Remote Sensing to Detect Nitrogen and Water Stress in Wheat

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Abstract
Spectral and thermal crop stress detection concepts were explored using hyperspectral, multispectral and thermal remote sensing data collected at a field site near Horsham, Victoria. Wheat was grown over two seasons (2004 and 2005) with two levels of rainfall/irrigation. This was combined with four levels of nitrogen (N) (0, 17, 39 and 163kg/ha) in 2004 and two levels of N (0 and 39kg/ha N) in 2005. The Canopy Chlorophyll Content Index (CCCI) and modified Spectral Ratio planar index (mSRpi), calculated from canopy-level hyperspectral (narrow-band) data in 2005, accounted for 76% and 74% of the variability of crop N status respectively, before anthesis. The Normalised Difference Red Edge (NDRE) index and CCCI, calculated via airborne multispectral imagery, accounted for 41% and 37% of crop N status respectively. Greater scatter was observed for the airborne data and was attributable to the difference in the spatial scale of the measurements (i.e. plotting point based sample against mean of whole plot). Nevertheless, the analysis demonstrated that canopy level theory could be transferred to airborne data capture, which could ultimately be of more use to growers. The irrigation regime influenced crop temperatures ($p<0.001$) as measured by thermal imagery acquired at near full cover with the mean temperature of the rainfed plots being 2.7°C warmer than irrigated treatments. For partially vegetated fields the Two Dimensional Crop Water Stress Index (2D CWSI) calculated using the Vegetation Index-Temperature (VIT) trapezoid method was employed to account for the contribution of the soil background to image temperature. The study concluded that opportunities exist to use airborne multispectral and thermal remote sensing for detection of spatial variation in N and water status. Use of these technologies has significant potential for maximising the efficiency of N applications for wheat growers

Key Words
Hyperspectral, multispectral, thermal, remote sensing, wheat

Introduction
Context
A key aspect of wheat production in Australia is the management of soil fertility. Nutrient removal from agricultural systems, especially the harvesting of crop products, generally exceeds natural inputs unless these are augmented by fertilisers. Nitrogen (N) is the largest agricultural input in many Australian cropping systems and applying the right amount of N in the right place at the right time is a significant challenge for wheat growers. The problem is confounded by spatial variation of available soil water. The response of a crop to fertiliser applications is heavily reliant on plant available water and rainfall. Matching N supply to water availability is therefore essential for a successful wheat crop. This requires an adequate assessment of N and water status variability in agricultural landscapes. Remote sensing techniques using both spectral and thermal approaches have been proposed as potential solutions to this problem allowing rapid identification of crop N status and water stress across large areas. This study involved processing and analysis of hyperspectral, multispectral and thermal remote sensing data collected from a research and development wheat farm near Horsham, Victoria.

Spectral sensing for N Detection
Electromagnetic (EM) energy reflected by vegetation in the visible region of the EM spectrum is influenced by the presence of chlorophyll pigments in the leaf tissues, which have been found to relate to the concentration of leaf N (Haboudane et al. 2002, Rodriguez et al. 2005). There are two main absorption bands, one in the blue (around 450nm) and another in the red (around 670nm), which are due to absorption by the two main leaf pigments, chlorophyll a and b (Lawlor 2001). In general, the higher the absorption at these wavelengths the higher the chlorophyll content. Approximately 75% of the plant's total N is contained in the chloroplasts (Lawlor 2001). Therefore, these spectral features can provide a

measure of plant N. Another significant portion of the spectrum for remote sensing of crop physiology is the Near Infrared (NIR) wavelengths. NIR reflectance is influenced by the internal leaf cell structure as spongy mesophyll cells strongly reflect infrared wavelengths. The spectral region between the red wavelength absorption feature and high NIR reflectance is generally termed the “red edge”. The position of the inflection point (maximum gradient) within the red edge has been correlated with plant chlorophyll content (Barnes et al. 2000). Therefore, measurements of reflected EM energy from crop leaves and canopies can be used to rapidly estimate chlorophyll concentration and, by implication, provide a measure of N content (Haboudane et al. 2002). A Vegetation Index (VI) relates crop spectral reflectance to the quantity and/or quality of vegetation on the surface and is mathematically derived from the combination of two or more spectral bands. Key VIs for this assessment are provided in Table 1.

Table 1 Vegetation Indices Used for Hyperspecatal and Multispectral Analysis

Abbreviation	Name	Vegetation Index	Parameter	Reference
RVI	Ratio Vegetation Index	RVI = NIR/RED	Green Biomass	Jordan 1969
NDVI	Normalised Difference Vegetation Index	NDVI = (NIR – RED)/(NIR + RED)	Green Biomass	Rouse et al. 1973
NDRE	Normalised Difference Red Edge	NDRE = $(R_{790} - R_{720})/(R_{790} + R_{720})$	Chlorophyll Content	Barnes et al. 2000
mSR	Modified Spectral Ratio	mSR = $(R_{750} - R_{445})/(R_{705} + R_{445})$	Chlorophyll Content	Sims and Gamon 2002
CCCI	Canopy Chlorophyll Content Index	Calibrated index using NDRE as function of NDVI.	Chlorophyll Content	Barnes et al. 2000
mSRpi	Modified Spectral Ratio Planar Index	Calibrated index using mSR as function of NDVI.	Chlorophyll Content	Rodriguez et al. 2005

The Canopy Chlorophyll Content Index (CCCI) (Barnes et al. 2000) was designed to provide a more accurate measure of the N status of crops relative to existing VIs. It is a two dimensional approach that uses the Normalised Difference Vegetation Index (NDVI) as an estimate of percent canopy cover and the Normalised Difference Red Edge (NDRE) index as a measure of chlorophyll content (Barnes et al. 2000). The NDRE values were plotted against NDVI and the maximum and minimum NDRE (chlorophyll content) lines drawn by eye from the resulting data cloud and then defined as linear functions of NDVI. The CCCI is the measured value minus the minimum value divided by the potential range (maximum minus minimum) at a given percent cover. A CCCI of 0 will typically represent a condition of low chlorophyll content and 1 corresponds to high chlorophyll content (Barnes et al. 2000). Rodriguez et al. (2005) used the same approach to calculate the modified Spectral Ratio planar index (mSRpi), which simply uses the mSR (Table 1) in place of NDRE. Rodriguez et al. reported that the ability to establish a linear association between the calculated indices (CCCI and mSR_{pi}) and plant % N was affected by irrigation treatment due to the crop growth rate and biomass accumulation influenced by water regime. To overcome this, they derived a Nitrogen Stress (NS) Index, which involved derivation of upper and lower limits of shoot %N as a function of shoot dry weight. The NS Index provides a measure of crop N status normalised for biomass per area and is defined as the measured N % minus the minimum N % divided by the potential range (as above).

Thermal sensing for detection of water stress

It has been long recognised that plant temperature may be a valuable qualitative index to detect differences in plant water regimes. Plants receiving sufficient water through their roots have cooler leaves than those that are water-stressed (Clarke 1997 and references therein). When a plant has sufficient available soil water, water is readily absorbed by the roots, transported to the leaves and evaporates via transpiration. The evaporation has a cooling effect, reducing the leaf temperature. Under water limited conditions, transpiration and associated evaporative cooling are reduced resulting in higher leaf temperatures (Jackson et al. 1977).

Work undertaken by Ehrler (1973) demonstrated that the canopy temperature (T_c) minus air temperature (T_a) differential decreased after irrigation, reaching a minimum several days later. The temperature difference would then increase as the soil water became limiting (Jackson et al. 1981). Following this work, Jackson et al. (1977) used the T_c-T_a differential to define the Stress Degree Day (SDD) parameter, which was related to yield and water requirements (Jackson et al. 1981).

A limitation of the SDD parameter is that it does not account for environmental factors that may affect the ability of the crop to transpire, such as Vapour Pressure Deficit (VPD), net radiation and wind. Studies by Ehrler (1973) indicated a linear relationship between the T_c-T_a differential and the VPD. VPD is the difference between the partial water vapour pressure of air compared to that of saturated air. At a high VPD transpiration is unconstrained, whereas transpiration is hindered at low VPD. Idso et al. (1981) investigated the effect of VPD on the T_c-T_a differential for well-watered crops and similar to Ehrler found that throughout the greater period of daylight a linear relationship existed between the two regardless of other environmental parameters except cloud cover. Idso et al. (1981) and Jackson et al. (1981) used upper and lower limits of T_c-T_a as functions of VPD to define the Crop Water Stress Index (CWSI). To facilitate calculation of the CWSI, Idso et al. (1982) defined non-water stressed baselines for 26 different crop species, including pre-and post-heading wheat crops.

Jackson et al. 1981 and Idso et al. 1981 recognised the potential interference of a soil background when collecting a thermal image of the crop (i.e., increased image temperature due to contribution of hot soil background). Therefore, application of the CWSI using thermal imagery was hampered by the difficulty of measuring foliage temperatures of partially vegetated fields (Moran et al. 1994). To overcome this, Moran et al. (1994) developed a theoretical Vegetation Index-Temperature (VIT) trapezoid, which is the shape resulting from the relationship between surface composite temperature (T_s) minus T_a as a function of fractional vegetation cover. The four points of the trapezoid are represented by the following extreme conditions: 1) well watered, non-stressed vegetation at full canopy cover; 2) maximum water stressed vegetation at full canopy cover; 3) saturated bare soil; and 4) dry bare soil. Theoretically, all variations of crop water stress for different vegetation cover should plot within this trapezoid. Clarke (1997) explained that the diagonal line connecting points 1 and 4 of the VIT trapezoid defines the condition where plants are transpiring freely but no evaporation is occurring from the soil surface, meaning that the canopy component is at minimum temperature and the soil component at a maximum. Any data point falling to the right of this line is not transpiring at the potential and is therefore experiencing some degree of water deficiency (Clarke 1997). This was the basis of the two dimensional CWSI (2D CWSI) defined by Barnes et al. (2000).

Methods

The experimental site comprised 48 plots (18m x 12m) planted to wheat. The 2004 experiment involved four rates of N fertilisation (0, 16, 39 and 163 kg N/ha) and two water regimes (irrigated and rainfed). In 2005, the field experiment again involved two water regimes, but was simplified with only two rates of N fertiliser (0 and 39 kg N/ha). In 2004, the rainfall (sowing to harvest) was 235mm for the rainfed treatment (including one irrigation of 25mm), and rainfall plus irrigation was 360 mm for the irrigated treatment. In 2005, the rainfall was 280 mm and rainfall plus irrigation was 330 mm.

Hyperspectral data were collected at canopy level using a FieldSpec® Pro (Analytical Spectral Devices, Boulder, CO, USA) portable spectroradiometer measuring spectral reflectance in the range 390-2500 nm. Destructive plant samples were taken within the field of view of the FieldSpec® Pro after each measurement and analysed for whole aboveground-plant N content. In 2004, field hyperspectral readings were collected on eight occasions throughout the growing season. These data are the focus of past papers (Fitzgerald et al. 2006 and Rodriguez et al. 2005) and were not analysed as part of this assessment. In 2005, field hyperspectral readings were collected on four occasions immediately prior to paddock scale imagery. Airborne images were captured using a DuncanTech (Redlake, Inc., San Diego, CA, USA) 3-band multispectral camera mounted to a light aircraft. The mutispectral camera captured three discrete wavelength bands across the red edge including 670 nm (Red), 720 nm (Far red) and 790 nm (NIR). A Therma CAM P40 (FLIR systems AB, Danderyd, Sweden) infrared camera measuring in the range of 7.5-13 µm was also mounted to the aircraft to collect thermal images of the experiment site at paddock scale.

The CCCI and other indices were calculated from the 2005 canopy level spectra and airborne multispectral images (using mean of whole plot). Correlation coefficients (r^2) were calculated to provide a summary of the strength of the linear association between the calculated indices and crop N status (% N and the NS Index). Mean plot temperatures from the thermal images were used to calculate the 2D CWSI using the VIT trapezoid approach. The method was similar to Barnes (2000) in that NDVI was used as a surrogate for canopy cover and points 1 and 2 were derived based on Idso (1982). Points 3 and 4 were measured using the image temperature from dry and wet soil plots located adjacent to the experiment site. The mean plot temperatures and calculated 2D CWSI values were analysed to determine if differences occurred between treatments. When comparing mean values a Shipiro-Wilks W test and Kolmogorov-Smirnov test for normality were first performed to ensure that the mean values were a good measure of central tendency. Then a factorial analysis of variance (ANOVA) was performed to test differences between treatments and/or dates. Tukey's unequal n HSD test was used to discriminate groups for which differences occurred.

Results & Discussion

Yield

The mean yield results for each treatment for 2004 and 2005 are presented in Table 2. These data show that for both seasons higher yields were obtained from the irrigated plots relative to the rainfed plots ($p<0.001$). In 2004, grain yield was not influenced by the 17 and 39 kg/ha N applications ($p>0.9$), although lower yields were obtained from the 163 kg/ha N treatments ($p<0.05$). This is attributable to the 'haying off' effect, which can occur when N is applied excessively too early encouraging the crop to produce excessive biomass and use extra water, reducing the amount of water available during the grain filling process *(Walker 2003)*. In 2005, N treatment did not influence mean yield ($p=0.29$). Thus, for both seasons the N treatment had little, if any, influence on grain yield with irrigation regime being the predominant limiting factor. This may indicate that there was sufficient N supplied to the crop from pre-sowing mineral N reserves and post-sowing mineralisation. The grain yield data indicate that on average the irrigated plots yielded 3.1 t/ha more than the rainfed plots in 2004 ($p<0.001$) whereas in 2005 the difference was only 0.55 t/ha ($p<0.005$). This is due primarily to the significantly higher yields obtained for the rainfed plots in 2005 (mean of 2.92 t/ha) relative to 2004 (mean of 1.21 t/ha) ($p<0.001$), which is attributable to the higher spring rainfall experienced in 2005 (September and October rainfall in 2005 was 100mm compared to 41mm in 2004). Moreover, lower yields were obtained for the irrigated plots in 2005 (mean of 3.46 t/ha) than 2004 (mean of 4.31 t/ha) ($p<0.001$), due to less irrigation in 2005.

Table 2 Mean Yield (t/ha) (± 95% confidence)

Treatment	2004	2005
Irrigated, 0 kg/ha N	4.16 ± 0.20	3.44 ± 0.25
Irrigated, 17 kg/ha N	4.62 ± 0.22	-
Irrigated, 39 kg/ha N	4.58 ± 0.20	3.48 ± 0.19
Irrigated, 163 kg/ha N	3.87 ± 0.41	-
Rainfed, 0 kg/ha N	1.48 ± 0.55	2.84 ± 0.17
Rainfed, 17 kg/ha N	1.39 ± 0.66	-
Rainfed, 39 kg/ha N	1.44 ± 1.03	3.00 ± 0.10
Rainfed, 163 kg/ha N	0.52 ± 0.30	-

Table 4 2D CWSI values (± 95% confidence)

Treatment	Oct 2004	Oct 2005
Irrigated, 0 kg/ha N	0.38 ± 0.05	0.09 ± 0.03
Irrigated, 17 kg/ha N	0.36 ± 0.10	-
Irrigated, 39 kg/ha N	0.31 ± 0.07	0.07 ± 0.04
Irrigated, 163 kg/ha N	0.21 ± 0.04	-
Rainfed, 0 kg/ha N	0.81 ± 0.07	0.30 ± 0.02
Rainfed, 17 kg/ha N	0.82 ± 0.04	-
Rainfed, 39 kg/ha N	0.72 ± 0.08	0.30 ± 0.01
Rainfed, 163 kg/ha N	0.75 ± 0.04	-

Nitrogen Stress Index

The development of the NS Index from field samples collected in 2005 is represented in Figure 1, where the measured values of shoot % N are plotted versus dry weight for each sample. The mean NS Index values for the different treatments are provided in Figure 2. These data indicate that the NS index decreases (more N stress) through the season ($p<0.001$) due to depletion of available N during crop growth. In September, the rainfed plots had higher mean NS Index values (less N stress) relative to the irrigated plots ($p<0.05$) indicating greater N deficiency due to the greater growth rate and hence higher demand for N in irrigated plots. There was no difference between N treatments in October ($p=0.91$) and November ($p=1$) inferring that the N status of the crop was not influenced by N treatment, which is reflected in the grain yield results that were likewise unaffected by N treatment. The variance in the data illustrates the variation in N status that can occur between plots with the same water and N treatments, potentially due to variations in soil parameters such as salinity, sodicity and permeability.

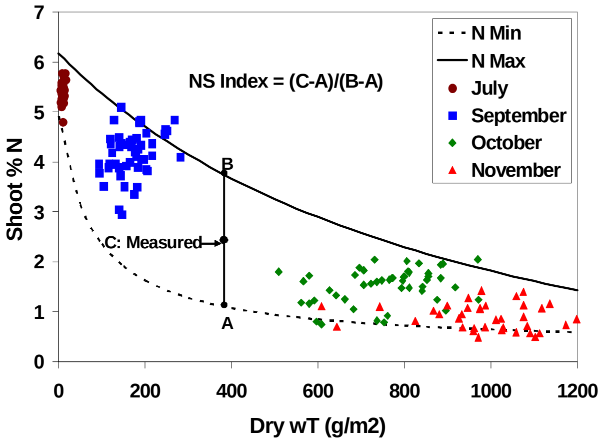


Figure 1 Development of Nitrogen Stress Index (after Rodriguez et al. 2005)

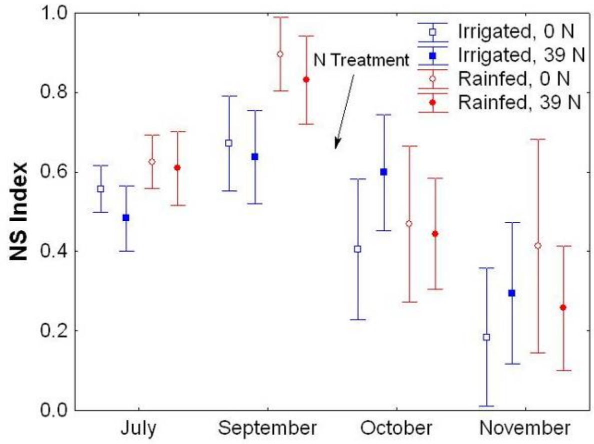


Figure 2 Mean Nitrogen Stress Index Values

Canopy Level Hyperspectral Data

Development of the CCCI from the 2005 canopy level hyperspectral data is presented in Figure 3a, where the measured values of NDRE are plotted against NDVI for each measurement date. The July measurements plot outside the minimum NDRE line (i.e., negative CCCI) suggesting that the minimum condition defined by Rodriguez et al. (2005) may not be low enough. The development of the mSR_{pi} is presented in Figure 3b, where the measured values of NDVI are plotted against mSR. The minimum mSR boundary of Rodriguez et al. (2005) holds true for this data set. Both Figure 3a and 3b indicate increasing chlorophyll content (inferred by increased NDRE and mSR) from July through September and October. The lower NDRE and mSR values observed in the November measurement indicate decreased chlorophyll content due to advanced senescence at this stage.

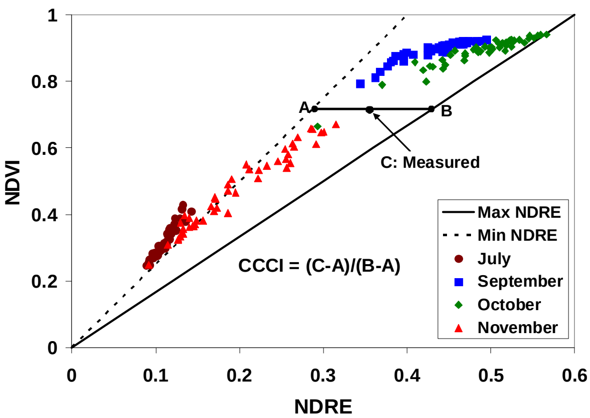


Figure 3a Development of CCCI (after Barnes et al. 2000)

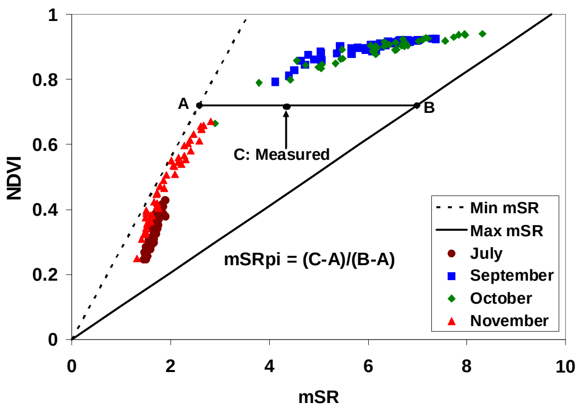


Figure 3b Development of mSRpi (after Rodriguez et al. 2005)

Linear correlation between the CCCI, mSRpi and other VIs calculated from the September 2005 field hyperspectral data (before anthesis) against plant N content and the NS Index are provided in Table 3. These indicate stronger correlations using the empirically determined NS Index as opposed to using % N, presumably because the NS Index accounts for the influence of biomass per unit area. The NDRE and mSR indices accounted for 68 and 69% respectively, of NS index variability whilst the CCCI and mSR_{pi} accounted for 76% (Figure 4) and 74% of the variability. Thus, improved correlations were achieved using calibrated boundaries.

Table 3 Linear correlation Coefficients (r^2) for Vegetation Indices versus % N and NS Index (September 2005)

	NDVI	RVI	NDRE	mSR	CCCI	mSR_{pi}
N %	0.19**	0.22**	0.40***	0.44***	0.49***	0.50***

NS Index	0.42***	0.47***	0.68***	0.69***	0.76***	0.74***

*Marked correlations are significant at * p<0.05, **p<0.01, and ***p<0.001.*

Airborne multispectral images:

Information obtained from the airborne multispectral images was consistent with the canopy level hyperspectral data. The NDRE and CCCI indices calculated from the September 2005 image (using plot means) accounted for 41% and 37% (Figure 5) of crop N status respectively. Greater scatter was observed for the airborne data and was attributable to within-plot variability of crop N content and the difference in the spatial scale of the measurements (i.e., plotting mean of whole plot versus point-based samples). However, these data demonstrate that the canopy level theory could be transferred to airborne data capture. The September 2005 multispectral image was processed to produce a map of CCCI (Figure 6). This map highlights the within-plot variability of CCCI values. In general, plots that returned low NS Index values from the point samples (represented by red circles) were generally characterised by low CCCI values. The irrigated treatments generally returned lower CCCI values than the rainfed treatments (P<0.005) indicating greater N deficiency due to higher demand for N. An exception to this was the low CCCI values observed for the rainfed treatments within the north-eastern area of the experiment site (top right of image). This is possibly due to poor soil conditions in this area of the site, which returned the lowest yields. Overall, the image processing demonstrated the potential to use paddock scale images of CCCI or NDRE to spatially identify N deficiency within the field.

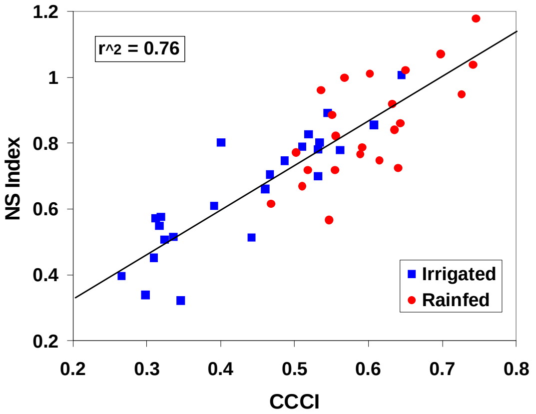
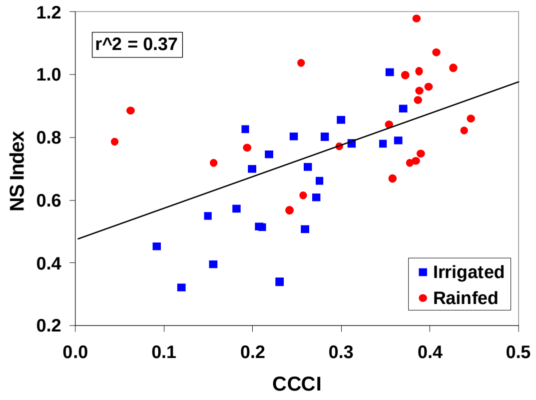


Figure 4 CCCI from canopy-level spectroradiometer versus the NS Index (September 2005)



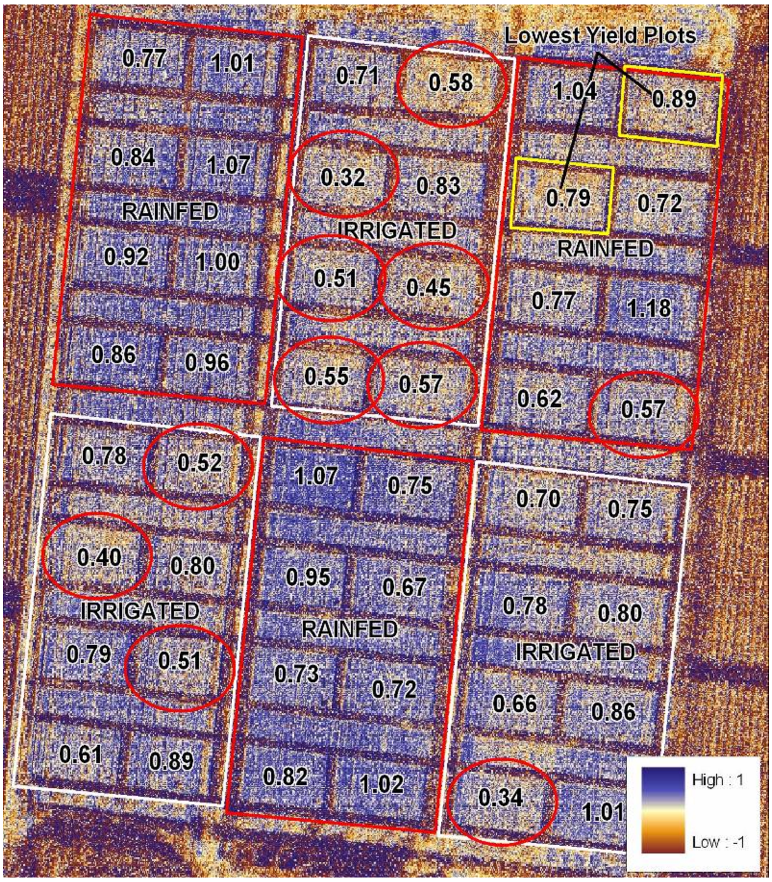


Figure 5 CCCI from airborne multispectral image versus NS Index (September 2005)

Figure 6 Image of CCCI (September 2005) ***(Numbers represent NS Index values from point sample, red circles denote NS Index <0.6)***

Airborne thermal images

Mean plot temperatures from airborne thermal images were well correlated to water regime with the mean temperature of the rainfed plots being 6.5˚C and 2.7˚C warmer than the irrigated treatments for the October 2004 (p<0.001) and October 2005 (p<0.001) thermal images respectively (Figure 7a and 7b). If water stress began in September then we would expect this response pattern to be similar. The mean plot temperatures were also influenced by N treatment, with lower mean image temperatures recorded with increasing levels of N application in Oct 2004 (p<0.001) and Oct 2005 (p=0.12). However, the effect of N was relatively minor compared to the influence of water regime.

As discussed, image temperatures can be influenced by the soil background. The high canopy cover observed in Oct 2005 (mean NDVI >0.85) would have limited the influence of the soil background. Therefore, the observed temperature difference for this image is attributable to restricted transpiration due to water limitation. However, in October 2004, canopy level thermal image temperatures collected four days prior to the airborne image acquisition were negatively correlated (r^2=0.76) to NDVI from canopy level hyperspectral readings. This suggested that as the NDVI increased, the image temperature decreased. Thus, for the Oct 2004 image, the canopy cover resulting from crop treatment is likely to have influenced image temperature (i.e. increased canopy cover resulting from irrigated and high N treatments limited the influence of the hot soil background resulting in cooler image temperatures relative to the rainfed and low N treatments that had lower canopy covers and a greater contribution from the soil).

In order to account for the influence of variable canopy cover on image temperature the 2D CWSI was calculated using the VIT trapezoid approach (Figure 8). Figure 8 highlights the variation in canopy cover in Oct 2004 relative to the near full cover at the time of image capture in Oct 2005. The mean 2D CWSI values are presented in Table 4 (see page before last). These data suggest that in Oct 2004 the rainfed plots were highly stressed (mean 2D CWSI = 0.78) and transpiring at a very low rate (theoretically a 2D CWSI of 1 equates to maximum water stress), whilst the irrigated plots were less stressed and transpiring at approximately 60 to 80% of the potential. The lower 2D CWSI values for the irrigated treatments relative to the rainfed plots ($p<0.001$) in October 2004 suggest that, even after allowing for the lower canopy cover and the influence of the hot soil background, the rainfed crops were still ‘warmer’ than the irrigated treatments due to restricted transpiration attributed to soil water limitation. The high 2D CWSI values recorded for the rainfed treatments in October 2004 were reflected in the very low yields obtained from these plots (1.2 t/ha on average). The 2D CWSI for the irrigated plots in October 2005 were low and positive (mean 2D CWSI = 0.08) indicating that at the time this image was captured the irrigated crops were well watered and transpiring at near full potential. The rainfed plots in this image returned higher 2D CWSI values than the irrigated plots ($p<0.001$) indicating greater soil water limitation. However, the values were still relatively low (mean 2D CWSI = 0.30), suggesting that the rainfed crops were not significantly water limited, which is seen in the relatively high yields from the rainfed treatments in 2005 due to higher rainfall.

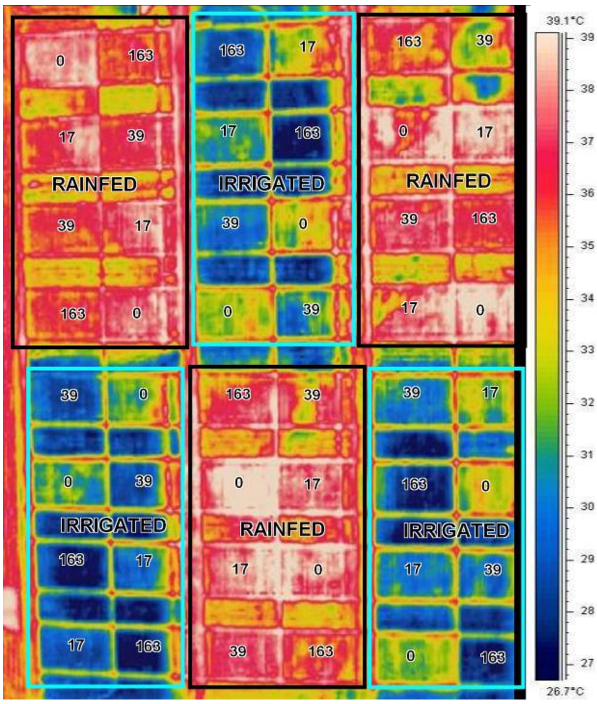


Figure 7a Thermal image of experiment site October 2004 ***(numbers denote kg/ha N applied)***

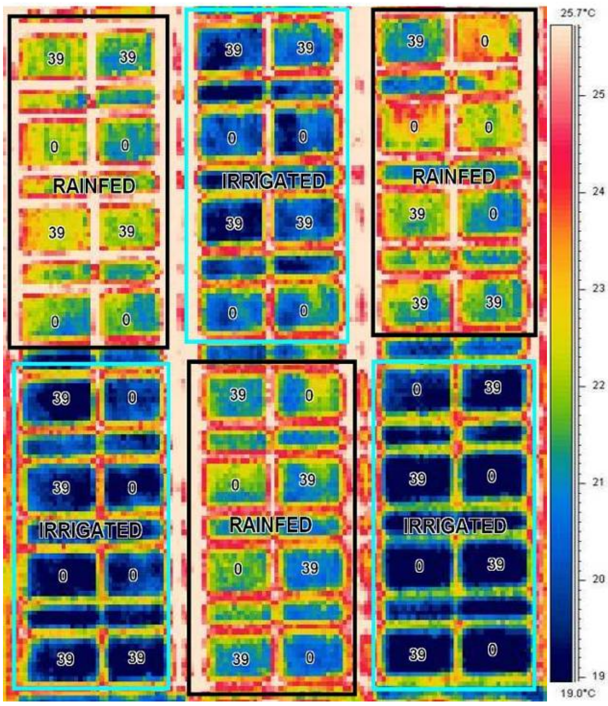


Figure 7b Thermal image of experiment site October 2005 ***(numbers denote kg/ha N applied)***

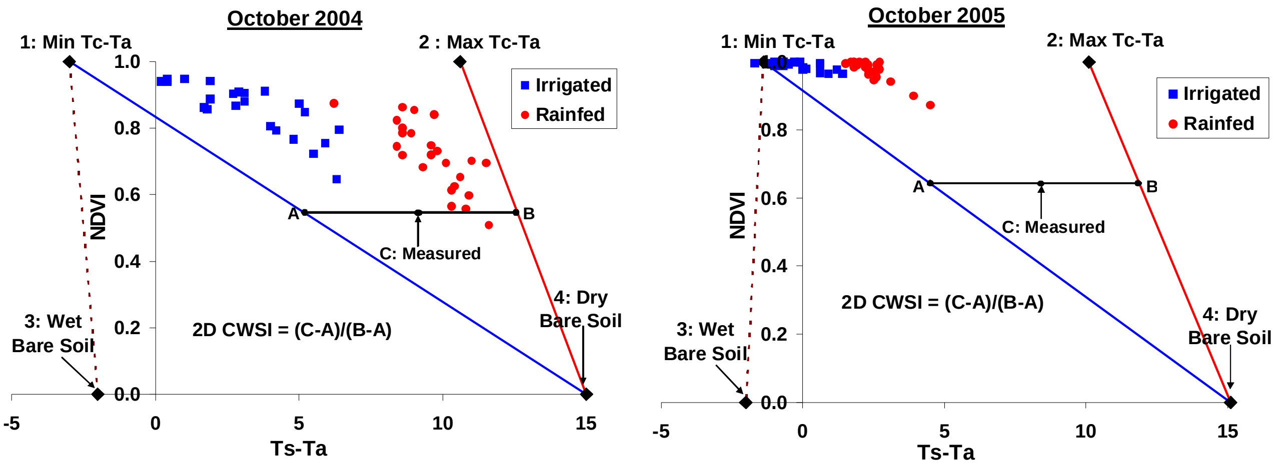


Figure 8 Development of 2D CWSI using VIT trapezoid boundaries

The 2D CWSI values for the October 2004 image were lower for the high N treatments (163kg/ha N) than the plots that were not treated ($p<0.005$), suggesting that N limitation may have had some impact on canopy temperature. In 2005, there was no statistical difference between the mean 2D CWSI values obtained for the different N treatments, indicating that N treatments had no effect on canopy temperature for this image. Thus, with respect to this experiment it remains inconclusive if N limitation further reduces crop transpiration or whether the observed temperature differences between N treatments are purely a product of the increased canopy cover resulting from the N applications. Either way, the influence of N treatments on image temperature was minor compared with the effect of water treatment.

Overall, the study concluded that measurements of canopy temperature can provide a meaningful indicator of crop water status. The major limitation, however, is the influence of the soil background on thermal images of partially vegetated fields. Although the 2D CWSI using the VIT trapezoid method returned theoretically sound results in the context of water treatments and final grain yield, the approach is relatively untested and difficult to validate. Further studies involving both well-watered and water-limited crops under a wider variety of canopy covers are required to fully explore the robustness of this approach.

Conclusion
Opportunities exist to use airborne and ground-based hyperspectral and multispectral remote sensing for detection of spatial variation in N status of the crop to allow more targeted N applications. Use of this technology has significant potential for maximising the efficiency of N applications for wheat growers. N status can be determined early enough for a grower to apply additional fertiliser if necessary. Thermal remote sensing has the potential to identify spatial variations in crop water status. For irrigated cropping systems, this information could be used for irrigation scheduling whereas growers in non-irrigated regions could use these data to avoid costly N applications on water-limited crops.

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