# Agricultural Applications of High-Resolution Digital Multispectral Imagery: Evaluating Within-Field Spatial Variability of Canola (*Brassica napus*) in Western Australia

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## Abstract

*This paper analyses the potential of a high-resolution airborne remote sensing system, the Digital Multi-Spectral Imagery (DMSI), for detecting canola growth variability within a field to help farmers for future incorporation of the system into site-specific crop management approaches for agriculture.*

*Transect sampling within a canola field of a broad acre agricultural property in the South West of Western Australia was conducted synchronous with the capture of one-meter spatial resolution DMSI. Four individual bands (blue, green, red, and NIR) and five image transformations namely the Normalized Difference Vegetation Index (NDVI), Normalized Difference Vegetation Index – Green (NDVI-green), Soil Adjusted Vegetation Index (SAVI), Photosynthetic Vigor Ratio (PVR) and Plant Pigment Ratio (PPR) of DMSI were investigated. Canola density was correlated with the four individual bands and five image transformations, while the LAI was correlated with the four individual bands.*

*The NDVI-green, red and near-infrared bands of DMSI produced the best correlations with the density of canola, whereas the LAI had significant ($\alpha = 0.05$) negative correlations with the blue (−0.93) and red (−0.89) DMSI bands, and a significant positive correlation were found with the near-infrared band (0.82).*

## Introduction

Precision agriculture has been defined as "observation, impact assessment and timely strategic response to fine-scale variation in causative components of an agricultural production process," and thus may cover a range of agricultural enterprises and can be applied to pre- and post-production aspects of agricultural enterprises (Australian Centre for Precision Agriculture, 2002). Site-specific crop management is one facet of precision agriculture and is defined as "matching resource application and agronomic practices with soil and crop requirements as they vary in space and time within a field" (Whelan and McBratney, 2000). The remote detection of crop growth variability can provide farmers with a spatially quantitative assessment of their fields' production. In turn, farmers can address causation and extent of poorer performing areas and evaluate alternative management practices appropriate to the conditions of the sites.

Remote sensing technologies offer the opportunity to evaluate variations in crop conditions within the growing season and as such, can provide farmers with timely information to assess alternatives to improve final production. A high-resolution airborne remote sensing system has been developed by SpecTerra Services of Perth, Western Australia. Their data, known as Digital Multi-Spectral Imagery (DMSI) can be applied for mapping and monitoring crop and soil variability, and therefore, the objective of this research is to evaluate its potential for determining within-field variability of canola *(Brassica napus)* as expressed by attributes such as crop density and LAI. To this end, we explore the relationship of DMSI data and derived image transformation techniques with the selected canola attributes. We concentrate on the extraction of digital numbers from four individual DMSI bands namely blue, green, red, and near-infrared, and a combination of those bands in the form of vegetation indices and ratios. The three vegetation indices being explored are the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Vegetation Index-Green (NDVI-green), and the Soil Adjusted Vegetation Index (SAVI). The two ratios are the Photosynthetic Vigor Ratio (PVR) and the Plant Pigment Ratio (PPR).

## Background

### Remote Sensing of Crops

The use of remote sensing applications for distinguishing between agricultural crop types and internal crop characteristics has been extensively researched during the past decade (Wiegand *et al*., 1991; Cloutis *et al*., 1996; Mogensen *et al*., 1996; Cloutis *et al*., 1999; Metternicht *et al*., 2000; Senay *et al*., 2000; Thenkabail *et al*., 2000). The trends being developed between specific crop types, maturity, nutrient levels, and their reflectance values in spectral bands and relationship to vegetation indices (VI), are becoming well known and useful when limited ground truth data is available (Senay *et al*., 2000).

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The underlying premise of using remote sensing to monitor crop condition is that important crop parameters related to growth and yield are manifested in the multispectral reflectance of crop canopies (Bauer, 1985). The Leaf Area Index (LAI), representing the ratio of leaf surface area to ground area, is the fundamental canopy parameter in two basic physiological processes: photosynthesis and evapotranspiration, which are most dependant on solar radiation (Bauer, 1985). Most models of crop growth and yield require an estimate of green LAI, thus the strong relationship of infrared reflectance to LAI of crop canopies provides the basic mechanism to link multispectral remote sensing to crop growth and condition (Bauer, 1985; Clevers, 1997).

A common approach in remote sensing for measuring or monitoring crop growth is the correlation of vegetation indices or ratios with such crop variables as percentage of vegetation cover and LAI (Moran *et al.*, 1997). Moran *et al.* (1997) suggest that measurements of crop properties at sample sites combined with multi-spectral imagery could produce accurate, timely maps of crop characteristics for defining precision management units. While research has been conducted evaluating the efficiency of differing remote sensing systems for monitoring crops (e.g. RADARSAT-1, SPOT, and CASI) limited investigations have examined the potential of DMSI for agricultural applications. DMSI is an innovative system; being airborne, it is flexible in terms of data acquisition times, it has a high spectral (20 *n*m bandwidth), spatial (0.25 m to 2 m depending on flying height above target), and radiometric resolution (12-bits). The system is of relatively low cost; a typical seamless digital mosaic covering a single discrete survey site of four DMSI bands will range from \$0.90 USD to \$22.00 USD per hectare for a spatial resolution of 2 m to 0.5 m, respectively, which will vary according to the total area, location of site, and level of post-processing (SpecTerra Services, 2003). By exploring the relationship of DMSI and derived image transformation techniques with canola attributes such as density and LAI, one can assess whether it is an appropriate remote sensing technology to incorporate into the infrastructure of image-based remote sensing for site-specific management given that high spatial resolution coupled with flexible data acquisition and rapid image turnaround have been indicated as high priorities.

### Remote Mapping of Canola Variability

Within Western Australia canola is grown as a rotation break crop, or profit driven alternative to cereal crops depending on the region that it is sown, but more often, a combination of the two. A rotation break crop is one that is grown in a continually cropped farm to assist in weed eradication and ground diseases. In terms of weed eradication, canola is useful due to its broad leave nature and, as such, herbicides that eradicate grass type weeds can be applied; whereas in other cereal crops, these herbicides would also affect the crop. Thus, it is important to evaluate techniques for assessing crop growth variability so the productivity of a canola rotation can be increased to assist in maximizing the profitability of a solid cropping program.

Past research distinguishing internal canola crop variations using passive remote sensors have included works by Mogensen *et al.* (1996) and Cloutis *et al.* (1996, 1999). For instance Mogensen *et al.* (1996) investigated the use of a spectral reflectance index (RI) for determining early water stress on canola grown under controlled field conditions (lysimeter tanks). The RI being defined as the ratio of incoming and reflected infrared radiation in the range of 740 *n*m to 820 *n*m, to the incoming and reflected photosynthetically active radiation between 400 *n*m and 700 *n*m. They simulated a drought-type effect within the trial and used a relative reflectance index (RRI) defined as the ratio of the reflectance index of the drought affected crops to the fully irrigated reference crops to analyze the effect of water stress on RI. The authors concluded that the RRI was a sensitive index to water stress seeming most appropriate in the vegetative stage of growth, as changes in spectral response of crop surfaces due to senescence or changes in architecture due to leaf wilting of the crop, may change the RI values. Though previous investigations provide support to the hypothesis that variations in canola growth may be depicted by remote sensed imagery, our research aims to evaluate the relationship without the assistance of controlled field trials for better representing the real conditions of the Western Australian farms on which this remote sensing tool could be used for site-specific crop management.

### Selected Spectral Indexes for Agricultural Applications

One of the most successful vegetation indices based on band ratios was developed by Rouse *et al.* (1973). They computed what is known as the Normalized difference vegetation index referred to as the NDVI, whereby a new image is created by transforming the pixels according to the equation:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \cdot \qquad (1)$$

The NIR and RED are reflectance values in those bands. Highly vegetated land uses produce a NDVI close to unity while in non-vegetated areas NDVI is close to zero or it assumes negative values (Eastman, 1999; Lamb, 2000).

The normalized difference vegetation index-green (NDVI-green) is a VI developed for the remote estimation of chlorophyll content in higher plant leaves. Chlorophyll content in the higher plant leaves changes throughout different stages of plant development. The vegetation being exposed to various stresses effects the content of the pigments. Thus, a measure of chlorophyll content can aid as a guide to detection of physiological states and stresses in plants (Gitelson and Merzlyak, 1997). Gitelson and Merzlyak (1997) found that the use of the reflectance in the green channels increases the sensitivity to the chlorophyll content with a wide range of chlorophyll variation. Thus, the use of the green channel increases the sensitivity of the NDVI to chlorophyll content by about five-fold. The equation is as follows:

$$NDVI\text{-}green = \frac{(NIR - GREEN)}{(NIR + GREEN)} \cdot \qquad (2)$$

As the chlorophyll content increases the absorption in the green band increases (i.e., low digital number). Thus, high chlorophyll content will determine a high *NDVI-green* value.

The Soil-Adjusted Vegetation Index (SAVI) is a transformation technique to minimize soil brightness influences from the spectral vegetation indices involving red and near-infrared wavelengths (Huete, 1988). A constant soil adjustment factor, $L$, is incorporated into the denominator of the NDVI equation. $L$ varies according to the reflectance characteristics of the soil (e.g., color and brightness) (Eastman, 1999). The equation takes the form:

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)} \times (1 + L) \cdot \qquad (3)$$

The $L$ factor chosen depends on the density of the vegetation cover being analyzed. Huete (1988) suggests that for very low vegetation density, use an $L$ factor of 1; for intermediate 0.5 or higher vegetation density, use a factor of 0.25.

The photosynthetic vigor ratio (PVR) uses the green band, as a reference band, and the strong chlorophyll absorption red band, the ratio is calculated as:

$$PVR = \frac{GREEN}{RED} \cdot \qquad (4)$$

This ratio is high for leaves with strong chlorophyll absorption (photosynthetically very active) and low for weakly active vegetation with lower chlorophyll absorption (SpecTerra Services, 1999b).

The plant pigment ratio (PPR) is a combination of the green band, as a reference band and the blue band related to pigment absorption (SpecTerra Services, 1999b). The PPR is as follows:

$$PPR = \frac{GREEN}{BLUE}. \tag{5}$$

The green band is intentionally made the numerator so that strongly pigmented foliage, absorbing more energy in the blue band, will have a high PPR value, while the weakly pigmented foliage will have a low PPR (Metternicht, 2003).

## Study Site and Materials

A field of approximately 46 ha of arable land located in the northern region of the Shire of Wickepin, which forms part of the South West of Western Australia (Figure 1), was selected as the test site. It is characterized by a very gently inclined slope (1 to 3 percent), loamy sand soil, and receiving about 230 mm of rain during the 2001 growing season (Butler, personal communication, 2001).

### The High-resolution Digital Multispectral Imagery (DMSI)

The DMSI was captured using SpecTerra Services' Digital Multi-Spectral Camera, which is comprised of four 12-bit digital CCD cameras recording 1024 pixels × 1024 pixels per line. Four interchangeable narrow band-pass interference filters (20 *n*m) were used to generate imagery in the blue (450 *n*m), green (550 *n*m), red (675 *n*m) and near-infrared bands (780 *n*m) (Specterra Services, 1999a). The imagery was captured in mid-July 2001 with a spatial resolution of one meter. Atmospheric corrections were not performed in the data set given that the airborne data was collected on a clear, dry day, close to noontime, when the solar zenith angle changes slowly with time. Other researchers (Karnieli *et al.*, 2001) have applied atmospheric corrections based on the 6S radiative transfer code (Vermote *et al.*, 1997) on a remote sensing data set of characteristics similar to ours (e.g., in terms of remote sensing platform, spatial and spectral resolution) reporting the effect of the atmosphere to be minimal. Given that clear sky conditions prevailed during data acquisition, it was assumed the atmospheric effects to be minimal. Image to image georeferencing of the individual frames to historical ortho-rectified aerial photography was performed using a first-order polynomial warping and nearest neighbor re-sampling. The mosaicing was performed using a technique based on a cut-line feathering over three pixels (PCI Geomatica, 2003). The radiometric correction was carried out using in-house developed software, based on inversion of the bidirectional reflectance model proposed by Roujean *et al.* (1992). Current corrections achieve a reduction of frame brightness from typically 20 percent of the dynamic range across individual frames, to less than 3 percent (SpecTerra Services, 2003).

### Field Data Collection

During the seeding operations for cereal crops, generally, a constant seed rate is set for the entire field. The number of plants established depends on factors such as soil moisture, surface crusting, seedling vigor, sowing depth, fertilizer level, disease, and insect attack (Martin and Gill, 1993). According to existing literature (Campbell and Bowyer 1990; Moore *et al.*, 1998; Atherton *et al.*, 1999; Dolling *et al.*, 2000) soil properties such as soil texture, organic matter, pH, and electrical conductivity are thought to influence crop growth, thus variability in growth expressed as changes in crop density and, consequently, yield can occur. An optimal sampling design would be required to cover areas of variable crop growth which can change from year to year within a field. A rapid method for determining the area within the field for sampling variable conditions could be with advice from the property manager, who usually keeps a historical record about areas that experience variability in crop growth over time.

Therefore, with advice of the property manager a 310 m transect was located across variable crop growth within the field, using guidance stakes and a 100 m tape measure. For correct geographic location of the transect, 3 $m^2$ white reflectors, constructed from white aerial plastic, were placed at each end of the transect and secured to the ground prior to the capture of DMSI. These were clearly visible from the air and would reflect strong contrast in the imagery. The canola crop in this research was seeded at a rate of 4.7 kg/ha with a row spacing of 25 cm and 6 cm seed band, 9.5 weeks prior to image capture. The field was fertilized during seeding with 55 kg/ha of NS51 (a sulfur/urea mix consisting of 36.9 percent nitrogen and 7.4 percent sulfur) and 85 kg/ha of Agflow Extra (12.7 percent nitrogen, 17.7 percent phosphorus and 5.5 percent sulfur). During sample collection, the growth stage of the canola plants ranged from seedling to vegetative (cabbage), as it can be seen in the field photos and plant samples shown in Figures 2 and 3. The rain-fed crop received 67.5 mm of rain at that stage of the growing season, being at a level that was causing moisture stress to the plants, particularly due to the minimal 5 mm of rain falling in June (the month prior to sampling)

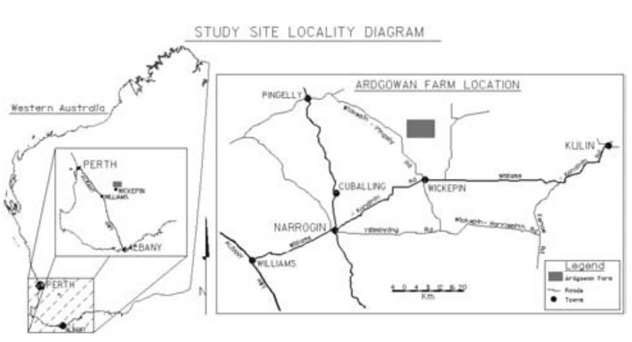


Figure 1. Study area location.

(a) (b)

Figure 2. Field Transect, canola variability: (a) Sample site C5 showing high density of canola; (b) Sample site C14 showing low density of canola.

Figure 3. Canola samples: (a) Sample C5 showing an average canola height of 20 cm; (b) Sample C14 showing and average canola height of 4 cm.

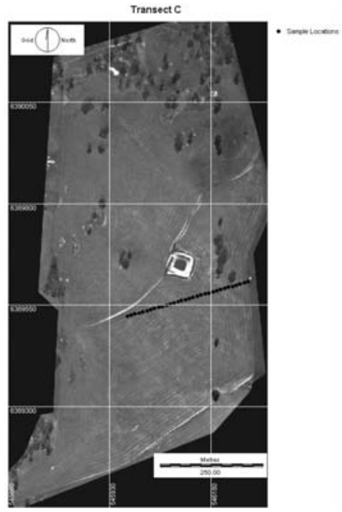

Figure 4. Interpolated transect line within the canola field.

(Butler, personal communication, 2001). Crop attributes (height, density, and plant cover) were recorded in 1 $m^2$ quadrants (Figure 2) at 10 m intervals marked with pegs with reference to the 100 m tape measure. The quadrants were aligned to the seeding rows as shown in Figure 2.

Figure 3 displays two samples collected within the canola field displaying the degree of variability in growth. Figure 3a and 3b are the samples collected at position C5 and C14 respectively, and corresponding with Figure 2a and 2b.

The field data was collected synchronous with the capture of DMSI. The canola density at 30 sample locations was determined using a combination of the row crop and the randomly distributed plants methods (TopCrop Australia, 1999) described in Table 1 within the 1 $m^2$ quadrant. The LAI was determined following the method described by Cihlar *et al.* (1987). The average leaf area of ten randomly selected canola plants within the 1 $m^2$ quadrant was determined using a LI-COR LI-3000A portable area meter coupled with the LI-3050A transparent belt conveyer accessory at seven sample locations. This was converted to a LAI utilizing the density calculated at the each corresponding location. The crop height was determined by averaging the measurement of five plants from ground to highest green leaf (cm), while for the plant cover a visual estimate of the percentage of green cover in the 1 $m^2$ quadrant. The presence and type of weeds were also recorded for each sample site given that another phase of this research project endeavored to evaluate the potential of DMSI for monitoring the presence of weeds within fields (Drysdale and Metternicht, 2003). This fact prescribed the time frame for image capture, as the research evaluated whether weeds could be identified at an appropriate time for farmers to pursue an eradication process.

The DMSI was imported into IDRISI 32 GIS software (Clark Labs, 2000) for data processing and analysis. The transect reflector end plates constructed in the field before the capture of DMSI were clearly visible in the imagery. The center pixel of each end plate reflectance was used to locate the field transect end point coordinates, and a transect line was strung between the points. The sample locations were interpolated at 10 m intervals along the transect line from the northeast to southwest coinciding with the direction of field data collection (Figure 4).

## Methodology

A flow chart of the research approach is presented in Figure 5, and the main steps are described hereafter.

### Computation of Vegetation Indices and Ratios

Using IDRISI 32, five image layers were created for the field, namely NDVI, NDVI-green, SAVI ($L = 0.5$), PVR and PPR according to the Equations 1 through 5 based on individual bands of DMSI using the *image calculator* function and output images were stored in the GIS.

### Extraction of Spectral Data

Within the GIS, digital numbers were extracted from the DMSI centred on the 1 $m^2$ sample locations in a $3 \times 3$ neighborhood window (9 $m^2$) and averaged, from the four individual bands (1 to 4) and five image transformations namely, NDVI, NDVI-green, SAVI (with $L = 0.5$), PVR, PPR. A summary of the mean and standard deviation values from the 30 sample sites is provided in Table 2.

### Correlation Analysis

Histograms of the canola density, LAI, mean digital numbers for individual bands, vegetation indices, and ratios were plotted to check for normality to determine the appropriate statistical technique, that is, Pearson's for normally distributed

Table 1. Crop Density Methodology

| Crop Cover | Visual Density | Count Method | Density $m^{-2}$ |
|---|---|---|---|
| Row Crops | N/A | $P_m$ = No. of stems per 50cm row × 2 rows. | $\frac{P_m \times 100}{Seeder\ row\ spacing\ (cm)}$ |
| Randomly distributed plants | High | $P_{25}$ = No. of stems in 25 $cm^2$ | $P_{25} \times 16$ |
| | Medium | $P_{50}$ = No. of stems in 50 $cm^2$ | $P_{50} \times 4$ |
| | Low | $P_1$ = No. of stems in 1 $m^2$ | $P_1$ |

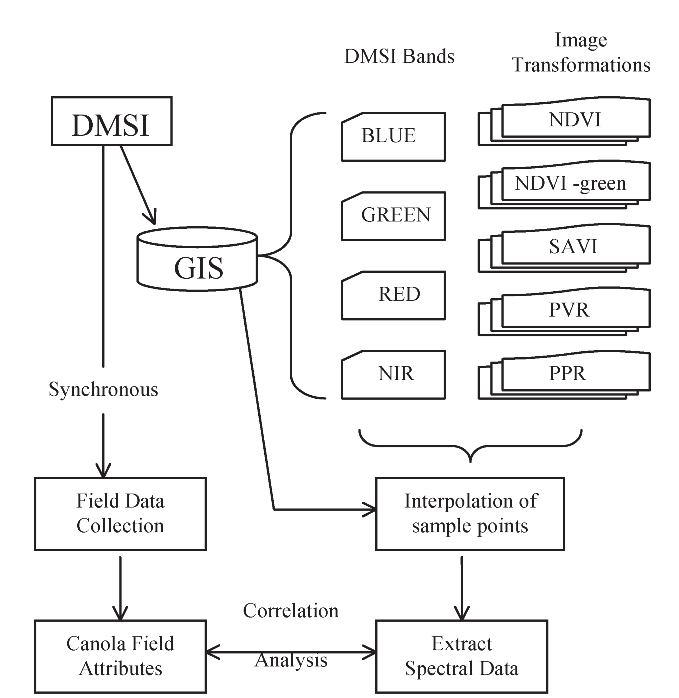

Figure 5. Flow chart of the research methodology.

TABLE 2. SUMMARY OF VEGETATION ATTRIBUTES AND SPECTRAL DIGITAL NUMBERS

| Vegetation Sample 1–30 | Mean | Standard Deviation | Coefficient of Variation | Distribution |
|---|---|---|---|---|
| Crop density m$^2$ | 55.87 | 37.97 | 0.68 | Normal |
| Band 1 | 115.19 | 4.33 | 0.04 | Normal |
| Band 2 | 99.03 | 6.26 | 0.06 | Normal |
| Band 3 | 72.49 | 8.20 | 0.12 | Non-parametric |
| Band 4 | 154.63 | 8.03 | 0.05 | Non-parametric |
| NDVI | 0.36 | 0.06 | 0.21 | Normal |
| NDVI-green | 0.21 | 0.04 | 0.21 | Non-parametric |
| SAVI | 0.54 | 0.09 | 0.21 | Normal |
| PVR | 1.51 | 0.21 | 0.13 | Non-parametric |
| PPR | 0.86 | 0.05 | 0.06 | Normal |
| **Vegetation 7 Samples** | **Mean** | **Standard Deviation** | **Coefficient of Variation** | **Distribution** |
| Leaf Area Index | 0.54 | 0.53 | 0.99 | Normal |
| Band 1 | 114.30 | 7.86 | 0.07 | Non-parametric |
| Band 2 | 99.08 | 5.17 | 0.05 | Non-parametric |
| Band 3 | 72.05 | 25.41 | 0.35 | Non-parametric |
| Band 4 | 158.76 | 26.15 | 0.16 | Non-parametric |

data and Spearman's for non-parametric data, in the correlation analysis. The distributions are listed in Table 2.

Correlation analysis was performed between the canola density and the mean digital number extracted for bands 1 to 4 and the vegetation transformations from the 30 sample locations. The LAI calculated at the seven sample sites was correlated with bands 1 to 4, and the correlation coefficients are displayed in Table 3. Graphs showing the significant correlations between the remotely sensed data and crop attributes are displayed in Figure 6.

TABLE 3. CORRELATION COEFFICIENTS ($r$) FOR JULY 2001 DMSI

| July 2001 | Crop Density m$^{-2}$ | Leaf Area Index |
|---|---|---|
| Blue (B 1) mean | −0.41* | −0.93* |
| Green (B 2) mean | −0.27 | −0.71 |
| Red (B 3) mean | −0.57* | −0.89* |
| NIR (B 4) mean | 0.58* | 0.82* |
| NDVI mean | 0.54* | |
| NDVI-green mean | 0.58* | |
| SAVI mean | 0.54* | |
| PVR mean | 0.52* | |
| PPR mean | 0.27 | |

Values followed by * are significant at 0.05 confidence level.

## Results and Discussion

### Vegetation Sampling

Table 4 provides a summary of the crop height, density, and LAI for the canola transect. Quadrants that fell within a headland were not included in the table summary to ensure that the results do not give a false representation of the variability in crop growth; thus, they represent the same seeding rate and date. The high standard deviation and coefficient of variation and range values provide an indication to the degree of variability that was apparent within the field. Figures 2 and 3 provide a visual impression of the degree of variability in canola growth along the transect with the pictures taken outside a headland location. The sample (C5) in Figure 2a and Figure 3a has a density of 88 plants/m and average height of 20 cm, while the sample (C14) in Figure 2b and Figure 3b has a density of 20 plants/m$^{-1}$ and average height of 4 cm. These sites do not represent the maximum and minimum crop density of the field, but are used to provide a visual representation of the within-field variability. Table 5 presents the field data and laboratory analysis of these particular sample locations, C5 and C14 pictured in Figures 2 and 3. The values in Tables 4 and 5 provide a clear indication of the range in crop density and crop growth that was evident in the field transect. This result also supports the evidence that the sampling strategy has captured the variability in crop growth.

### Correlation Analysis

Correlation analysis was performed between the crop density, LAI and DMSI using Pearson's or Spearman's rank coefficient of correlation, as described in Selvanathan *et al.* (2000) and Steel and Torrie (1980). The correlation coefficients are presented in Table 3 and Figure 6 and discussed in the following sections.

*Canola Plant Density and DMSI*

The canola density had significant ($\alpha = 0.05$) negative correlations with the blue (−0.41) and red spectral bands (−0.57). Significant positive correlations were found with the near-infrared band and all image transformations (0.52 to 0.58), except the PPR. The NDVI, NDVI-green, SAVI and PVR transformations performed similarly to the red and near-infrared bands, though better than the blue and green bands. The NDVI-green showed the strongest correlation (0.58).

The NDVI has shown significant correlation (0.54), similar to previous research (Cloutis *et al.*, 1996; Corner *et al.*, 1998, Edirisinghe *et al.*, 2000; Senay *et al.*, 2000; Thenkabail *et al.*, 2000; Yang and Anderson, 2000) in which NDVI showed good correlation with plant growth variables (i.e., height, LAI, biomass, and yield). In particular, NDVI was found highly related to yield, and therefore Yang and Anderson (1996) suggested that it could be used to estimate

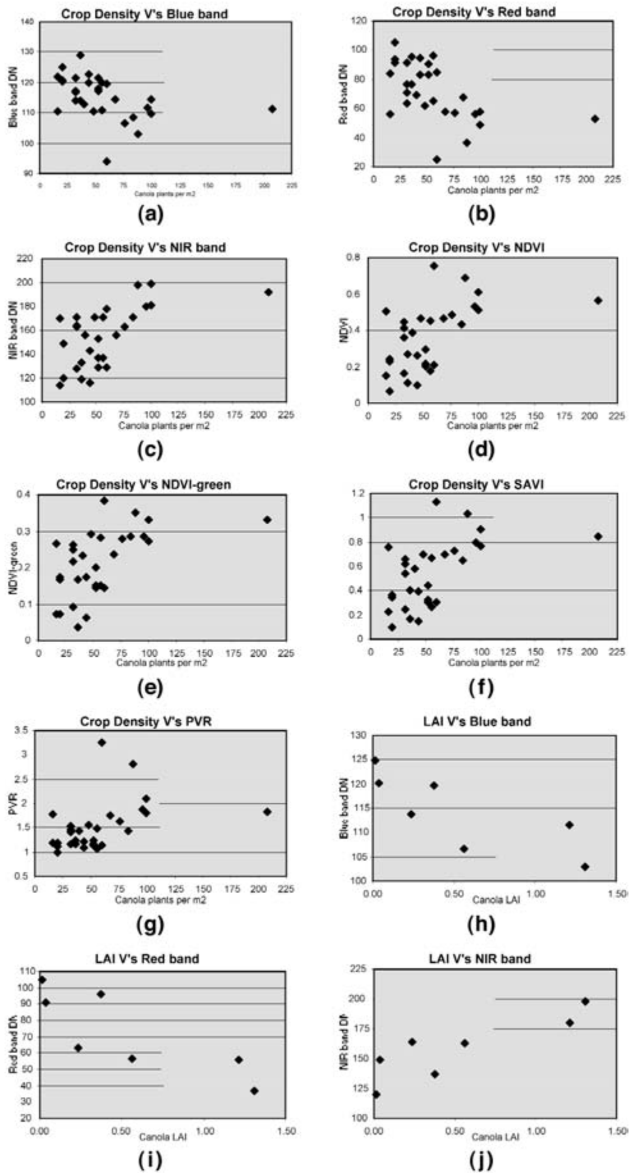

Figure 6. Significant correlation graphs of DMSI against LAI and crop density (a) Blue band and crop density (−0.41), (b) Red band and crop density (−0.57), (c) NIR band and crop density (0.58), (d) NDVI and crop density (0.54), (e) NDVI-green and crop density (0.58), (f) SAVI and crop density (0.54), (g) PVR and crop density (0.52), (h) Blue band and LAI (−0.93), (i) Red band and LAI (−0.89), (j) NIR band and LAI (0.82).

TABLE 4. TRANSECT VEGETATION SUMMARY

| | Mean Crop Height (cm) | Crop Density $m^{-2}$ | LAI |
|---|---|---|---|
| No. of samples | 26 | 26 | 7 |
| Minimum | 3.6 | 16 | 0.01 |
| Maximum | 19 | 96 | 1.31 |
| Range | 15.4 | 80 | 1.30 |
| Mean | 9.38 | 45.54 | 0.54 |
| Standard deviation | 4.21 | 21.17 | 0.53 |
| Coefficient of Variation | 0.45 | 0.46 | 0.99 |

TABLE 5. SAMPLES C5 AND C14 FIELD DATA AND LABORATORY RESULTS

| Samples Transect C: Canola | C5 | C14 | Range |
|---|---|---|---|
| Crop Density $m^{-2}$ | 88 | 20 | 68 |
| Leaf Area (10 plants) $cm^2$ | 1490 | 63 | 1427 |
| Leaf Area Index | 1.31 | 0.01 | 1.3 |
| Dry Weight (10 plants) grams | 11.09 | 0.44 | 10.65 |

within field management zones. The NDVI-green is a VI developed for the remote estimation of chlorophyll content in higher plant leaves (Gitelson and Merzlyak, 1997), as previously discussed. Of interest is the condition of the canola when sampled, during July 2001. At that time the crop was suffering from moisture stress caused by a lack of rain, post seeding, which may have resulted in the increased sensitivity to chlorophyll content represented by the strongest correlation with the NDVI-green (0.58).

In a similar manner to that of Senay *et al.* (2000), who performed correlations between a 12-band airborne multispectral scanner (e.g., Deadalus Enterprise Model 1260 Instrument) and corn and soybean crops, the near-infrared band of the DMSI was overall more highly correlated to the crop variables than the visible bands (Table 3). The image transformations performed better than the green band, but similar to the near-infrared band. The correlation coefficient between crop density and SAVI (0.54), designed to minimise the soil brightness effect (Huete, 1988), did not provide better results than the NDVI correlation results (0.54).

### *Canola LAI and DMSI*

The canola LAI had significant correlations with three of the four DMSI bands. Significant ($\alpha = 0.05$) negative correlations were found with the blue band (−0.93) and red band (−0.89), while a significant positive correlation was found with the near-infrared band (0.82).

The strong positive correlation with the near-infrared band is similar to that found by Cloutis *et al.* (1996) using a Compact Airborne Spectrographic Imager (CASI) with an average spatial resolution of 5 m. Cloutis *et al.* (1996) performed a linear correlation at the 99 percent level between the LAI of canola and 13 spectral bands of the CASI. Though the authors found no significant correlations with the individual bands, the near-infrared range provided the highest correlation coefficients. Cloutis *et al.* (1999) extended the work of Cloutis *et al.* (1996) by incorporation an airborne C-band HH-polarized Synthetic Aperture Radar (SAR) imagery. They performed correlations at 99 percent significance between a range of ratios, indices and combination of CASI bands and or SAR images with the LAI from 11 samples of irrigated canola crop. The inclusion of the SAR images generally increased the correlation coefficients many of which were statistically significant. A thorough explanation of the combination methods and significant correlations values can be found in Cloutis *et al.* (1999).

Senay *et al.* (2000) performed correlations between the LAI of soybeans and corn, from a temporally pooled data set (i.e., four and three flights, respectively) with six bands of an airborne multispectral scanner captured with a spatial resolution of one meter. The results for the soybeans showed good negative correlations (−0.59 to −0.73) for the wavebands that correspond to that of the green and red of DMSI, and a good positive correlation (0.71) was found with the equivalent near-infrared band. Correlations between the corn derived LAI and DMSI bands were less successful, with only the near-infrared band showing a significant good positive correlation (0.47).

The improved result in the correlation between LAI and DMSI bands and image transformation techniques, as compared to the relationship between the spectral bands and crop density reported in this paper, are attributed to the leaf shape of the canola plant. Canola is a broad-leafed plant in the early growth stage, as it can be seen in Figures 2 and 3. The LAI not only takes into account the broad leaf shape but the density of the crop, and, as such, it provides a better representation of the amount of vegetation cover on the ground, thus improving the link between field conditions and the amount of energy reflected or absorbed within the DMSI bands.

These results indicate that simple high-resolution remote sensing based approaches could be applied to detect growth variability at a relatively early stage of crop development, so that a prompt investigation on the causes and spatial extent of variability can be undertaken. A rapid assessment of causes of crop variability and the production of image-based maps representing its spatial distribution can assist in management improving efficiency in the application of inputs, such as, fertilizers or herbicides. In turn, these actions can help not only to lower input costs, but also to decrease harmful runoff into the landscape. Other approaches, such as yield meters, can detect crop variability as well. However, the output results (e.g., within field yield variability maps) cannot be used for improving crop production within a growing season.

## Conclusions

The initial results of the research presented here indicate that DMSI could be a suitability tool to be incorporated in image-based remote sensing approaches for site-specific crop management. The results are encouraging given that the study site represents *real* farming conditions of Western Australia, rather than a trial under controlled conditions as done in previous investigations on canola variability. Significant correlations were found between the crop density of a canola field and selected individual bands and image transformations of DMSI. The LAI showed significant correlations with the blue (−0.93), red (−0.89) and near-infrared (0.82) bands. These correlations indicate that the blue, red and near infrared bands and the image transformations of DMSI were suitable for early detection of canola growth variability in rain-fed farms. The NDVI-green was the most successful transformation technique, as it provided a significant correlation of 0.58 with crop density.

The success of the correlation results between DMSI and LAI are promising, however we recommend conducting further research to increase the number of sample sites where the LAI is measured. This data could then be used to calibrate the DMSI to ground LAI values by developing a fitting curve, which could subsequently be applied for estimating LAI values of an entire field sensed with DMSI.

Utilizing the field data and the knowledge of the strength of the correlations, image classification techniques (supervised or unsupervised) could be implemented to subdivide the image into spectral categories and delineating within-field management units on the basis of the spectral changes as related to variations in crop growth.

An $L$ factor of 0.5 was used in the SAVI equation suggesting intermediate vegetation cover. Due to the variability in crop growth, it is recommended to investigate the effect of varying the $L$ factor values for the SAVI layer. This factor has not been examined in this research, and it may improve the results of the SAVI correlation with crop density.

Further work is planned to evaluate the effect of different atmospheric correction techniques on DMSI data sets. To this end, it is envisaged to perform correlations between raw, atmospherically corrected DMSI imagery, and crop attributes. Likewise, further research could be conducted for assessing the performance of vegetation indices such as the Atmospherically Resistant Vegetation Index (ARVI) (Kaufman and Tanré, 1992), Aerosol Free Vegetation Index (AFRI) (Karnieli *et al.*, 2001), and crop attributes investigated in this paper.

These first results insinuate that DMSI, with its high spatial resolution, relatively narrow bandwidth (e.g., 20 *n*m), rapid turnaround time, and flexible data acquisition time has the potential to be applied as a non-invasive technique for growers to become aware of regions within their fields of variable growing conditions. Improving the management of a canola rotation will maximise the profitability of a solid cropping program. Further work is in place to examine its use on other cereal crops.

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