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REMOTE SENSING FOR SITE-SPECIFIC CROP MANAGEMENT: EVALUATING THE POTENTIAL OF DIGITAL MULTI-SPECTRAL IMAGERY FOR MONITORING CROP VARIABILITY AND WEEDS WITHIN PADDOCKS

G. Drysdale* and G. Metternicht**

Department of Spatial Sciences
Curtin University of Technology
GPO Box U 1987, Perth, WA 6845

**drysdalg@ses.curtin.edu.au*
***graciela@vesta.curtin.edu.au*

Abstract

This paper analyses the potential and limitations of airborne remote sensing systems for detecting crop growth variability and weed infestation within paddocks at specified capture times. The detection of areas of crop growth variability can

cereal crops is crucial for lessening their impact on the final yield.

Transect sampling within a canola paddock of a broad acre agricultural property in the South West of Western Australia was conducted synchronous with the capture of 1m spatial resolution DMSI. The four individual bands (blue, green, red and near- infrared) of the DMSI were correlated with LAI and weed density counts collected in the paddock.

Statistical analyses show the LAI of canola had strong negative correlations with the blue (-0.93) and red (-0.89) bands and a strong positive correlation was found with the near-infrared band (0.82). The strong correlations between the canola LAI and selected bands of the DMSI indicate that this may be a suitable technique for monitoring canola variability to derive information layers that can be used in creating meaningful "within-field" management units. Likewise, DMSI could be used as a non-invasive tool for in season crop monitoring.

The correlation analysis with the weed density (e.g. self sown wheat, ryegrass and clover) attributed to only one negative weak correlation with the red band (-0.38). The less successful detection of weeds is attributed to the minimal weed

density within the paddock (e.g. mean 34 plants m^{-2}) and indistinct spectral difference from canola at the early time of imagery capture required by farmers for effective variable rate applications of herbicides.

Keywords: LAI, remote sensing, crop density, vegetation indices, weed mapping.

Introduction

Precision Agriculture (PA) 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 (SSCM) 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 detection of crop growth variability can help farmers become aware of regions within their paddock where they may be experiencing above and below average yields.

Vegetation amount and condition may be measured based on the analysis of remote sensing spectral measurements (Goel and Norman, 1992). Often the goal is to reduce the multiple spectral band data down into a single value per pixel that can assess canopy characteristics such as biomass, leaf area index (LAI), and / or percent vegetation ground cover (Larsson, 1993)

Remote sensing applications for distinguishing between agricultural crop types and internal crop characteristics have been extensively researched during the past decade (Wiegand *et al.*, 1991; Cloutis, *et al.*, 1996; Thenkabail *et al.*, 2000; Metternicht *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), or when extensive areas need to be mapped in a short time span.

A common approach in remote sensing for measuring or monitoring crop growth is the correlation of vegetation indices with such crop variables as percentage of vegetation cover and LAI (Moran *et al.*, 1997). There are several algorithms used to extract such information from remotely sensed data and collectively are referred to as Vegetation Indexes (Jensen, 1996). A Vegetation Index (VI) is a mathematical combination of several bands and utilises the significant differences in reflectance of vegetation in the blue, green, red and near-infrared wavelengths. The index is typically a sum, difference, ratio or other linear combination that reduces multi-band observations to a single numerical index (Wiegand *et al.*, 1991). 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. By exploring the relationship of DMSI with canola attributes such as LAI, one can assess weather it is an appropriate remote sensing technology to incorporate into the infrastructure of image-based remote sensing for precision crop management.

The applicability of remote sensing for determining the spatial distribution of weeds within arable fields has been examined for satellite (Fitzpartrick *et al*., 1990) airborne (Lamb, 2000a; Lamb, 2000b; Lamb *et al*., 1999; McGowan, 2000) and field scanner (Robins, 1998) systems. For the remote sensing technology to be successful in the detection and subsequent mapping of weeds, Lamb (2000b) suggests two requirements: (1) There are suitable differences in spectral reflectance or texture between weeds and their background soil or plant canopy; and (2) The remote sensing instruments have appropriate spatial and spectral resolution to detect the presence of weed plants. In regards to the spatial resolution, Rew *et al*. (1997) comment that as a general "rule of thumb" a resolution of less than the minimum expected size of the weed patches is required, and this may be sub-metre.

For the information about weed detection and extent to be delivered to farmers, the option of following such a requirement is overpowered by time constraints and the cost of acquiring such high spatial resolution imagery. In order for the farmer to make appropriate management decisions, weed detection and extent must be mapped prior to the time when the weeds will hinder the crop's growth, so that a suitable eradication process can take place. It is therefore important to investigate practical applications of remote sensing and determine what, if any, information about the weeds can be extracted from these data, considering the above-mentioned requirements. This paper explores the relationship of DMSI and derived image transformation techniques with canola attributes such the LAI, and weed density; to assess whether this is an appropriate remote sensing technology to incorporate into the infrastructure of image-based remote sensing for precision crop management.

Data Sets and Study Area

The DMSI system

The field selected for the study falls in the northern region of the shire of Wickepin, located in the South West of Western Australia (Figure 1). The DMSI was captured using SpecTerra Services Digital Multi-Spectral Camera (DMSC), which is comprised of four 12 bit digital CCD cameras recording 1024 pixels of 1024 pixels per line. Four interchangeable narrow band-pass interface filters (25nm) were used to generate imagery in the blue (450nm), green (550nm), red (650nm) and near-infrared bands (750nm) (Specterra Systems, 1999a). The imagery was captured over a paddock sown with canola in mid July 2001 (10 weeks after planting) at a spatial resolution of one metre.

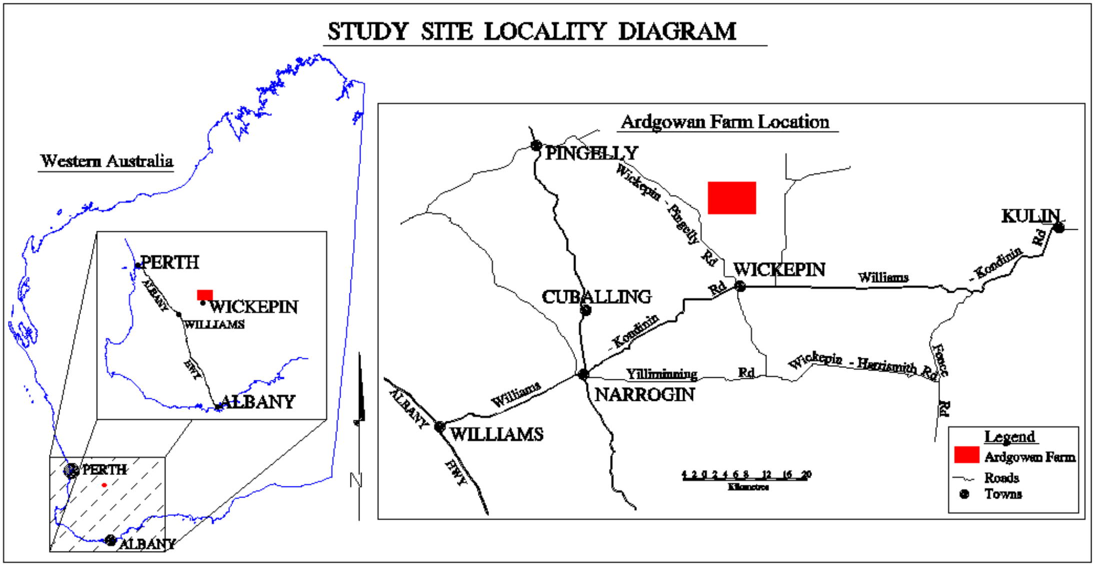


Figure 1. Study area location.

Field data collection

During the seeding operations for cereal crops, generally, a constant seed rate is set for the entire paddock. The number of plants established depends on factors such as soil moisture, surface crusting, seedling vigour, sowing depth, fertiliser level, disease and insect attack (Madin *et al*., 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 (e.g. changes in crop density) and subsequent yield can occur. An optimal sampling design would be required to cover areas of variable crop growth and weed infestation. The spatial variation of crop growth and extent of weeds within a paddock can change from year to year. Therefore, an appropriate method for determining the area within the paddock for sampling variable conditions would be established with advice from the property manager.

With guidance and assistance of the property manager a 310m transect was located across areas of variable crop growth and weed infestation within the field, using guidance stakes and a 100m tape measure. For correct geographic location of the transect, 3m^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. Crop attributes (height, density, plant cover) were recorded in 1m^2 quadrants (Figure 2) at 10m intervals marked with pegs with reference to the 100m tape measure. The quadrants were aligned to the seeding rows as shown in Figure 2.

Figure 2. Quadrants of the field transect: a) Sample site C5 showing high density of canola and weeds; b) Sample site C14 showing low density of canola and weeds.

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

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

The field data was collected synchronous with the capture of DMSI. The canola density at 30 sample locations was determined using either the row crop or the randomly distributed plants method described in Table 1, within the $1m^2$ quadrant. While the weed density was determined using the randomly distributed plants method (Table 1). The LAI was determined following the method described by Cihlar *et al.* (1987). The average leaf area of 10 randomly selected canola plants within the $1m^2$ quadrant was calculated using a leaf area meter at seven sample locations. This was converted to a LAI utilising the density calculated at the each corresponding location.

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 x 2 rows.	$\frac{P_m \times 100}{\text{Seeder row spacing (cm)}}$
Randomly	High	P_{25} = No. of stems in $25cm^2$	$P_{25} \times 16$

distributed plants	Medium	P_{50} = No. of stems in $50cm^2$	P_{50} x 4
	Low	P_1 = No. of stems in $1m^2$	P_1

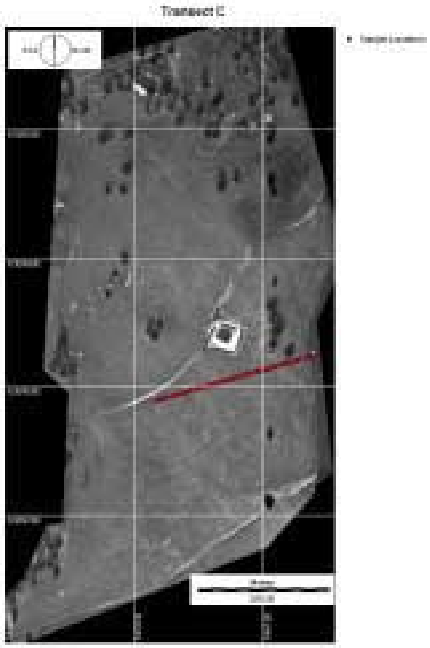
Table 2 lists the weeds that were identified in the canola transect providing their botanical and common names, as indicated by Dodd *et al*. (1993) and Cummins and Moerkerk, (1997), and average density of plant m^{-2} across the entire transect to give an indication of the dominant weed.

Table 2. Weed Identification and average density (m^{-2}) across transect.

Transect C Canola Sample 1-30 Paddock 16		
Common Name	Botanical Name	mean density m^{-2}
Wheat	**Tritcum aestivum**	25.33
Clover	*Trifolium spp.*	8.13
Annual ryegrass	*Lolium rigidum*	0.40
Erodium	**Erodium botrys**	0.13

The DMSI was imported into a GIS 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 centre pixel of each end plate reflectance was used to locate the field transect end point coordinates, and a transect line strung between the points. The sample locations were interpolated at 10m intervals along the transect line from the northeast to southwest, coinciding with the direction of field data collection (Figure 4).

Figure 4. Interpolated transect line within the canola field



Methodology

Computation of vegetation indices and ratios

There is a wide range of image transformation techniques available for remotely sensed data. Five transformations have been investigated in this project and are described below.

1. Normalised Difference Vegetation Index (NDVI).

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

(Rouse *et al*. 1973)(Equation 1)

2. Normalised Difference Vegetation Index - Green (NDVI-green)

$$NDVIgreen = \frac{(NIR - GREEN)}{(NIR + GREEN)}$$

(Gitelson and Merzlyak, 1997)(Equation 2)

3. Soil-Adjusted Vegetation Index (SAVI)

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

(Huete, 1988)(Equation 3)

The *L* factor chosen depends on the density of the vegetation cover being analysed. Huete (1988) suggests using a *L* factor of 1 for very low vegetation density, *L*= 0.5 for intermediate and *L*=0.25 for higher vegetation density.

4. Photosynthetic Vigour Ratio (PVR)

$$PVR = \frac{GREEN}{RED}$$

(SpecTerra Systems, 1999b)(Equation 4)

5. Plant Pigment Ratio (PPR)

$$PPR = \frac{GREEN}{BLUE}$$

(SpecTerra Systems, 1999b)(Equation 5)

Equations (1) to (5) were applied to the DMSI data and the output images stored in a GISystem.

Extraction of Spectral Data

Within the GIS, digital numbers were extracted from the DMSI for the $1m^2$ sample locations in a 3 x 3 neighborhood window ($9m^2$) using the four individual bands (1-4) and five transformations namely, NDVI, NDVI-green, SAVI (with L=0.5), PVR, PPR which have been described in the preceding section. A summary of the minimum, maximum, mean and standard deviation values from the 30 sample sites is provided in Table 3.

Table 3. Summary of vegetation attributes and spectral digital numbers.

Vegetation Sample 1-30		Mean	Standard deviation	Coefficient of Variation	Distribution
Total Weed density m^{-2}		34.00	40.15	1.18	Normal
Crop density m^{-2}		55.87	37.97	0.68	Normal
July 2001	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
July 2001	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

Correlation analysis

Histograms of the canola LAI, mean digital numbers for individual bands, vegetation indices and ratios were plotted to check for normality, so that the appropriate statistical technique for correlation analysis could be determined (e.g.

Pearson's for normally distributed data and Spearman's for non-parametric data). The distributions are displayed in Table 3.

Correlation analysis was performed between the total weed 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 obtained as results are displayed in Table 6.

Results and Discussion

Vegetation Sampling

Figures 2 and 3 provide a visual display of the degree of variability in canola growth and weed infestation along the transect. It is important to note here that neither of these quadrants were placed in a headland, thus they represent the same seeding rate and date. The sample (C5) in Figure 2(a) and 3(a) has a density of 88 canola plants m^{-1} with an average height of 20cm and total weed density of 44 plants m^{-1}, while the sample (C14) in Figure 2(b) and 3(b) has a density of 20 canola plants m^{-1} with an average height of four cm and total weed density of 4 plants m^{-1}. Table 4 presents the field data and laboratory analysis for the samples C5 and C14 pictured in Figures 2 and 3.

Table 4. Samples C5 and C14 field data and laboratory results.

Samples Transect C: Canola	C5	C14	Difference
Total Weed density m $^{-2}$	44	4	40
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

The results in Table 4 provide a clear indication of the difference in crop density, growth and weed infestation that was evident in the canola transect, while Table 5 provides a summary of the crop height, density and total weed infestation. This also supports the evidence that the sample strategy has depicted the variability in crop growth and presence of weeds.

Table 5. Transect vegetation summary.

Transect C : Canola Sample 1-30	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
Avg Crop Height	3.6	19	9.38	4.21	0.45
Crop Density m $^{-2}$	16	96	45.54	21.17	0.46
Total Weed density m $^{-2}$	0	180	36.92	41.76	1.13

Correlation Analysis

The correlation coefficients, using either Pearson's or Spearman's technique, as described in Selvanathan *et al*. (2000) and Steel and Torrie (1980), derived from the analysis between field data collection of weed density, LAI and DMSI are displayed below in Table 6 and discussed hereafter.

Table 6.Correlation coefficients (r) for July 2001 DMSI.

July 2001	Total Weed density m $^{-2}$	Leaf Area Index
Blue (B 1) mean	-0.294	-0.929*
Green (B 2) mean	-0.287	-0.714

Red (B 3) mean	-0.379 *	-0.893*
NIR (B 4) mean	0.321	0.821*
NDVI mean	0.267	
NDVI-green mean	0.362	
SAVI mean	0.267	
PVR mean	0.320	
PPR mean	0.021	

Values followed by * are significant at 0.05 confidence level.

Total Weed Density and DMSI

From the correlations performed there was only one negative significant correlation between the total weed density m^{-2} and the red band (-0.38). This may be due to the fact that the dominant weed present was self sown wheat while other weeds, such as clover, were only present under the leaf canopy of the canola. Wheat is a very thin leaved plant while canola is broad-leaved. This is clearly visible in Figure 3 (a), which displays canola and wheat plants collected at sample site C5. Using the samples that were collected in transect C, which accounts for growth variability, the results of the leaf area calculations show that, on average, a canola plant has a leaf area of $74cm^2$, wheat is $12cm^2$ and clover is $3cm^2$. It also must be considered that the broad leaf canola spreads its leaves as opposed to the wheat standing tall and thin.

Lamb *et al*. (1999) achieved correlations of up to 71% between the NDVI and SAVI with the density of wild oats (*Avena* spp.) in a cropped field. The authors' research investigated image resolution from 0.5 to 2m with six differing L factor values used within the SAVI equation, ranging from 0.1 to 1. When analysing their NDVI results from an image resolution of 1m (i.e. same as this research) the correlation coefficient was 0.687. The SAVI correlations, using an *L* factor of 0.5 (i.e. same as this research) resulted in 0.602 and 0.702 for 2 and 0.5m resolution respectively. These results are significantly higher than the correlations with NDVI and SAVI achieved from this research. A non-significant positive correlation of 0.267 was calculated for both the NDVI and SAVI. It is thus important to determine why such a difference in correlation coefficients was achieved between the two studies.

As discussed earlier, there is high variability in crop growth and weed infestations within transect C. As shown in Table 5 the total weed density within transect C ranged from 0 to 180 plants m^{-2} in conjunction with the canola density ranging from 16 to 96 plants m^{-2}. Figure 3 (a) and the preceding paragraph highlight the difference in the average leaf area for a canola plant ($74cm^2$) to that of the dominant weed self sown wheat ($12cm^2$). Within Lamb *et al*. (1999) research, the crop and predominant weed had a similar leaf shape (thin) and were at similar growth stage (two- to five-leaf stage). The mean crop density was 36 plants m^{-2} and the weed density ranged from 0 - 1750 plants m^{-2}. In this manner, the research by Lamb *et al*. (1999) has performed correlations with a much higher maximum density of weeds, in addition to reducing the number of variables that would influence the reflectance, such as crop growth attributes, of the target scene to the factor of weed density. Thus, the opportunity for better correlations was improved. Variability in weed infestation was not the sole objective of the vegetation sampling strategy performed in this research. The timing of DMSI capture in this research was based on on-farm herbicide application. Thus, it stands that the influence of other factors, such as the difference between crop and weed leaf area, crop growth variability within the target scene, and the timing of DMSI capture will affects the success of the correlation between DMSI and weed density.

Canola LAI and DMSI

The canola LAI had significant correlations with three of the four DMSI bands. Significant (α=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). Cloutis *et al.* (1996) performed a linear correlation at the 99 percent level between the LAI of canola and 13 spectral bands captured using a Compact Airborne Spectrographic Imager (CASI) with an average spatial resolution of 5m. Though the authors found no significant correlations with the individual bands, the near-infrared bands provided the highest correlation coefficients.

Likewise, Senay *et al*. (2000) performed correlations between the LAI of soybeans and corn, from the temporally pooled data sets (i.e. 4 and 3 flights respectively) with six bands of the multispectral scanner captured with a $1m^2$ resolution. 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 DMSI, and a good positive correlation (0.71) was found with the equivalent near-infrared band. The corn LAI was less successful, and only the near-infrared band showed a significant good positive correlation (0.47).

These results indicate that simple high resolution remote sensing based approaches can be applied to detect crop growth variability at an early stage of crop development, so that corrections to improve yield can still be implemented, if the farmer judges that corrective measures are cost-effective. 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 findings of the research can be summarised as follows:

- The leaf area index showed strong correlations with the blue (-0.929), red (-0.893) and near-infrared (0.821) bands;
- These correlations indicate that the blue, red and near infrared bands were suitable for early detection of canola growth variability using leaf area index;
- The DMSI individual bands and transformation techniques did not show significant correlations with weed density, for weed counts less than 180 plants m^{-2} , therefore failing to detect accurately the presence of weeds at a stage early enough for farmers to undertake an eradication procedure;
- Utilising the field data and the knowledge of the strength of the correlations, image classification techniques (supervised or unsupervised) could be implemented to sort the image into spectral categories. Thus combining DMSI in the infrastructure of image based remote sensing for precision crop management by delineating within-field management units;
- The success of the correlation results between DMSI and LAI offers initial suggestion that this remote sensing system could be implemented into crop growth models;
- Lastly, it is recommended conducting further research to increase the number of sample sites where the LAI is determined, to enhance the justification of its success.

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