NEC11 – Final Project Report Attachment 3

Relationships Between Plant Based Measurements and Remotely Sensed Data for Irrigation Scheduling of Cotton

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Executive Summary

There has recently been an increased interest in the use of plant based sensors for improving irrigation scheduling of cotton in Australia. While point-based sensors provide detailed information on individual plant responses, there is significant infield spatial variability in both plant stress and irrigation response which needs to be identified and included in field scale irrigation decision making. Both proximal (e.g. infield ground-rig systems) and remote (e.g. satellite) plant condition sensors provide an opportunity to assess the variation in crop stress across fields. However, the success of remote sensing based field condition models depends on the availability of cloud-free satellite imagery and an appropriate level of proximal information to verify or ground-truth the particular model or wavelength indices. The high cost of imagery acquisition also currently limits the commercial application of satellite technologies.

Ground based proximal sensors such as the Greenseeker normalised difference vegetation index (NDVI) sensor and handheld radiospectrometer devices are both readily available and increasingly being used for nutrient management and detecting variance in crop vigour at a field level. Their main advantages over satellite imagery are reduced data acquisition costs, improved timeliness of data acquisition and increased operational flexibility. However, the ability to implement a radiometric system for irrigation scheduling in cotton requires the identification of radiometric bands which are well correlated with the changes in leaf water potential (LWP) which occur within the range of 'commercial' irrigation practices.

This project collected multispectral satellite imagery, field radiometric spectroscopy and NDVI data under commercial conditions on two sites to evaluate their ability to identify (a) spatial variability in cotton crop stress at the field level and (b) crop stress thresholds appropriate for irrigation scheduling. Correlation analysis of specific radiometric wavelengths and leaf water potential measurements were also undertaken.

The active sensor technology (i.e. NDVI) was able to identify varietal differences and varying yield responses under all climatic conditions encountered. However ground rig speed, distance above the canopy and data point positioning information is critical for mapping and comparison with other data sources. The passive sensors (i.e. satellite or handheld radiometric) were found to be hampered by poor atmospheric conditions and high variability in localised sunlight intensity. Operational difficulties associated with plant material handling and LWP measurement techniques in the field made it difficult to obtain reliable plant stress data sets suitable for identifying relationships with the remotely sensed data. Daily time constraints (11am-2pm) associated with the use of the radiometric sensor limit the number of leaf samples that can be assessed and subsequently used for correlation with spectral data. Hence, this work was unable to identify significant correlations between a range of commonly used radiometric "water bands" < 1075 nm and LWP. Limited availability of the hyperspectral sensor also prohibited evaluating the relationships between the longer radiometric wavelengths (1100-2500 nm) and LWP.

There are still considerable opportunities to improve the spatial and temporal resolution of remotely or proximally sensed agroecological parameters by developing algorithms to increase the spatial resolution of reflectance data derived from satellite images and proximal sensors. Further work is required to extend the data sets across a wider range of commercial conditions and to identify opportunities to ground-truth the satellite imagery using either the proximal sensing and/or direct plant based measurements.

1. Introduction

Agricultural field information is crucial in environmental modelling as it has a direct impact on water holding capacity, evapotranspiration, carbon sequestration and water quality. Gowda *et al*., (2008b) developed a set of Thematic Mapper (TM)-based linear logistic models for mapping tillage practices and verified with an independent dataset. However, success of remote sensing-based field condition models depends on the availability of cloud-free Satellite imagery and an appropriate level of ground based information to verify or ground-truth the particular model or wavelength indices. Remote sensing may be used for monitoring distributed actual ET as described by Chavez *et al*., (2008), but it is not straight forward. In their study over prediction of ET was caused by errors in estimating the fraction of LAI that is green, the clumping factor, the vegetation fraction, soil heat flux, and/or the soil resistance to heat flux term.

Remote sensing is a well recognised and accepted method for determining plant health, where actively growing canopies reflect/transmit up to 60% of infra-red solar radiation compared to incomplete, stressed or diseased canopies (Robson *et al.,* 2007, Curtis and Goetz, 1994). Infrared reflectance (770-1100 nm) provides an insight into a plants internal structure where the amount of reflectance is predominantly governed by the turgidity of interfaces between cell walls with air, protoplasm or chloroplasts. Changes in the chemical constituents of the plant including hydrogen, carbon, nitrogen, oxygen, water, starch, cellulose, lignin etc can also be determined (Shenk *et al.,* 2001, Osborne *et al.,* 1993). As these compounds form the fundamental components of a plants biochemical process including photosynthesis, respiration, evapo-transpiration and decomposition, the ability to measure them offers a strong insight into plant health and production capacity (Bowman, 1989).

Field spectroscopy, multispectral aerial and satellite imagery are all currently used methods for measuring the spectral reflectance characteristics of a growing plant. Field spectroscopy measures the electro-magnetic radiance from a target in a continuous spectral signature ranging from the visible to near infrared spectral regions and generally has a spectral resolution of around 10nm, with a sampling interval between 2-3nm. For agricultural uses, field spectroscopy has been used to predict a number of biotic and abiotic parameters that effect plant vigour (Maas, 1988; Richardson and Everitt, 1987; Carter, 1994). By identifying specific wavelengths that correspond to constituents affected by either growth constraints of economical importance such as disease or water stress, or those strongly correlated to beneficial traits such as yield and quality, the possibility exists to develop simple sensors that can be tuned to these wavelengths. An example of this technology is the Greenseeker NDVI sensors, which are readily available and are increasingly being used in nutrient management and detecting variance in crop vigour at a field level. Their advantage over satellite imagery is timeliness, data acquisition costs and flexibility in operation.

Multi-spectral imagery, comprised of four spectral bands; blue, green, red and near infra-red (NIR), has been shown to accurately quantify variations in crop vigour for many decades and across many cropping systems (Jackson et al 1986, Robson et al 2007). The subsequent formulation of vegetation indices has increased the accuracy of imagery in the prediction of more specific parameters such as yield, water stress, disease etc. by minimising ‘noise’ errors arising from atmospheric attenuation, plant shading and darker soil reflectance etc. The most commonly used index is the Normalized Difference Vegetation Index (NDVI) where highly vegetated regions exhibit an NDVI value close to one while for non-vegetated targets the value is close to negative one (Jackson and Huete, 1991).

Several authors have established radiometric indices and individual wavelengths for the estimation of plant water status (Table 1).

Table 1. Radiometric indices and individual wavelengths used for the estimation of plant water status in cotton and other crops (after White and Raine 2007)

Author	Year	Indices	Formulae	Crop	Measure
Bajwa	2006	NDVI	(R810-R660)/ (R810+R660)	cotton	Irrig. applied & soil moisture
Bajwa	2006	GNDVI	(R810-R550)/ (R810+R550)	cotton	Irrig. applied & soil moisture
Wanjura	2004	(1)R750, (2)R880	R750	cotton	LWP
Bowman	1989	(1)R810, (2)R1665, (3)R2210	R810	cotton	LWP (leaf water potential), RWC (relative water content) & Ψp
DeTar	2006	DeTar (1)	R850 & R686	cotton	canopy temp
		DeTar (2)	R686, R811 & R860	cotton	canopy temp
Penuelas *et al*		Water Index (WI)	R900/R970 (or nearby trough)	Trees, shrubs & grasses	Plant water concentrations
NA		Designated Water Absorption	R1000		
Kakani *et al*	2007	Kakani	R1689/R1657	cotton	LWP
Hardisky *et al*	1983	NDII (Normalised Difference Infrared Index)	(R850-R1650) /(R850+R1650)	Cord grass	Leaf moisture
Hunt & Rock	1989	MSI (Moisture Stress Index)	R1650 / R850	Trees, soybeans	LWC, RWC & EWT
YongChao *et al*	2005		R810 / R460	rice	Leaf and plant water content?
USQ GISlect10slide30		Designated water response	R1190 (trough)		

Notes: LWP = Leaf Water Potential, RWC = Relative Water Content, LWC = Leaf Water Content, EWT = Equivalent Water Thickness (of canopy)

Continued drought pressure and ever increasing fuel and fertilisers costs is threatening the viability of the Australian cotton industry. It is therefore hypothesised that through remote sensing technologies a more accurate prediction of crop variability can be made including the causal agent through coordinated agronomic assessment and the extent in which it occupies. By understanding this, growers and agronomists alike can make informed management decisions on how to limit productivity costs through targeted irrigation scheduling and fertiliser applications etc. whilst maximising productivity.

Commercial practices and current guidelines for irrigation scheduling based on plant measured parameters are currently limited to LWP measure taken on the top fully expanded leaf (Browne, 1986; Meron *et al.,* 1987). Unfortunately previous work conducted in cotton (Bowmann, 1989; Wanjura & Upchurch, 2004) comparing radiometric data was conducted in cotton subject to a wide range of soil moisture deficit and resulted in measures of LWP taken far outside the normal range of fully irrigated crops (severe stress). Work conducted by Bowmann (1989) on detached leaves under progressive dehydration was highly correlated, but is only of limited value for use in commercial

scheduling. Therefore, there are still considerable research opportunities to improve the spatial and temporal resolution of agro ecological parameters such as LWP by developing algorithms to increase the spatial resolution of reflectance data derived from satellite images using same/other-sensor high resolution multi-spectral images (Gowda *et al*., 2008a). In this study multispectral satellite imagery, field spectroscopy and Greenseeker sensors were assessed to determine their ability to identify the spatial variability in cotton crops and predict specific growth constraints of economical importance. Specific wavelengths correlated with LWP were also determined from the statistical analysis of radiometric hyperspectral data.

2. Methodology

2.1 Sites

Trial site 1 was located near Brookstead on the Darling Downs in south-east Queensland. 27°41'21.15"S and 151°25'49.46"E. The site was part of a cotton nutrient emissions trial conducted by Incitec and QUT. The site was irrigated by a 6 x 45m span lateral move irrigator with application socks on 2m spacing's and soil moisture monitored by DPI&F Dalby. Cotton (Sicot 71BR) was planted 19/10/2007 and harvested on the 16/5/2008 with average yield of 9bales/ha. Four irrigations were applied on: 17/01/08 (50mm), 25/01/08 (50 mm), 7/03/08 (50 mm) and 14/03/08 (42mm).

Trial Site 2 was located near Cecil Plains on the Darling Downs in south-east Queensland. 27°35'57.70"S and 151°15'33.98"E. The site used was part of a CSD cotton variety trial assessing 6 varieties in 16 rows per variety across 2 replicates and 8 rows per variety across a further 2 replicates. Following a heavy application of manure in winter 2006, cotton was planted on the 17/10/2007 at a rate of 13 kg/ha resulting in 9-11 plants per linear metre. It was harvested 03/5/2008. Furrow irrigations and rainfall dates for the cropping season are shown in Figure 1. CSD reported yields from 11-14bales/ha across the varieties, however there was a ~3bales/ha difference between the top and bottom of the field across the trial.

2.2 Satellite Imagery

During the post December growth phases cloud cover severely limited the number of images available for analysis. Imagery for the Cecil Plain's site was unavailable due to cloud cover. Quickbird (QB) imagery near Brookstead was captured on the 9th of March, 145 days after planting (DAP) (Figure 9). The QuickBird sensor provides 2.4 m spatial resolution imagery in the visible (blue 450- 520nm, green 520- 600nm and red 630- 690nm) and infrared (IR 760- 900nm) bands as well as an additional 0.6m panchromatic band. The geometric accuracy error of the corrected satellite imagery is 23m circular and 17m linear, however this can be improved through further image warping with non-differential/differential GPS control points. Images have a radiometric precision of 11 bit.

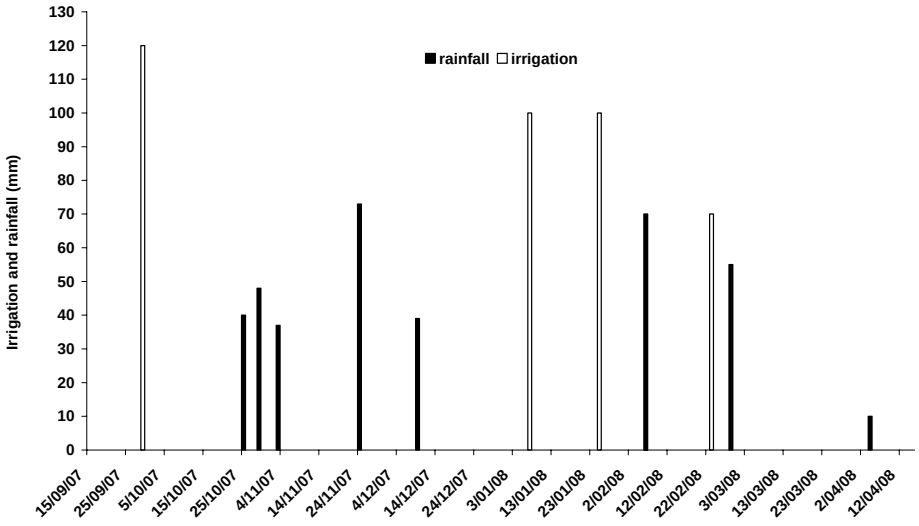

Figure 1. Rainfall and irrigation dates and volumes for the 2007/2008 cropping season near Cecil Plains.

2.3 Greenseeker NDVI

The Greenseeker (GS) (NTech Industries) NDVI data was collected on the 5th of March (141 DAP) with no extreme weather events occurring between the dates, however an irrigation of 50mm was applied on the 7/3/08 between the two capturing events. The high clearance machine was fitted with four sensors mounted one metre apart, 70 cm above the plant row and each covering one cotton row. The GPS receiver was positioned between the second and third sensor. Using the heading reading and the single GPS coordinates the position of all four sensors was able to be calculated. The machine moved very slowly (~5 kph) when collecting the data which resulted in several repeat values for the same point due to the GPS coordinates not changing as often as the output from the GS. These values were averaged so there was only one NDVI value for each point. Four swaths were completed with the GS sensors (Figure2). This equated to about 2 hectares over 6000 data points once averaged as discussed above.

The GS sensor measures incident and reflected light from the plant at 660 ± 15 nm and 770 ± 15 nm. In this case, energy is emitted from separate diodes in alternate bursts such that the visible source pulses for 1msec and then the near infrared (NIR) diode source pulses for 1 msec at 40000 Hz. Each burst from a given source amounts to ~40 pulses before pausing for the other diode to emit its radiation (another 40 pulses). All reflected radiation is measured by one detector. The illuminated area is ~60 by 1 cm, with the long dimension typically positioned perpendicular to the direction of travel. The field of view is approximately constant for heights between 60 and 120 cm above the canopy because of light collimation within the sensor. Outputs from the sensor include NDVI, visible/NIR, IR /Visible, Soil adjusted-NDVI and Wide Dynamic Range-NDVI.

Both the image and point data were loaded into a GIS. The point data obtained from the Greenseeker unit was overlaid upon the QuickBird image. Where the GS data points intersected the QB image the value of the red and near-infrared band was added to that point. Following this the

NDVI formula was able to be applied to these values as shown in the attribute table (Table 2). Using this method NDVI derived from GS and QB were able to be compared.

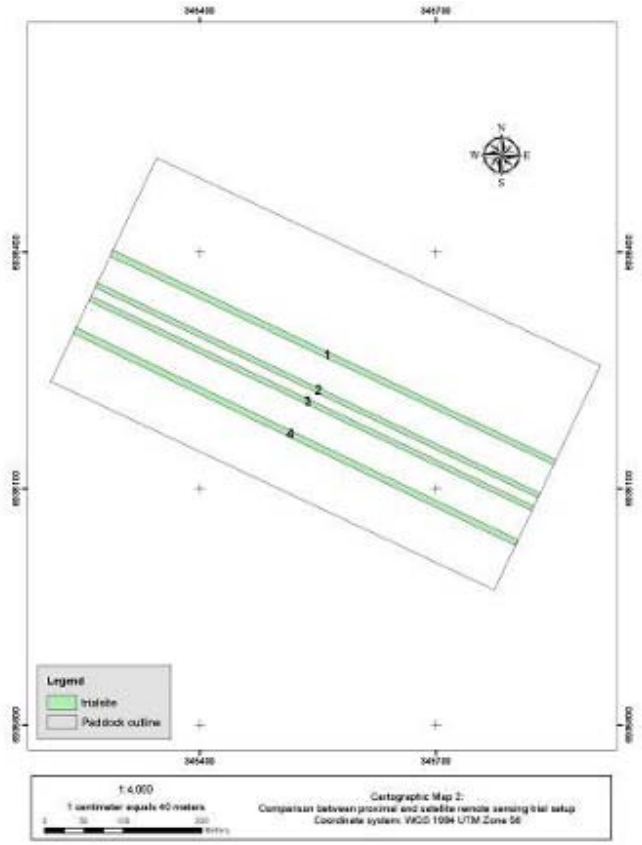

Figure 2. Swath paths taken by the Greenseeker Ground rig at Brookstead.

Table 2. Sample data from point attribute table. Initially point data from GS, QB red and NIR bands have been extracted from image allowing calculation of QB NDVI and furthermore comparison of results.

NO.	GS NDVI	X	Y	QB red	QB NIR	QB NDVI
12	0.33	151.4306193	-27.6886566	64	134	0.353535
13	0.232	151.4306196	-27.6886595	65	131	0.336735
14	0.855	151.4306199	-27.68866181	65	131	0.336735
15	0.272	151.4306203	-27.68864292	41	189	0.643478
16	0.32	151.4306204	-27.6886527	64	134	0.353535
17	0.284	151.4306208	-27.68865682	64	134	0.353535
18	0.124	151.4306214	-27.68866921	63	131	0.350515

2.4 Proximal Radiometric Sensors

Two devices were used during the 2007/2008 season:

1. Hyperspectral FieldSpec® 3 from Analytical Spectral Devices (Boulder, Colorado) (ASD) is the industry standard for a wide range of challenging remote sensing/earth science applications, with high resolution over a 350nm - 2500nm spectral range.
2. Multispectral ASD FieldSpec® Handheld spectroradiometer measuring from 350nm to 1075nm range.

Spectral measurements were taken on various dates within the two sites. On each of the measurement dates, a range of individual plants were measured at 20cm above the top of the crop canopy to ensure a 'pure pixel' field of view (FOV) was achieved. The reflectance measurement of a 20 cm area of growing leaf also ensured negligible background interference, such as from soil was not collected. During the setup and initialisation of the spectrometer, you 'optimise' based on current sunlight levels and by a reflectance measure of a 'white reference' disc. This white reference disc is assumed to reflect 100% of the incoming light and therefore subsequent readings from the cotton canopy are a fraction of the light reflected off the white reference disc and expressed as a reflectance value for each wavelength between 0 and 1.

Re-optimisation and measurements of the white reference needs to be carried out at regular intervals during measurements if there are changes in the incidence of sunlight. There were continual changes in incidental light as not all measurement where conducted on clear, cloudless days between 12 and 2pm and therefore continual re-optimisation was required, often between measurements. Coincident measurements of a Spectralon panel were used to convert the radiance measurements from the growing leaves into reflectance, by providing an irradiance value. The use of a calibration target also ensured spectral 'noise' errors such as those associated with atmospheric attenuation did not influence the data. However atmospheric interference over the sampling period caused considerable postponements and rendered considerable data unusable.

The radiometric output from both the multispectral and hyperspectral devices was used to determine the listed indices and wavelengths (Table 1) to find a correlation with LWP under the conditions found at the two trial sites.

There is often considerable spectral 'noise' from ground based sensors due to the proximity of the sensor to the canopy and the effect of water vapour in the relative small intervening space. Figure 4 provides an example of the noise around the wavelengths of 1400, 1900 and 2400nm. This reflectance data >1 and < than zero was arbitrarily removed (Figure 5) prior to analysis for all data sets, including that from the preceding project of White and Raine (2008).

The Unscrambler® ver (9.2) is a complete multivariate analysis and experimental design software solution, equipped with powerful methods including, Multivariate Curve Resolution (MCR), Partial least squares (PLS) Regression, 3-Way PLS Regression, and Clustering (K-Means) etc. The Unscrambler® has become an accepted tool for this purpose because this program offers the most efficient and flexible approaches to evaluate continuous spectral data in terms of qualitative discrimination and quantitative determination of responses to plant and soil water status.

All reflectance data was smoothed using a Savitzky-Golay 2nd derivation, with a smoothing interval of four wavelengths to the left and 4 to right of each wavelength. A second polynomial - analysis

was conducted with PLS_R where the difference in spectra from each sample is assessed in terms of the variable (y) being measured (LWP). In 2007 Unscrambler® was unavailable to analyse previous work conducted by National Centre for Engineering in Agriculture (NCEA) (White and Raine, 2008). Therefore at the completion of the 2007/2008 cotton season the multispectral LWP relationship gathered in 2007 was reanalysed and included in this report.

Analysis using Unscrambler was conducted on combined and individual site data sets, under three scenarios:

- Firstly all data from the previous project and the current project were analysed separately and then collated for an all data correlation.
- Secondly, individual site data (Cecil Plains and Brookstead), regardless of sampling date, were collated and analysed using Unscrambler.
- Finally all data from the 2008 season was combined for simple linear analysis using MS Excel®

2.5 Leaf Water Potential

Pressure chambers (e.g. Scholander pressure chamber) are devices used to measure leaf water potential (i.e. how much tension/suction force is being exerted by the plant on its water supply due to evaporative demand and soil moisture availability). To measure leaf water potential, a plant sample (e.g. stem or leaf) is placed into a chamber and a pressure applied until moisture is exuded from the plant material. The pressure at which moisture is extruded from the plant material is termed the "endpoint" and the water potential of the plant material is reported as the negative of the endpoint pressure applied to the chamber. Leaf water potential is normally reported in measurement units of -Bar or -MPa (note: 1 Bar = 0.1 MPa = 100 kPa).

Midday measurements of plant water status (limited to clear days only) will give the lowest leaf water potential (negative value) a plant is exposed to as evaporative demand peaks at or soon after solar noon, typical midday tensions in the xylem (Ψ_p of –1 to –2MPa) Values over 2.4MPa in this study were excluded as being outside the normal range as observed by Bahatteri *et al* (2005) when replacement irrigating at 50% of daily ET. Accuracy and repeatability of measurements is a function on consistence in measurement procedure and uniformity in size, shape, orientation, age and position of leaves sampled. Upon cutting an appropriate leaf it was placed in an envelope inside a dark, humid, insulated box. Measurements were conducted on 20 leaf sample sets within 40 minutes of cutting.

2.6 Data smoothing

Considerable spectral 'noise' was often found in ground based sensors. Figure 4 provides an example of the noise around the wavelengths of 1400, 1900 and 2400nm. Figure 5 provides an example of reflectance data >1 and < than zero that was arbitrarily removed.

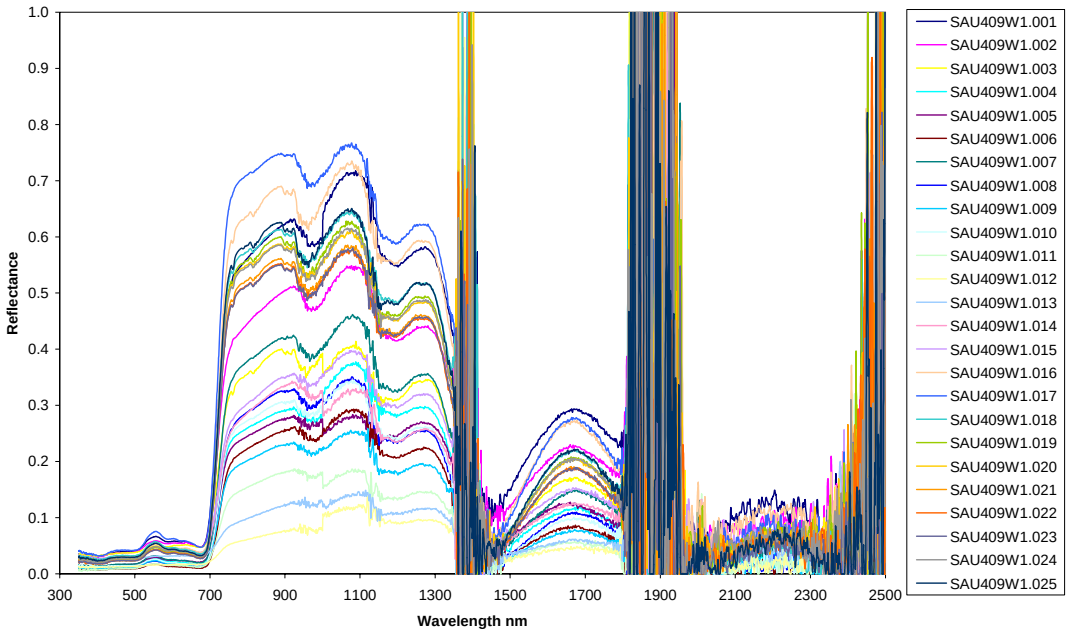

Figure 3. Example of a Hyperspectral data set that displays considerable noise in the 1400nm, 1900nm and 2400nm range.

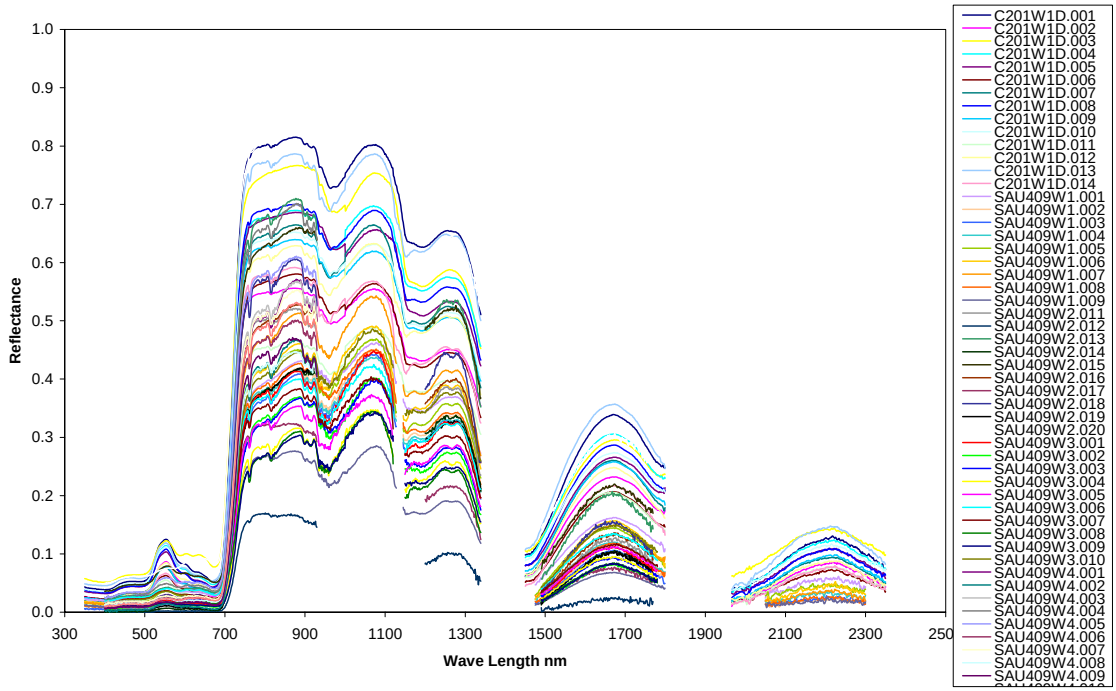

Figure 4. Example of an Hyperspectral data set with the noise in the 1400nm, 1900nm and 2400nm range arbitrarily removed prior to analysis with Unscrambler.

3. Results

3.1 Analysis of hyperspectral data from the 2007 season

Figure 5 shows the output of the unscrambler analysis of the 2006/2007 data as reported by White and Raine (2008) previously. Figure 5a describes the distribution of samples across the first (x-axis) and second (y-axis) principal component axes with 71% of the spectral variance explained in terms of y or LWP. Figure 5b identifies those wavelengths (x-axis) with significant (black circles) regression coefficients in explaining the LWP prediction model. The nominated wavelengths in Figure 5b generally correlate with chlorophyll 540, 685 and the 'red edge' 768nm, but it was noted that 810nm had a significant regression coefficient. Figure 5c identifies that most of variance in predicting a LWP spectral model can be explained by the first two principal components where these two principle components are not clearly identified. Figure 5d shows the correlation between the measured LWP with that of the predicted value using the spectral model. Therefore the correlation of the calibration model is 0.7, with a RMSEP (root mean square error of prediction) of 0.22 (this is a real number in the same units as those used for LWP and not a %).

This confirms that there were indeed multi-collinearity effects identified in the previous report that elevated the R^2 values and the statistical significance of individual indices and particular wavelengths. The previous report cited R810 as having an R^2 of 8.6% with non significant correlation, when in fact, once the spectral noise was removed, it had a significant regression coefficient with measured LWP. Generally, numerous wavelengths were identified in the unscrambler analysis citing a spectral model to explain the measured LWP (Figure 5b).

Field measurements were attempted at Brookstead and Cecil plains sites on numerous occasions, however sampling windows through the solar noon period were short due to highly variable or inappropriate sunlight conditions for optimum operation of passive sensors. Successful data acquisition that provided comparative data sets between radiometric and leaf water potential measurements occurred on 24 January, 1 February, 9 April and 16 April 2008. Comparative data sets for GS NDVI, Radiometric spectra and LWP was only gained on one occasion on the 9 April 2008. A complete set of data layers sampled on the same date from Satellite imagery, GS NDVI, handheld radiometric spectra and leaf water potential was never achieved. QB NDVI and GS NDVI were sampled on the 9th and 6th of March respectively at Brookstead, but were separated by an irrigation event of 50mm on the 7th March. QB imagery was not available for the Cecil Plains site.

3.2 Satellite imagery and GS NDVI

Brookstead

Initial analysis of March 2008 results showed that one of the Greenseeker (GS) sensors results were consistently lower than the others. This was explained by a malfunctioning cable, so all data collected by this sensor was removed so results were not hindered by a technical fault. Histograms at the points of the GS data points were created for the QB red and NIR band. Furthermore, histograms of the GS and QB calculated NDVI were also produced (Figure 7). The red band was slightly skewed, but close to a normal distribution. In comparison, the NIR band was not normally distributed with almost all of the values being 255, in a range from 0-255. This is a result of saturation in the NIR band of the QB image. This is not uncommon with extremely high biomass areas (A. Robson 2008 Pers. Comm., 17 June).

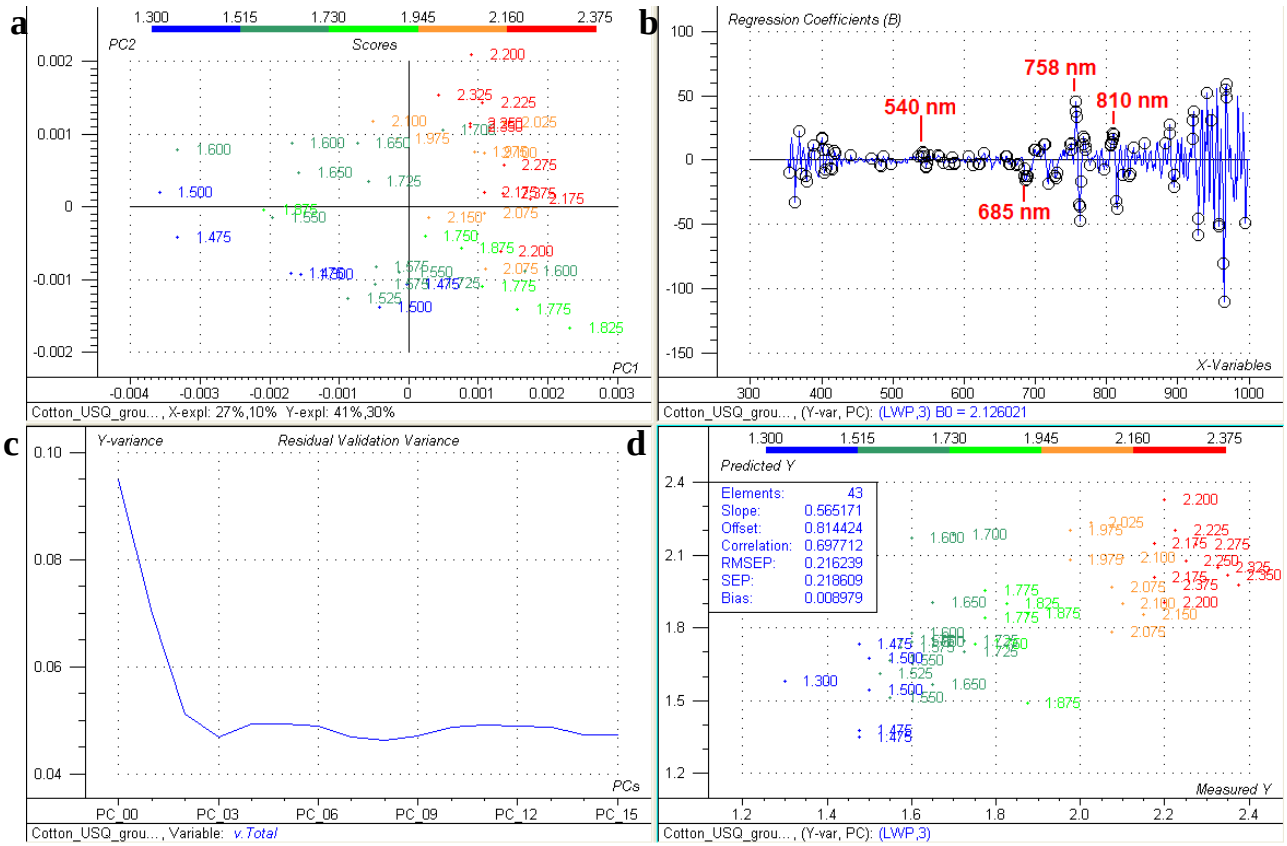

Figure 5. Unscrambler analysis of the relationship between radiometric spectra and LWP from the 2006/2007 cotton season (a) distribution of samples across the first and second principle components, (b) significant regression coefficient of wavelengths, (c) variance in predicting LWP, and (d) correlation between the measured LWP with that of the predicted value using the spectral model.

Despite the NIR saturation, it was still valid to test NDVI as it uses both the red and NIR bands and exploits the differences between them. Since the red band was normally distributed it resulted in the QB NDVI being normally distributed also, despite the saturated NIR band.

A scatter plot was produced showing GS verses QB calculated NDVI (Figure 7). The aim was to be able to create a regression or similar to enable conversion of GS data to a QB NDVI equivalent or vice versa. A secondary aim (if high correlation) was to see if there was any extra value in the higher spatial resolution capable from ground sensors over the QB imagery. Unfortunately, there was no strong correlation between these two different sources of data, which meant our secondary objective could not be achieved. A linear regression resulted in an R^2 of 16%. According to the scatter plot (Figure 7) a large number of high range GS values were grouped together and similarly for the low range GS values with a large amount of variability were grouped.

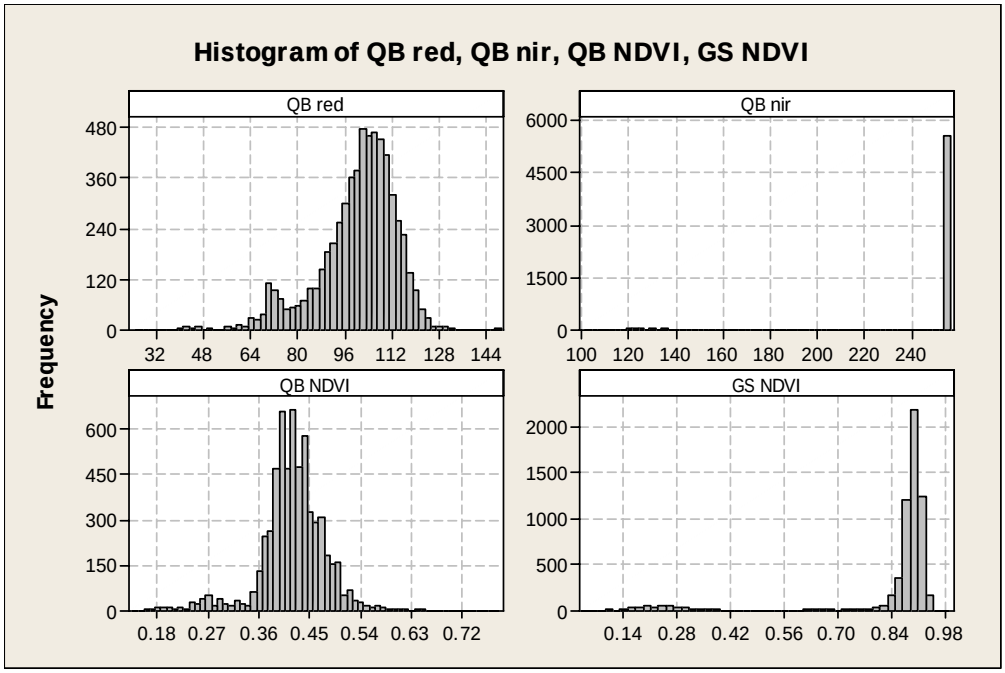

Figure 6. Histogram of relevant QB bands at GS points and GS and QB calculated NDVI.

Some points in this data set (low range) were collected over bare or low biomass areas, for example when turning the machine around. These points were not excluded as it increases the range of values in the data set, which is especially important in such a uniform paddock with a completely saturated NIR band within the paddock. So the two visible groups in the scatter plot can be roughly described as 'in the paddock' (Group 1) and 'edge of the paddock' (Group 2). If these groups were separated out, i.e. edge of paddock excluded, there was no increased correlation. However Figure 8 was produced by excluding the low biomass areas to highlight the subtle differences in crop vigour over the field. These being the northwest quadrant and the "H" pattern in the Southwest end, most probably relics of previous trial work and anecdotal incidence of Fusarium wilt.

These results suggest that the GS sensors produced an exaggerated result in comparison to the QB image. This is based on the observations of the high value group (Group 1) which indicate that GS NDVI ranged between 0.8 and 0.95, whereas the QB NDVI range for that same group ranged from 0.35 to 0.55. It is important to remember that this scatter plot contains over 6000 samples. Most of these values lie in group 1. The distribution of values is also spread out more with the QB NDVI than GS sensor as can be seen in the histogram (Figure 6) and scatter plot (Figure 7).

The QB and GS maps Figures 9 and 10 respectively failed to detect any considerable difference in varietal/nutritional performance or plant stress in the areas in which they overlap. However the QB NDVI image appears to indicate an area of marginally increased vigour (0.2) in the north western quadrant of the field. The field was irrigated 2 days prior to the QB image being taken, therefore it could be expected that image would not tend to indicate large differences. Generally because the variance was relative to the rest of the image and as the whole IR image was saturated, it appears extremely good growth was seen throughout which may account for the higher overall vigour (NDVI) measurement captured by the GS. Unfortunately there wasn't any other ground based radiometric or plant based data taken on the same day to make any comparison with this QB NDVI

data and an irrigation event between these two sampling times only led to confounding the comparison of the two NDVI data layers available.

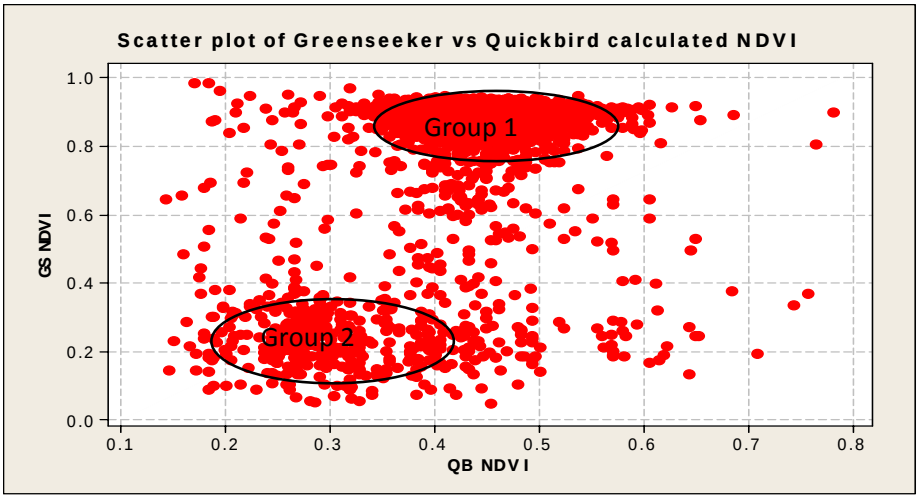

Figure 7. Scatter diagram of GS NDVI verses QB calculated NDVI at GS points, illustrating the the groupings of particular data points associated with large biomass readings and areas of limited biomass readings.

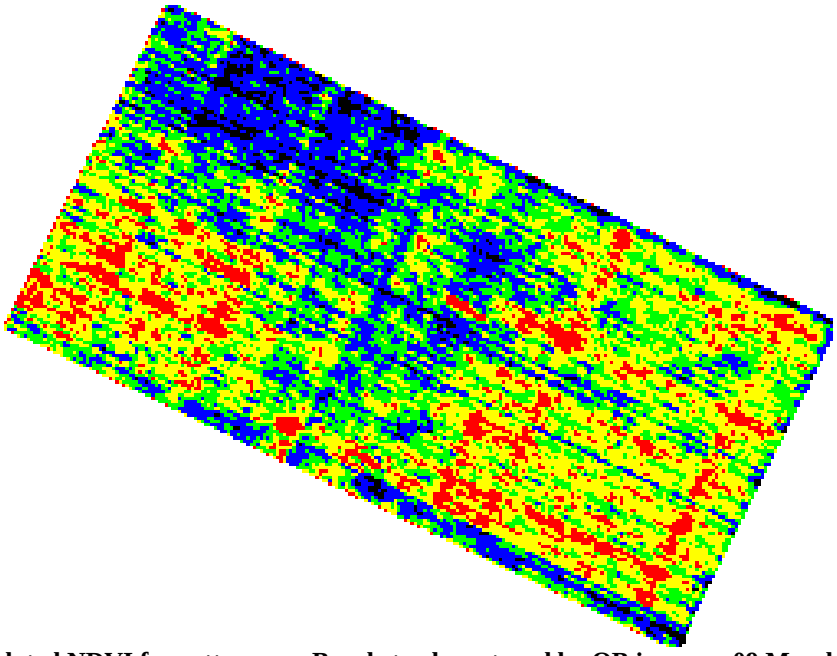

Figure 8. Calculated NDVI for cotton near Brookstead, captured by QB imagery 09 March 2008. The colour range has been modified to highlight the very subtle changes in crop vigour. The "H" patterns may be relics of previous trial sites.

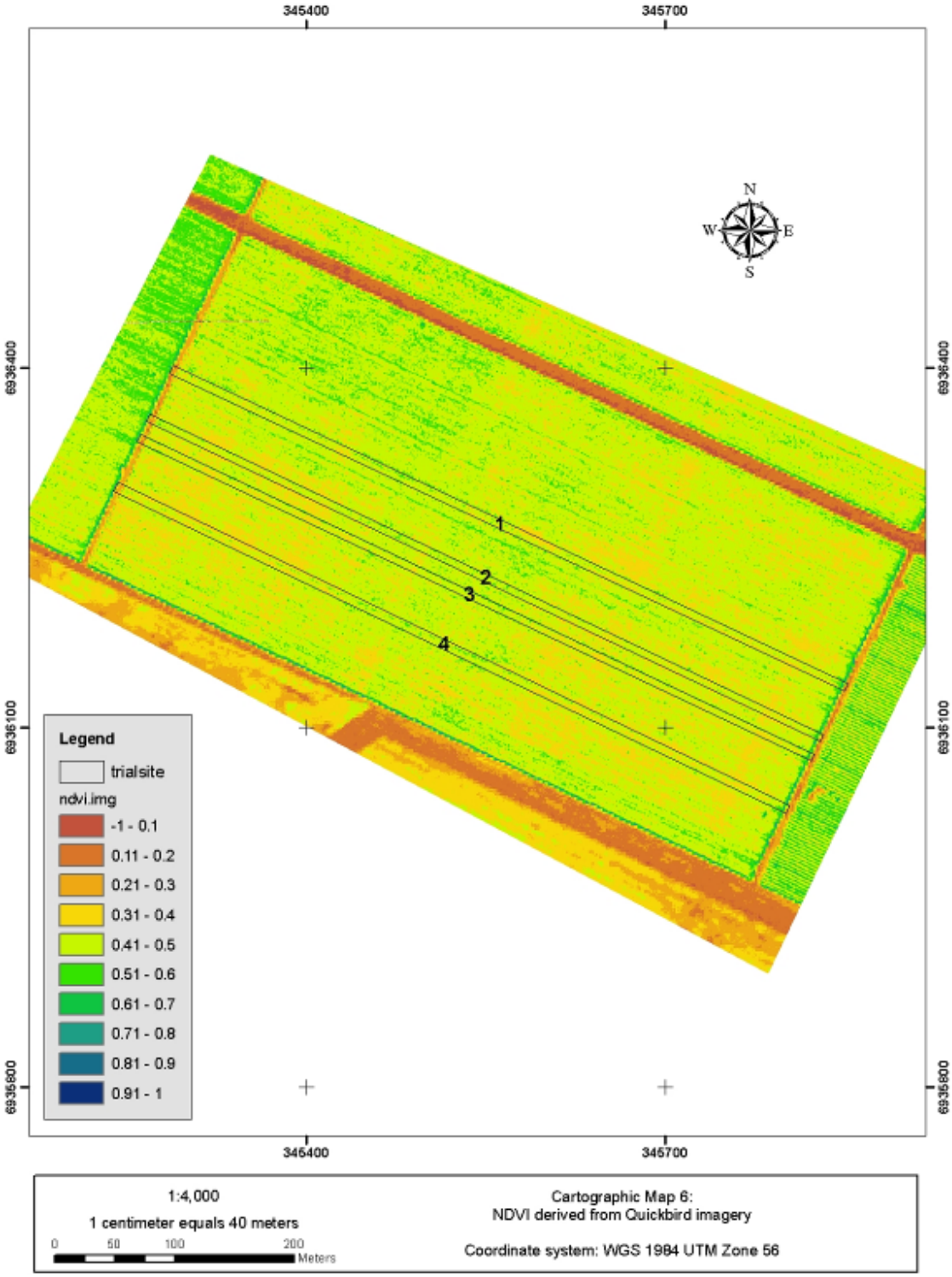

Figure 9. Calculated NDVI for cotton near Brookstead, captured by QB imagery 09 March 2008. Also displaying an overlay of Greenseeker runs made on the same day.

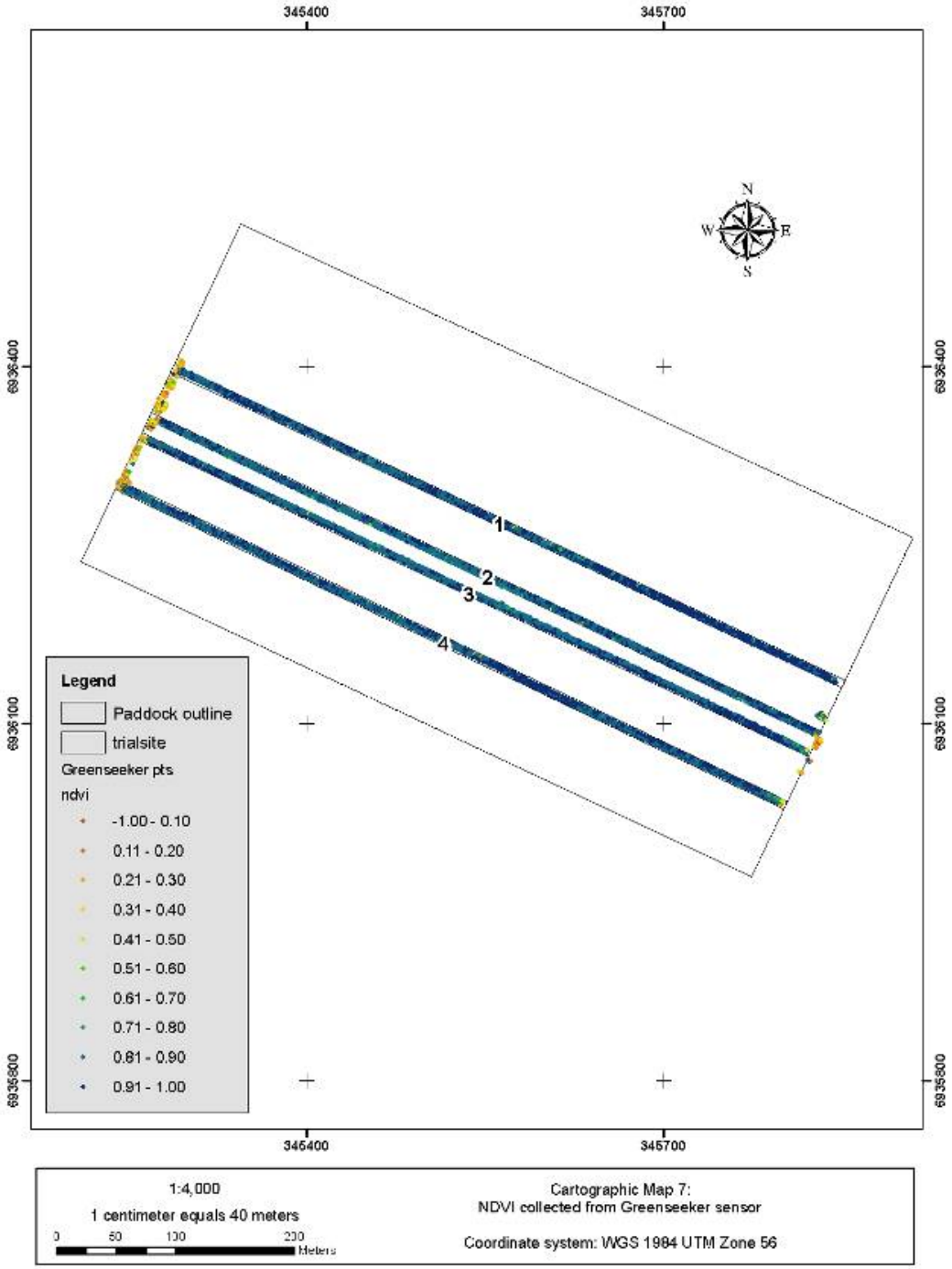

Figure 10. Greenseeker NDVI of cotton near Brookstead, taken 05 March 2008 by 4 individual sensors in 4 passes.

3.3 Proximal Radiometric Sensor analysis

2008 data

There were no significant correlations between previously published indices or wavelengths and leaf water potential at either site for any date whether analysed separately or lumped (all data). Slopes of relationships at individual sites on the same dates were shallow and with very low R^2 values when

evaluated over the range of leaf water contents in which physiological activity occurs (irrigated range). Table 3 summarises the correlations the lumped 2008 data with the various indices. The highest correlation between reflectance and LWP at a wavelength of 2210nm was 18%, closely followed by R750; R810 and R880 at 15 and 14% respectively (Table 3). Figure 11 demonstrates the very low correlation for the individual dates and sites and for lumped 2008 (all) data.

Table 3. Radiometric indices and individual wavelengths used for the estimation of plant water status in cotton and other crops and their relationship with measured LWP of cotton measured during the 2007/2008 cotton season near Brookstead and Cecil Plain.

Author	Indices	Formulae or wavelength	Relationship to LWP (R^2)
Bajwa (2007)	NDVI	(R810-R660)/ (R810+R660)	0.00
Bajwa (2007)	GNDVI	(R810-R550)/ (R810+R550)	0.03
Wanjura (2004)	(1)R750, (2)R880	(1)R750, (2)R880	0.15 0.14
Bowman (1989)	(1)R810, (2)R1665, (3)R2210	(1)R810, (2)R1665, (3)R2210	0.15 0.07 0.18
Penuelas *et al* (1993)	Water Index (WI)	R900/R970 (or nearby trough)	0.04
NA	Designated Water Absorption	R1000	0.04
Kakani *et al* (2007)	Kakani	R1689/R1657	0.01
Hardisky *et al* (1983)	NDII (Normalised Difference Infrared Index)	(R850-R1650) /(R850+R1650)	0.05
Hunt & Rock (1989)	MSI (Moisture Stress Index)	R1650 / R850	0.06
Tian YongChao *et al* (2005)	Vegetation Index Ratio	R810 / R460	0.00
USQ GISlect10slide30	Designated water response	R1190 (trough)	0.03

Reflectance at 810nm previously used by Bowman, (1989) as an example, Figure 11, demonstrates that reflectance did not vary independently ($R^2 = 0.15$) as a function of leaf water potential. However there appears to be a varietal effect on LWP for those cotton varieties (C409-W1 to C409-W4) sampled on the same date, 9/4/2008 (Figure 12). Where W1 tended to be clustered between 20 and 24 bar, W2; between 18 and 22 bar, W3; between 17 and 22, and W4; between 14 and 18 bar. These LWP clusters tended to coincide with the yields of the particular varieties at the Cecil Plains site. ie W3 (lower LWP) achieved a higher yield than W1 and W2.

Yield data was not available for W4. The 09 April 2008 GS NDVI map of the Cecil Plains site (Figure 13) clearly shows increased vigour in W3 compared to that of W1 and W2. This NDVI map

clearly differentiates a vigour differences between the top and bottom of the field across the all varieties. According to the local agronomists this was indicative of the 3 bale/ha yield difference between the top and bottom of the field. What is also clear is that the handheld radiometric device measurements taken in W1–W4 on the same date at Cecil Plains (Figure 11) are in general agreement with the GS NDVI values sampled in the southern end of the field. The clustering of LWP values, as mention previously, is in similar with the information observed in the Greenseeker data, in that the lower the LWP values the higher the NDVI vigour values. This data, although just one point in time, was mirrored in the yield data, which were 10.73, 11.13, and 12.45 bales/ha for W1, W2, and W3 respectively.

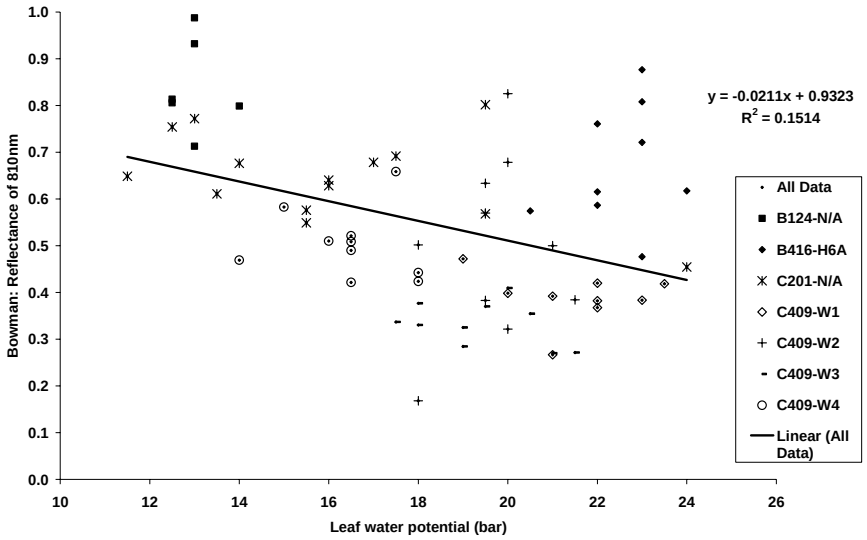

Figure 10. The relationship between reflectance of 810nm (Bowman, 1989) and LWP for all data gathered at Brookstead and Cecil Plains during the 2007/2008 cotton season

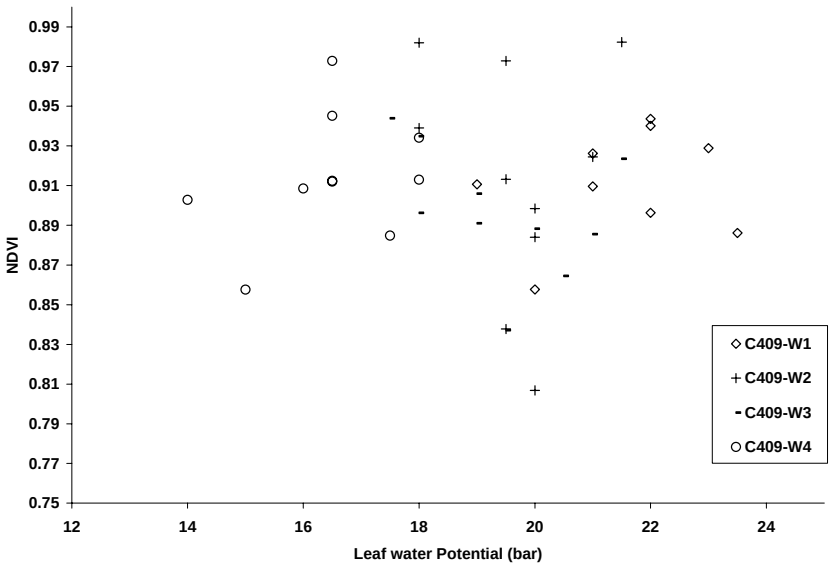

Figure 11. Handheld multispectral NDVI and its relationship to LWP of the Cecil Plains site for the W1–W4 Varietal 8 m wide zones taken on the 9 April 2008, 39 days after substantial rain.

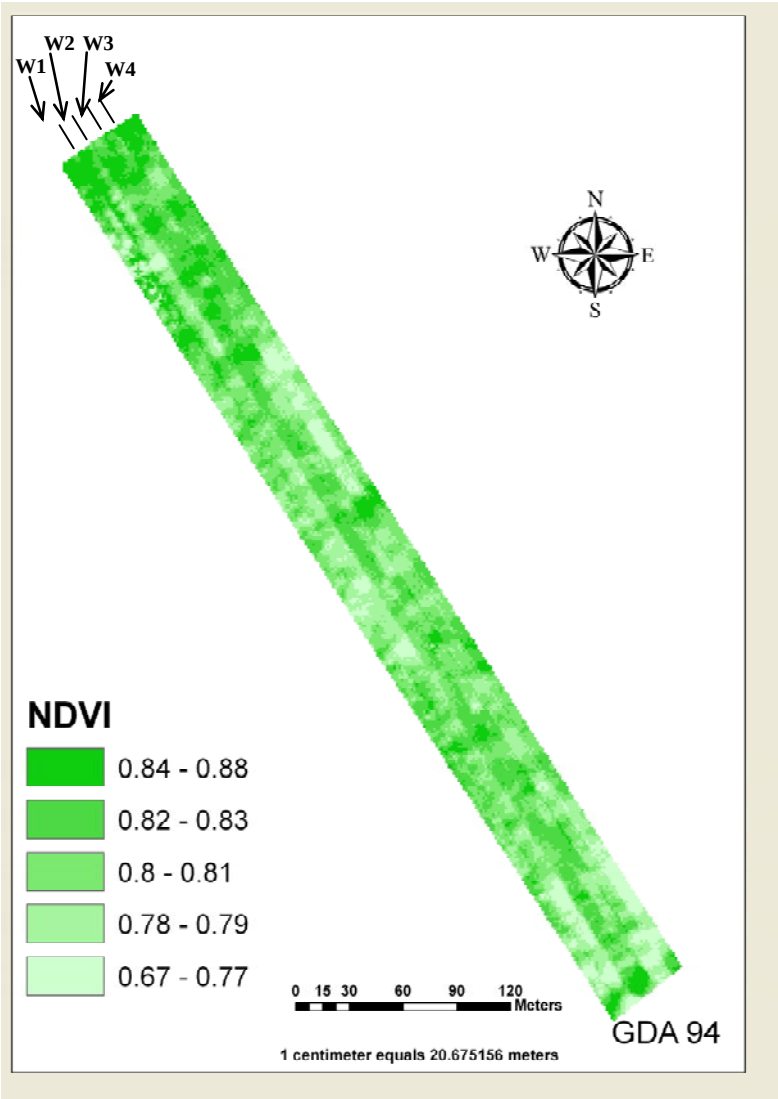

Figure 12. Greenseeeker NDVI of the Cecil Plains site for the W1–W6 Varietal 8m wide zones taken on the 9 April 2008, 39 days after substantial rain.

To visualise the relationship between radiometric spectral data and LWP the data from the preceding project and that of the 2007/2008 cotton season was combined for those published indices and wavelengths used previously. There was no increase in correlation against any indices or wavelengths. The relationship between R810 nm and LWP was used as an example and is indicative of the very low correlation and R^2 values (0.15 in both studies) (Figure 14).

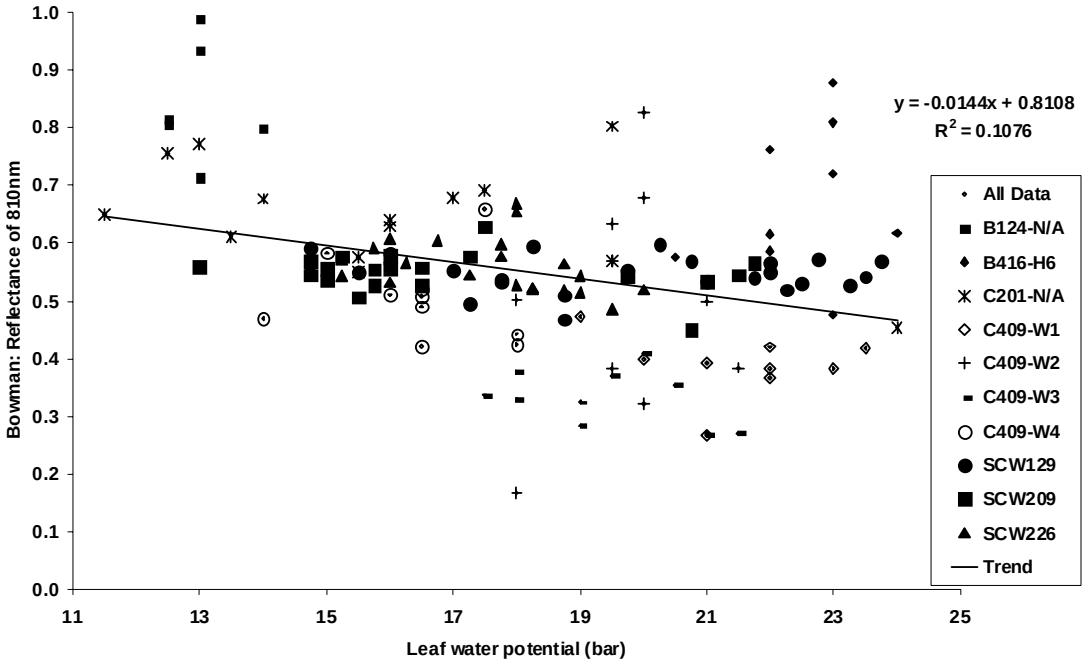

Figure 13. Combined 2008 and 2007 cotton season data describing the relationship between R810nm and leaf water potential

4. Discussion

4.1 Satellite and Greenseeker

The averaging method of points as described in the method may need to be revised as critical points may have been averaged out. It works out to be the average of an area less than 1m, so if the overall process was successful a high correlation between GS and QB derived NDVI should still exist. However, a more accurate GPS system with RTK 2cm accuracy would allow every single data point from the GS to be accurately mapped. This would also require a more accurate method of geo-referencing the image to the GS points, but is very necessary to accurately position identifiable objects in the image.

The study may have been more effective if the field had a higher biomass variation. As the image was taken late in the season of an irrigated crop the canopy had closed in and all the plants across the paddock seemed healthy, according to the image. However there was considerable anecdotal and observed evidence of large areas (>2m^2) effected by fusarium wilt, that is not apparent in this image. The GS also did not recognise these low biomass areas, but considerable interference from the faulty sensor may have contributed to the apparent NDVI saturation.

Another consideration is the height of the GS sensor. Considering the overall high value and less distributed GS NDVI points when compared to the QB derived values the sensors may have been too close to the crop, less than 60cm (T. Neale 2008 pers. Comm., 18 July). In other situations (especially commercially) the area seen by the sensor is much greater, which would give an overall

smaller spatial resolution, but a better indication of crop biomass, which may have contributed to a small degree.

NDVI has the limitation that it saturates asymptotically under conditions of moderate-to-high aboveground biomass (LAI greater than 2) (Gitelson et al., 1996; Miyneni et al, 1997). While reflectance in the red region (ρred) exhibits a nearly flat response once the leaf area index (LAI) exceeds 2, the near infrared (NIR) reflectance (ρNIR) continue to respond significantly to changes in moderate-to-high vegetation density (LAI from 2 to 6) in crops. However, this higher sensitivity of the ρNIR has little effect on NDVI values once the ρNIR exceeds 30%. Gitelson (2004) proposed a modification of the NDVI, the Wide Dynamic Range Vegetation Index, WDRVI = (a * ρNIR–ρred)/(a *ρNIR+ρred), where the weighting coefficient a has a value of 0.1–0.2. In a recent study Viña *et al* (2004), demonstrate how WDRVI increases sensitivity in moderate to high vegetation stands when compared with NDVI, which may be useful in future comparisons of remote and proximal NDVI sensing of full canopy cotton.

Active sensors like the Greenseeker also measure reflected light from crops much like passive sensors (ASD Hyperspectral). The main difference is that active sensors produce their own source of light, and therefore, are independent of time of the day and light intensity. However there are some limitations associated with active sensors 1) sensitivity to distance to the target that affects reflectance, 2) low energy when compared with sunlight, which may affect the number of layers penetrated, 3) the field of view and 4) the rate at which each sensor acquires information also varies among commercially available active sensors. When working with satellites and airborne imagery the impact of variation in distance between source and receiver is not important. However, if working with ground based mounted sensors where oscillations around 10 cm in canopy height and or oscillations in sensor height are expected, we need to identify whether a low value is due to low crop vigour or variations in sensor outputs.

Values from individual bands decrease as the distance between the sensor and target increase, therefore positioning the sensor closer than 60 cm significantly increases the dependence on distance. The reality of the situation is that both NIR and red reflectance increase as distance between the sensor and canopy decreases. The situation with active sensors is that it does not take very much vegetation to absorb all of the red light emitted. As such, fluctuations in visible light reflectance are much more likely to be caused by changes in the distance between the sensor and target than by changes in chlorophyll status (Solari, 2006). Based on these results, a reasonable distance window for ground sensors is probably between 80-110 cm. however it is important to note that vegetation indices involving a ratio of reflectance values (i.e. NIR/amber) are largely immune to the effect of distance between the sensor and target, but reflectance data from the individual bands are not. Therefore when measuring NDVI with the GS at the Brookstead site distance to canopy was not an issue although fluctuations in canopy height >10cm may have occurred. The data acquisition was erroneous most probably through a mechanical fault. Once it was repaired subsequent use on full canopy cotton, late in the season at the Cecil Plains site, the sensors produced data that fitted with other agronomic information and observations. It was unfortunate that other satellite imagery was not available for ground-truthing.

4.2 Spectral water bands

The use of published 'water bands' as predictors of cotton plant water potential properties (leaf water potential) are not suitable (White and Raine 2008). Even using analytical methods previously not available only one individual wave band (R810) was identified that could explain some of variance in measurements. However the variability could be explained by a 15 parameter spectral model, which is not practical for field application, when a simple response curve is required to schedule irrigation events. Measurements conducted in this study using these same wavelengths did not correlate well with LWP and nor did those wavelengths >1075 nm that were analysed. Even when considerable care was taken, as to only analyse data from those moisture conditions within a normal irrigation range, correlation was not improved. The majority of measurements taken in the 2007/2008 season were taken during the last 3 months of cotton maturation and therefore correlation between reflectance and LWP may have been affected by individual leaf age, leaf senescence, plant structure and that the plants had ceased active growth.

NDVI is based on the red and near-infrared bands, which are located in the strong chlorophyll absorption region and high reflectance plateau of vegetation canopies respectively. Therefore, NDVI represents chlorophyll rather than water content (Gamon *et al*., 1995; Gao, 1996). Thus considering the majority of published wavebands used in this and the previous study it was unlikely that a correlation would have been found. A potentially better way of estimating vegetation water content (VWC) is to use indices based on the longer wavelength reflective infrared range (1240–3000nm), for example, the short-wave infrared (SWIR) reflectance (1300–2500 nm) (Chen *et al.*, 2005). It has been found that vegetation indices (VI) based upon NIR and SWIR are better than those employing VIS and NIR when retrieving leaf water content information (Ceccato *et al*., 2001; Gao, 1996; Serrano *et al*., 2000; Sims and Gamon, 2002). The SWIR (1640, 2130 nm) bands are water absorption dominated and as a result they are sensitive to VWC variations. Therefore a set of NDWI functions using the NIR and the SWIR bands would be a better alternative for VWC estimation after Chen *et al.*, (2005) would be a better alternative for the future:

$$NDWI_{1640} = (NIR_{858\ nm} - SWIR_{1640\ nm}) / (NIR_{858\ nm} - SWIR_{1640\ nm}) \quad (1)$$

$$NDWI_{2130} = (NIR_{858\ nm} - SWIR_{2130}) / (NIR_{858\ nm} - SWIR_{2130\ nm}) \quad (2)$$

A simple reflectance ratio, R1689/R1657, had a significant ($R^2 = 0.68$; $P < 0.001$) linear relationship with LWP under greenhouse conditions according to Kakani *et al.*, (2007). However further validation of this ratio is required under field conditions as there was no relationship found in this study.

5. Conclusions

The results of this study were inconclusive because of the limited data sets available to ground truth satellite imagery from multiple layers of proximal sensing and plant based measurements. Passive sensors (satellite and handheld) were severely hampered by poor atmospheric conditions and consistent variability in localised sunlight intensity. No significant correlations between published "water bands" and LWP were found in this study. Longer wavelength bands may be more suitable. The NDVI active sensor technology was able to identify varietal differences and varying yield responses under all climatic conditions encountered. However, ground rig speed, distance above the canopy and data point positioning information was found to be critical for mapping and comparison with other data sources.

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