pixel size is determined by the height of the aircraft. In this particular project, image pixels have a 20 cm × 20 cm footprint on the ground. Each camera was fitted with an interchangeable 25 nm band-pass inference filter. A standard desktop computer containing a 4-channel frame-grabber board captures and digitises 4-band composite images from the cameras. The system is mounted in a Cessna 182 or 210 aircraft utilising a purpose built door through which the cameras can view the ground. While imaging, high and low reflectance homogeneous "Lambertian" targets of known spectral characteristics were placed on the ground and included in the image. These were used for converting image pixels from raw digital numbers to reflectance values.

Standard vegetation inference filters were used in all of the imaging missions centred at 440 nm (blue), 550 nm (green), 650 nm (red) and 770 nm (near infrared). A central feature of this study involves examination of vegetative vigour. The four band raster images were converted to a single vegetation index; the normalised difference vegetative index (NDVI). Spectral vegetation indices reduce the multiple-waveband data at each image pixel to a single numerical value (index), and many have been developed to highlight changes in vegetation condition (for example, Wiegand et al., 1991; Price and Bausch, 1995). Vegetation indices utilise the significant differences in reflectance of vegetation at green, red and near infrared wavelengths. NDVI images are created by transforming each multispectral image pixel according to the relation (as presented by Rouse et al., 1973):

$$NDVI = \frac{(\text{near infrared}) - (\text{red})}{(\text{near infrared}) + (\text{red})} \quad (1)$$

where 'near infrared' and 'red' are respectively the reflectances in each band. The NDVI, a number between -1 and +1, quantifies the relative difference between the near infrared reflectance 'peak' and red reflectance 'trough' in the spectral signature, and is the most widely used indicator of plant vigour or relative

biomass. For highly vegetated targets, the NDVI value will be close to unity, while for non-vegetated targets the NDVI will be close to zero. Negative values of NDVI rarely occur in natural targets.

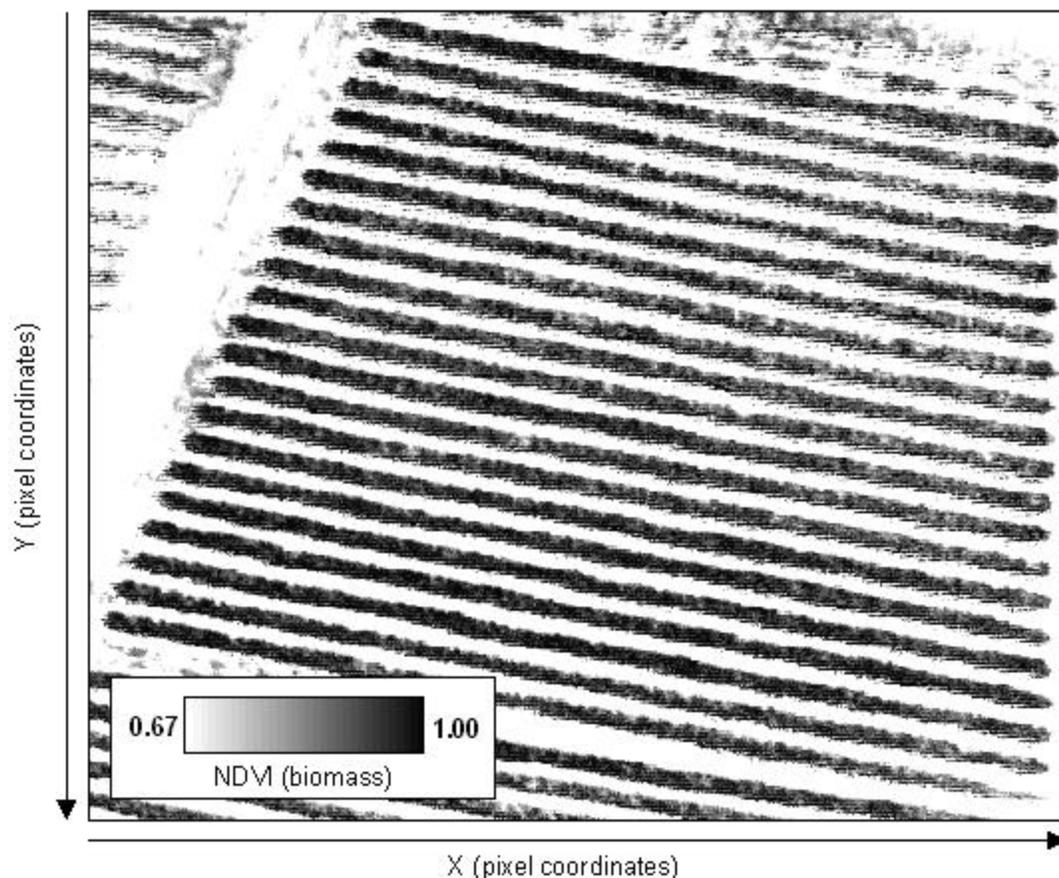
One important advantage of ratio indices like the NDVI is that the intensity of the total light reflected from a target does not influence the calculation. An object under shadow will reflect light reduced by approximately the same amount across the entire spectrum. Therefore, although there is a reduction in the precision of NDVI for areas in shadow, because of a reduction in the total range of reflectance levels, the ratio of two spectrally similar features will be invariant regardless of shadow. Shadows, which may otherwise be a significant problem in imaging a vineyard with closely spaced rows, are effectively removed.

Figure 1 shows a grey-scale representation of the NDVI calculated for the CSU site at flowering. The brightness of the pixels in the figure refer to different NDVI values, where white represent the lowest vegetative vigour and black the highest levels of vigour. Since all pixels

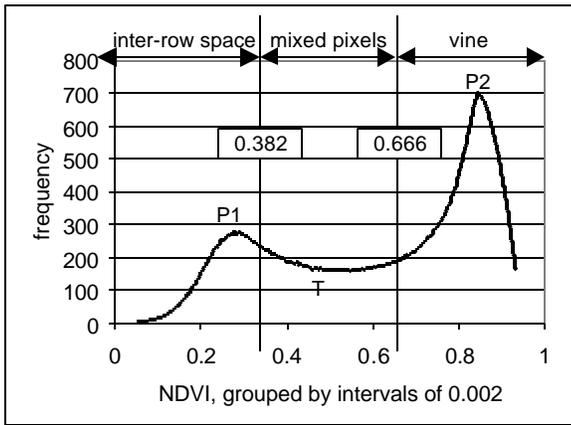
below a certain NDVI value have been removed, it can be seen that the rows in this particular vineyard block are clearly recognisable. In addition, spatial differences in the level of vigour are easily identifiable. This type of image (more so when produced using a colour scale) allows a vineyard manager or viticulturist to quickly identify areas of poor growth over the whole vineyard. However, such qualitative assessments may be missing important details that could be shown to be causing variability in the fruit to the extent of reducing overall quality. The focus of this research so far completed, therefore, has been to process the images to find the most detailed information on vine vigour that can be identified from the images.

## 2.2 On-ground Biophysical Data

In conjunction with the airborne imagery, several on-ground measures of vine characteristics were also collected. Sixty vines from the study block were targeted in a stratified-random sampling scheme. For



**Figure 1:** Grey-scale NDVI representation of the study vineyard block at harvest. All pixels with NDVI values below 0.67 are set to zero and are therefore white in the image.



**Figure 2:** Histogram of NDVI values from an image taken at anthesis, smoothed with a 51-point moving average. Two vertical lines separate the three classes of pixels. The pixels included in an analysis are only those to the right of the line at 0.666 on the x-axis.

each vine, various biophysical productivity parameters including winter pruning weights (a measure of the growth of the vine during the year), nutritional status from petiole samples at anthesis, fruit yield at harvest, and grape quality parameters such as baume, acidity, colour and berry size were measured.

### 3. VINEYARD IMAGE PROCESSING

#### 3.1 Measuring and Mapping Vine Vigour

##### 3.1.1 Image Thresholding

Having converted the image data from digital numbers to reflectance values, corrected for vignetting and band to band geometric anomalies and georectified the image by assigning each pixel its own UTM coordinates, an NDVI raster is calculated using Equation 1. Two sets of pixels are defined. Those with high NDVI values represent the vine and those with low NDVI values represent non-vine space. The smoothed histogram of NDVI pixels for the image shown in Figure 1 illustrates the bimodal distribution of pixel values (Figure 2). Even with a pixel size of 20 cm, pixels at the fringes between vine rows and inter-row space contain radiation reflected from both the grapevines and the ground. These mixed pixels are centred in the histogram distribution at the trough between the two peaks.

Using the histogram, image pixels are grouped into one of the three categories – non-vine, vine and mixed. The method used to categorise the pixels uses the peaks and trough of the histogram smoothed with a 51 point moving average (Figure 2). The mid-point on the x-axis between the peaks of the first peak and the trough separates the non-vine classification from the mixed pixels. Similarly, the mid-point on the x-axis between the trough and the second peak separates the mixed-pixels from the vine pixels. Since the amount of ground reflection and vine reflection cannot be determined in the mixed pixel set, analysis of vine only pixels was

completed. For this particular image, the NDVI threshold used to separate vine pixels from the others was 0.666. To complete the thresholding process, any pixel with an NDVI value less than 0.666 was set to zero. The difference between vine and inter-row space is clearly distinguishable in the resultant image (Figure 1), with the NDVI of the vines consistently higher than the sparsely vegetated space in between.

#### 3.1.2 Data Extraction

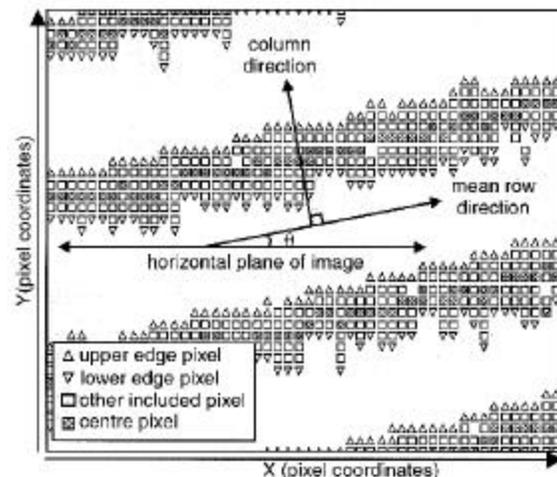
Figure 3 is a representation of a section of the image shown in Figure 1. This figure shows the pixels included in the analysis. An S-Plus algorithm has been developed to extract the NDVI data from these pixels in a spatially meaningful way. A problem with working with images of rows of vines that are made up of square pixels is the angle of the rows relative to the horizontal plane of the image (see Figure 3). Within the algorithm, the coordinates used are real numbers with high levels of precision, when in reality the coordinates of the pixels are integers. Figure 3 shows the position of the pixels according to their integer coordinates. An indication of the coordinate system used by the algorithm can be gleaned from the arrow showing the column direction. The arrow passes through seven pixels that are represented in Figure 3.

The logic of the algorithm to process a vineyard image can be summarised in seven steps –

1. Locate the starting point of the first or next row.

Search both up and down in the direction of the column direction for the upper and lower edge pixels of the vine row (see Figure 3).

Since the image has already been thresholded, a pixel with a value of zero indicates a pixel beyond



**Figure 3:** Graphical representation of pixels and basic geometry used in data extraction algorithm.

the edge of the vine row. Occasionally, vine growth can envelop the inter-row space at sections along

certain rows. This means that there is no pixel with a zero value at the edge of the row. Without intervention, the algorithm would continue across the rows until the next pixel with a zero value is found.

However, the search is restricted to a distance of half the vine row spacing. Once this distance is reached, the pixel at this position is considered the end pixel.

2. Record the vector of NDVI values from the pixels in the column between the upper and lower edge pixels. This characterises the vegetation for that column of the vine row.
3. Locate the mid-point of the vector of NDVI values that represent this column of the vine row.

The mid-point of a column is located not simply as midway between the upper and lower edge pixels, but as “the weighted centre” of the column. Each pixel’s weighting is its NDVI value. For example, an extracted column may be represented by a vector of NDVI values of (0.84, 0.94, 0.54, 0.62, 0.56). The equivalent cumulative vector would therefore be (0.84, 1.78, 2.32, 2.94, 3.50), the midpoint of which would be calculated as half the sum of the vector, i.e.  $3.50 / 2 = 1.75$ . This value is less than the second value of the cumulative vector (1.78); therefore, the centre pixel is the second in the column. More precisely, the distance ( $d_{mp}$ ) to the mid-point of the column is calculated as a ratio along the line transecting the row, i.e.  $(0.94 - (1.75 - 1.78)) / 0.94 + 1 \approx 1.97$  pixels along the transect.

With the distance along the column known, the X and Y coordinates of the central point ( $X_{cp}$ ,  $Y_{cp}$ ) is calculated precisely using the coordinates of the upper edge pixel ( $X_{upper}$ ,  $Y_{upper}$ ) and the mean angle of the row direction to the horizontal plane of the image ( $\theta$ ), i.e.

$$X_{mp} = X_{upper} + d_{mp} \sin \theta \quad (2)$$

$$Y_{mp} = Y_{upper} + d_{mp} \cos \theta \quad (3)$$

4. Record the pixel coordinates of the mid-point. This will be the location of the descriptors calculated for this particular point in the vines.
5. Move along one pixel width from the mid-point in the direction of the mean row direction (see Figure 3).

In practice,  $X_{mp}$  is increased by  $\cos \theta$  and  $Y_{mp}$  is increased by  $\sin \theta$ . On occasion, the pixel located at this position has been thresholded to zero, due to missing or dead vines. If this occurs the algorithm executes a sub-process to search for the next pixel in the row that is not zero. A search is made in the plane of the column direction both up and down a distance of 40% of the row spacing. If no pixel above zero is found, the search will move on one pixel width in the row direction and search in the plane of the column similarly again. This is repeated until a pixel that does not have an NDVI value of zero is found.

6. Repeat steps 2 to 5 until the end of the image is reached.
7. Repeat process until all rows in block have been mapped.

The outcome of executing the algorithm is a table containing one row of data for every column identified in the image. Each row contains an identifier of the vine row from which the column originated, pixel coordinates of the centre of the column, and a vector of ordered NDVI values for that column. An example of such an output is shown in Table 1. The vine row identification number is simply an integer that is 1 for the first row and which increases by one for every new

**Table 1:** A section of the table produced by the data extraction algorithm. Four columns added at the right describe qualities of each NDVI vector.

Vine Row	Coordinates		NDVI Vector							Mean NDVI	Column Length	Max. NDVI	Second Derivative
	X	Y	1	2	3	4	5	6	7				
5	250.99	205.72	0.73	0.82	0.88	0.85				0.82	4	0.88	$-2.80 \times 10^{-2}$
5	250.07	206.80	0.76	0.81	0.87	0.84	0.88	0.73	0.77	0.81	7	0.88	$-1.11 \times 10^{-2}$
5	250.15	207.79	0.77	0.82	0.84	0.83	0.82	0.72	0.84	0.80	7	0.84	$-3.15 \times 10^{-3}$
5	251.22	208.71	0.78	0.83	0.87	0.84	0.83	0.72		0.81	6	0.87	$-1.78 \times 10^{-2}$
5	251.30	209.71	0.79	0.84	0.87	0.84	0.82			0.83	5	0.87	$-1.34 \times 10^{-2}$
5	251.38	210.70	0.82	0.84	0.90	0.82	0.91			0.86	5	0.91	$-1.79 \times 10^{-4}$
5	251.46	211.70	0.84	0.86	0.85	0.78	0.88			0.84	5	0.88	$-5.91 \times 10^{-3}$
5	251.54	212.70	0.73	0.87	0.85	0.83	0.74	0.75		0.80	6	0.87	$-1.73 \times 10^{-2}$
5	251.62	213.70	0.77	0.88	0.86	0.84	0.70	0.83		0.81	6	0.88	$-5.84 \times 10^{-3}$
5	251.69	214.69	0.80	0.88	0.86	0.89	0.72	0.83		0.83	6	0.89	$-7.47 \times 10^{-3}$

row encountered in the image. The NDVI vector and (X, Y) coordinates are formed as described by steps 2 and 4 of the algorithm (respectively).

#### Parameterisation of Biomass

The four columns added to Table 1 contain parameters that describe some aspect of the NDVI vector. The mean NDVI quantifies the density of vine biomass. Vector size (column length) quantifies the width of the vine row at that particular point along the row. The maximum value in the vector (maximum NDVI) gives a measure of vine vigour (with no mixed pixels). Although not shown in this table, another valuable parameter is the sum of the vector. This quantifies the total biomass signature within the row.

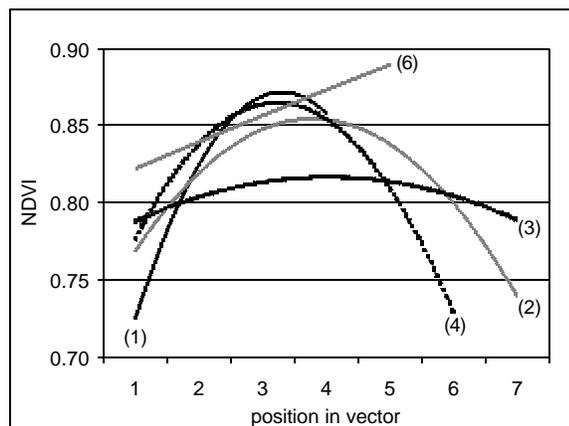
#### Parameterisation of Vine Shape

The final column of Table 1 (second derivative) gives an example of a parameter developed to describe a shape characteristic of the vine at a particular point along the row. The value contained in this column is the second derivative of a quadratic line of best fit. This parameter quantifies the curvature of the spatial distribution of the values of the NDVI vector. Figure 4 shows a selection of quadratic lines of best fit for the NDVI vectors shown in Table 1. Usually the pattern results in a convex curve. Greater convexity of the curve results in a higher second derivative (in absolute terms) of the fitted quadratic. For example, the curve resulting from vector 4 results in a highly-convex curve and a high value for the parameter ( $-1.78 \times 10^{-2}$ ), whereas for the flatter line described by vector 3, a lower value results ( $-3.15 \times 10^{-3}$ ). A linear profile results in a value close to zero (e.g. vector 6). On occasion, a concave curve results in a positive second derivative.

This parameter is a useful descriptor of the density of vegetation in the centre of the row in comparison to the outside of the row. As discussed in Section 3.2, this parameter is shown to alternate between high and low values within the space of about one vine length and is very useful in mapping individual vines. It may also be used to identify areas of the vineyard that have more or less open canopies. Those vines with high values for the second derivative may show significantly different berry characteristics due to various degrees of shading by different canopy shapes.

#### 3.1.3 Mapping Extracted Data

Each parameterisation process results in a vector (“row vector”) that describes a particular quality of the vine. Individual items of this vector are associated with the pixel coordinates of the centre of the original column of pixels produced by the data extraction algorithm. The pixel coordinates are transformed into map coordinates using an IDL algorithm and on-ground GPS measurements. However, images are not resampled.



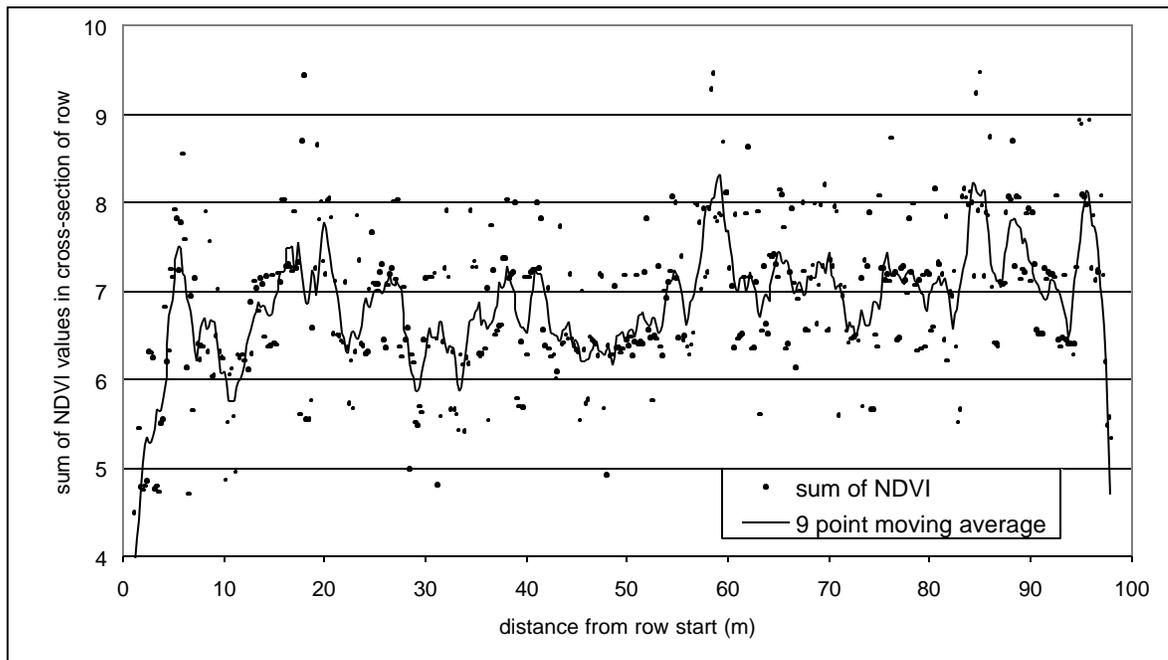
**Figure 4:** Selection of quadratic lines of best fit for the NDVI vectors shown in Table 1.

Therefore, the spectral integrity of the original images is maintained. However, any spatial distortion introduced by the imaging system itself is not accounted for in terms of pixel size and location relating to ground area.

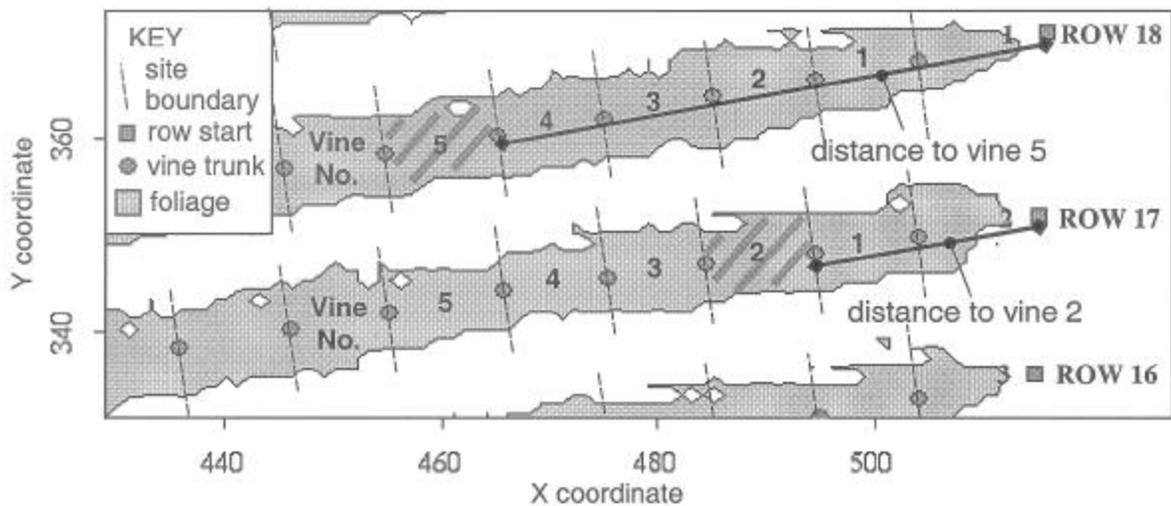
This process results in row vectors that characterise a narrow area of the vine row about one pixel size in width, reducing a two dimensional object on an image to a one dimensional vector. The row vector itself contains spatial information since it is known that each value in the vector is approximately one pixel apart. By plotting a line graph of the vector values, a particular quality of the vine can be examined along a row. As well as calculating the vine parameter, a record of the distance from the row start point to the centre of the cross-section (see Figure 6) is calculated from the UTM pixel coordinates is recorded by the algorithm. Using this spatial data, a more accurate representation is available for analysis. For example, Figure 5 shows how total biomass (sum of NDVI values for a column) changes with distance along row 18 at harvest.

As is common in most viticultural practice, individual vine location is determined with (row, vine) coordinates. Figure 6 illustrates this coordinate system. The row number is the number of rows in from the edge of the block and the vine number is the number of vines along the row from one end of the block to the vine. For this project, the distance along a row to a vine is measured in the vineyard. In the figure the distance to (row 18, vine 5) and the distance to (row 17, vine 2) are highlighted. It should be noted that a sample area from which biophysical data is taken is in fact the space between the trunk of the vine at (row, vine) and the trunk of the next vine along the row, i.e. (row, vine+1). Using these distance measurements, coordinates of (row, distance along a row) are formed.

A point along a row in an image is found using this same coordinate system. The location of a vine in the image is calculated by interpolating a line in the direction of the row from the row start point the same distance as measured in the vineyard. In effect, then,



**Figure 5:** A plot of the biomass row vector. This shows how total biomass (sum of NDVI values for a column) changes with distance along row 18 at harvest.



**Figure 6:** Close up view of a section of the vineyard illustrating the (vine, row) coordinate system and the measurements used to map extracted image data.

the only coordinates required from the field to interpret the data are (row, distance along the row). Therefore, rather than accurately surveying each individual sample location, only a few GPS locations are required to initially georectify the image. In addition, this is an easy and convenient method to apply during fieldwork in the vineyard.

Finally, the vegetative characteristics of a single sample vine are calculated as either the sum or mean of several concurrent items from a row vector. With 20 cm image resolution and vine spacing of 1.8 metres, a set of 9 items from the vector are included. These items are from the position between the sample vine trunk and the adjacent vine trunk. This parameter provides a quantitative descriptor of the vegetative shape or quantity that can be used in statistical analyses to

assess relationships between the image data and the biophysical data collected in the vineyard.

### 3.2 Extracting (row, vine) Coordinates from a Vineyard Image

Individual vines are identified by relating a measurement of their real world distance along a row to the distance along the row in a georectified image. Individual vines are therefore identified and mapped, and vigour parameters can be calculated for them on an individual vine basis. Specifically, the method used here involves use of a global positioning system (GPS) to accurately map points in the vineyard that could be recognised in the images. The image processing language, IDL is then used to georectify the images using these points. In order to retain the spectral integrity of every image pixel, the images are not

resampled. Instead, each pixel of the image is assigned its own Universal Transverse Mercator (UTM) coordinates.

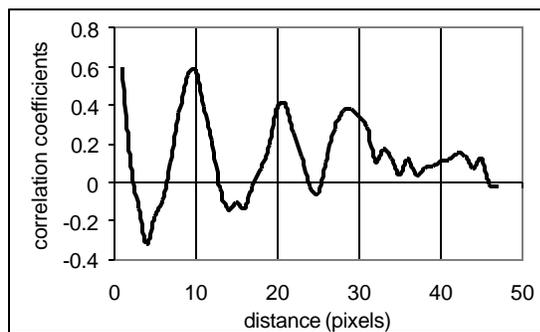
Although reasonably accurate, this method is time consuming and impractical. As an alternative, a vineyard can be discretised into single vine units, without the need to record GPS points or map the vineyard on the ground, by identifying a regular pattern that can be used to infer vine spacing.

In order to investigate whether regular spacing of vines is discernible in the images, autocorrelation analysis was performed on the extracted series of numbers that describe a particular vine characteristic. Analyses of each of the series shows that many have one discernible periodic component contingent with the vine spacing. The second derivative of the quadratic line of best fit series, in particular, has a high level of the periodic component (Figure 7). The series presented in Figure 7 was obtained by summing each autocorrelation series obtained from each row of the vineyard. Given this particular vineyard block contains 21 rows, the series presented could range from between 21 to -21. On closer inspection, many of the rows did not exhibit any significant periodic component. It is reasonable to assume that the random series produced for these rows have cancelled each other out, leaving a residual signal produced by only several of the rows. Yet, since vines are spaced at the same distance throughout a vineyard block, this method is able to find the mean spacing between the vines.

The mean distance between the first three peaks of the aggregated autocorrelation series presented in Figure 7, is 9 pixels. At 20 cm per pixel, 9 pixels are equivalent to 1.8 m. This distance is consistent with the measured mean spacing of vines in this particular block. The disadvantage of using this technique is that it must be assumed that the vines are equally spaced and that there are no missing vines. Such conditions only occur in the most meticulously managed vineyards. Almost universally, there are varying degrees of missing vines and irregularities in spacings and growth. Nevertheless, the technique does give a good impression of growth at the single vine scale based on shape and vigour characteristics. In addition, the irregularity of the spacing of the peaks indicates that this is not a reliable method of estimating the mean spacing. A more robust and accurate technique based on Fourier analysis of the series is currently under development.

#### 4. CONCLUSION

The techniques and algorithms described here provides a workable method to measure and map vine vigour at accurate and precise locations using airborne multispectral images. By exploiting the regular pattern



**Figure 7:** Aggregated autocorrelation series of row vectors describing curvature of column vectors. The peaks of this series have a mean spacing of 9 pixels indicating a vine spacing of 1.8 m.

of alternating rows of vegetative intensity levels exhibited by multispectral images of vineyards, a method of analysis and mapping has been developed that is easily transferable to the vineyard.

Preliminary analyses of relationships between biophysical data and vine descriptors derived from the image data have shown some strong correlations. For example, vine biomass (sum of NDVI) at flowering during 2000 has a direct linear relationship ( $p < 0.01$ ) with the number of berry clusters produced by the vine during the last season. At the same time, vigour intensity (calculated using the highest two NDVI values per row cross-section) is shown to be inversely related ( $p < 0.001$ ) to berry size. Interpretation of such statistical relationships between vine vegetation and fruit character is a difficult task due to the complex nature of vine variability and interrelationships within individual vines and the environment, particularly the soil. In addition, relationships are not necessarily linear. For example, high levels, as well as low levels, of vegetative vigour can both lead to a reduction in yield and fruit quality. The interpretation of the results and isolation of the most instructive vine vegetation parameters is an ongoing task. Nevertheless, the ability to quickly produce accurately located information that quantifies vine vegetation is a valuable research tool and has the potential to provide valuable detailed information to viticulturists and vineyard managers.

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