

Field Trial Report (2006/07)



Optimising Irrigation Scheduling With the Use of Continuous 'Real time' Plant Monitoring Sensors

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1.0 Introduction

Crop water use and stress is not solely based on soil water potential or content (even though it is commonly used for scheduling) but is also influenced by the plant root density and extent as well as the atmospheric conditions imposed upon the plant (i.e. the evaporative demand). Hence, techniques which monitor the plant stress should provide additional benefits in identifying appropriate irrigation schedules. Measurements of leaf water potential (LWP) taken on the top fully expanded leaf of cotton plants have been used for irrigation scheduling (Browne 1986, Meron *et al.* 1987). However, these measurements are destructive and tedious so are more commonly used in research applications rather than commercial practice. Hence, there is a need to evaluate techniques to non-destructively measure plant water stress.

The 2005/06 field trial for this project involved a preliminary evaluation of stem diameter sensors (SDS). While the SDS data was well correlated with the soil capacitance probe data these relationships are expected to be affected by varietal and seasonal differences as well as crop conditioning. The 2005/06 trial also conducted some preliminary crop reflectance measurements using a handheld radiometer. Hence, there is a need to further evaluate SDS responses under different crop varieties and moisture stress conditions and further explore the potential to use radiometric plant sensing technologies for irrigation scheduling.

Relationships have been identified between both visible and near infra-red (NIR) reflectance of plant leaves and plant water status. However, radiometric research conducted in cotton (e.g. Bowmann 1989; Wanjura and Upchurch 2004) has typically used high soil moisture deficits which may be appropriate for evaluating stress in dryland crops but is inappropriate for irrigated crops (i.e. the measurements of LWP were far outside the normal range of fully irrigated crops). Bowmann (1989) also conducted the radiometric measurements on detached leaves under progressive dehydration which is only of limited value for use in commercial scheduling. Problems experienced in radiometric sensing under field conditions include background effects associated with difficulties in targeting the sensor field of view to include only the target plant component (e.g. leaf) and the loss of plant water content when leaves are destructively sampled. Hence, there is a need to identify radiometric sensing strategies which accurately observe the plant component without destructive sampling.

The recent development of vision based plant monitoring systems for cotton (e.g. McCarthy *et al.*, 2006; 2007) potentially enables the automated identification of the top fully expanded leaf (TFEL) in the field and provides the prospect that a radiometric sensor/camera able to observe appropriate wavelengths could be used to non-destructively measure the plant stress by targeting the TFEL. However, the ability to develop and implement such a system for irrigation scheduling in cotton is dependent on the identification of radiometric bands which are well correlated to LWP within the range of 'commercial' irrigation deficit strategies.

The aim of this project was to (a) evaluate SDS responses under different crop variety and moisture stress conditions and (b) identify temporally stable radiometric bands which adequately explain changes in plant water potential (within a 'commercial' irrigation range). The identification of these bands would potentially enable the development of a low cost radiometer (measuring up to a maximum of 5 bands) to be constructed. This would enable real-time irrigation control based on a sensing tool which is related to an industry accepted plant based measurement (i.e. leaf water potential). Hence, the specific objectives of this activity were to:

- Evaluate SDS responses under different crop variety and moisture stress conditions.
- Collect radiometric data over a range of dates in cotton subject to a range of soil moisture (and hence, LWP) conditions.
- Correlate radiometric data collected to previously know water bands and indices, stated as being well correlated to plant water content and plant water status (cotton and non cotton specific).
- Identify the proportion of the LWP variability which can be explained by changes in reflectance values in the VIS and NIR region (up to 5 parameters) under commercial irrigation LWP values.

2.0 Material and Methods

2.1 Trial Site and Management

An initial trial was established under a Bauer racecourse irrigator at ‘Macquarie Downs’ (S270 54.176°E1510 30.871) located between Leyburn and Millmerran. This site was established to enable the collection of intensive plant based sensor data. However, a violent storm passed over the field after the trial was established destroying the crop with hail and blowing the irrigator over into a tangled mess (Figure 1). The crop did not recover and the machine was left inoperable for the season. Consequently this site was abandoned.



Figure 1. Macquarie Downs trial site showing crop damage and irrigation machine down after storm

A second trial site was established on a commercial surface irrigated farm in the Nandi area near Dalby. This site was operated in collaboration with the Queensland Department of Primary Industries and Fisheries Rural Water Use Efficiency (RWUE) Initiative team. The 25 ha trial site consisted of commercial sized plots (32 rows each) sown to three cotton varieties and overlaid with three irrigation scheduling strategies. Eight buffer rows were sown between each irrigation strategy treatment to ensure that there were no effects associated with lateral water movement. At the grower’s instigation, a further 40 rows of single skip were

sown beside the trial area to compare the performance of solid with single skip. The varieties assessed were Sicot 71B, Sicot 80B and Sicot 43B (Sicot 80B was sown in the single skip). The three irrigation treatments applied were:

1. Early (Strategy A) – 80mm deficit
2. Commercial (Strategy B) – 100mm deficit
3. Late (Strategy C) – 120mm deficit

The deficits were measured using a Diviner capacitance probe (as per commercial practice). A calibrated neutron probe was also used to measure the true deficit. All irrigations were measured and evaluated using Irrimate™ technologies. In September 2006, 260 kg/ha of urea, 100 kg/ha of Starter Z and 40 kg/ha of muriate of potash were applied based on soil tests.

The site was sown on the 31st October 2006 at 13.2 seeds/m for Sicot 71B, 12.9 seeds/m for Sicot 80B and 13 seeds/m for Sicot 43B. Starter Z fertiliser @ 20kg/ha was applied. Emerging seedlings experienced every adverse condition possible - from hot windy conditions directly after sowing to cool, cold conditions thereafter. This affected final plant populations (see Table 1).

Table 1. Final plant populations

Variety	Irrigation A	Irrigation B	Irrigation C
Sicot 71 B	8.7	7.8	7.8
Sicot 80 B	7.7	8.6	8.6
Sicot 43 B	6.7	6.9	6.9

A weather station was installed at the trial site for the duration of the trial (Figure 2). The irrigation strategies were implemented after the first in-crop irrigation. All irrigations were measured and evaluated using Irrimate™. The irrigations were not optimised as the aim was to evaluate current commercial practice. The final irrigation was strategically implemented to achieve desired soil moisture conditions at defoliation. Five irrigations were applied to strategy A, four to strategy B and strategy C, and three to single-skip. Forty-six Irrimate™ evaluations in total were conducted during the season. Irrigation water applied throughout the season (including pre-water) is shown in Table 2. Overall on average an additional 0.35 ML/ha of irrigation water was applied to the early strategy compared to the commercial strategy.

Table 2. Water applied to each treatment

	71 B	80 B	43 B	Irrigations
A (Early)	6.98	6.96	6.94	5
B (Commercial)	6.58	6.66	6.58	4
C (Late)	6.52	6.66	6.74	4
Single skip		5.19		3

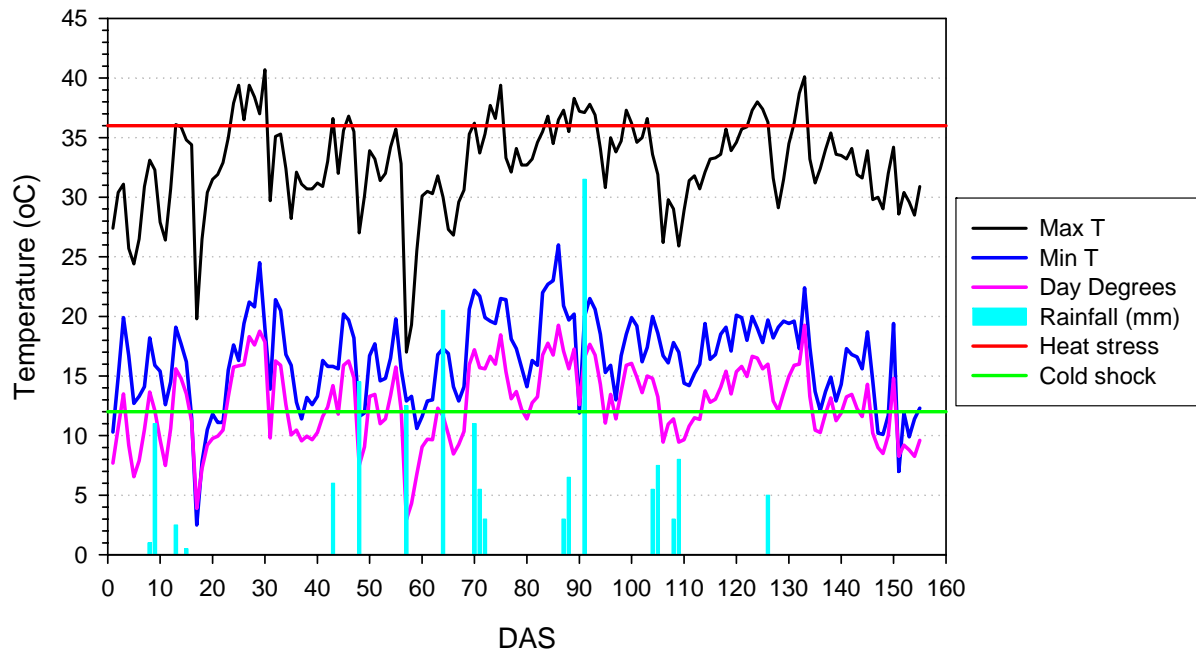


Figure 2. Climatic data for the trial site during the 2006/07 season

2.2 Instrumentation and Monitoring

Stem Diameter Sensor

A Phytech stem diameter sensor was installed in each of the irrigation by variety treatments. A representative plant was selected in the same row and in close proximity to the soil moisture monitoring equipment. All SDS sensors were installed 25 mm below the cotyledons on each selected plant. In the 2005/06 field season, neighbouring representative plants were used for leaf water potential (LWP) measurements. However, in the 2006/07 trial, the plant which was instrumented with the SDS was also sampled for LWP. The top most full expanded leaf was used for LWP measurements using a Scholander pressure chamber. As LWP measurement is a destructive process, the day after LWP sampling the SDS was transferred to a neighbouring plant. This method was used to overcome any impact of the destructive cutting of a leaf from the instrumented plant may have on the diurnal fluctuations in stem diameter. The majority of measurements made for LWP were taken late in the season after each of the irrigation treatments had been well established. This ensured an adequate representation of the interaction of varieties and previous irrigation history (i.e. the treatments imposed) may have on the response of the measured stem increment in comparison to measures of leaf water potential.

Hyperspectral Analysis

Radiometric data was collected using an ASD FieldSpec Handheld Spectroradiometer (Analytical Spectral Devices, Boulder, CO) measuring in the 350 to 1075 nm range (Figure 3). The setup and initialisation of the spectrometer involves ‘optimising’ the reflectance signature for the incident sunlight levels by measuring the reflectance from 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 using the white reference needs to be carried out at regular intervals during the sample measurement period to account for changes in the sunlight intensity and

incidence angle. All measurements in this trial were conducted on clear, cloudless days between 12(noon) and 2 pm and re-optimisation was conducted after every 10 plant leaf measurements.



Figure 3. ASD FieldSpec Handheld radiometer used to measure crop canopy reflectance prior to leaf water potential measures.

Radiometric plant measurements were taken at three dates (29/01/07, 09/02/07 and 26/02/07) within treatment 71B Commercial of the trial area. On each measurement date, a number of individual plants were measured above the top of the crop canopy to ensure a ‘pure pixel’ field of view (FOV) was achieved. Hence, the reflectance measure attained was based only on the reflectance of the crop canopy from a leaf area approximately 20 cm in diameter. This ensured that there were no background (e.g. soil) effects and that the spectral data gathered was associated only with the leaf reflectance. Three strata for each individual plant were measured and the average used for the subsequent analyses.

Soil Moisture Monitoring

Soil moisture was measured by calibrated neutron probe (3 tubes in each plot), Diviner (2 tubes in each plot) and an EnviroSCAN in each plot (to demonstrate plant extraction rate from continuous soil moisture monitoring). The neutron probe access tubes were installed at the top and bottom of the field. An array of tubes was installed across the single skip area to investigate soil moisture extraction of the crop into the skip. These tubes were installed between the rows, on the planted row, in the furrow and on the top of the next skip. A total of 82 tubes were installed at the site. Soil moisture was monitored 2-3 times a week with the Sentek Diviner 2000®. The neutron probe was used less regularly, but data was collected prior to, and after, irrigation events.

2.3 Data Interpretation and Analysis

Stem Diameter Sensor

The daily contractual amplitude (DCA) values obtained from the SDS were downloaded from the Phyttech software for all days where calibrated soil moisture measurements were collected and also for days when the LWP were measured. Values for DCA were calculated as the difference between the day-time value for stem diameter measured directly before LWP sampling (i.e. day-time minimum) and the preceding night's maximum stem diameter value (i.e. night time re-hydration). Outliers and obvious erroneous values were removed prior to statistical analysis. The calibrated soil moisture data was combined with climatic data recorded using a weather station installed on site and used as predictors (independent variables) in a correlation analysis against DCA conducted using SPSS 15.0 for Windows.

Hyperspectral Analysis

The spectral data was treated to remove noise from the higher wavelengths and uncharacteristic signatures and obvious outliers were removed. Stepwise linear regressions using the main spectral bands identified by other workers (Table 3) were conducted for both each separate measurement day and for the three combined measurement days. All analyses were conducted using SPSS 15.0 for Windows.

Table 3. Radiometric indices and individual wavelengths used for the estimation of plant water status in cotton and other crops

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) & Ψ_p
DeTar	2006	DeTar (1)	R850 & R686	cotton	canopy temp
		DeTar (2)	R686, R811 & R860	cotton	canopy temp
Penuelas <i>et al</i>		Water Index (WI)	R900/R970 (or nearby trough)	Trees, shrubs & grasses	Plant water concentrations
NA		Designated Water Absorption	R1000		
Kakani <i>et al</i>	2007	Kakani	R1689/R1657	cotton	LWP
Hardisky <i>et al</i>	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
Yong Chao <i>et al</i>	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)

Some concerns arose after the initial analysis over how well this method of analysis accounted for multi-collinearity. Multi-collinearity can be a major concern in hyperspectral

analyses. These analyses normally involve both the use of a large number of predictors (in comparison to the number of predictant values) and a high level of correlation may exist between neighbouring predictor variables (non-independence). Multi-collinearity can result in an overestimate of the co-efficient of determination (R^2) which exists between a dependent variable and a number of predictor variables. Put another way is that multi-collinearity causes an unacceptably high level of intercorrelation among the independents, such that the effects of the independents cannot be separated. If there is significant multi-collinearity, estimates are unbiased but assessments of the relative strength of the explanatory variables and their joint effect are unreliable.

Initial statistical advice suggested the effects of multi-collinearity should be accounted for in the analysis conducted. However, subsequent multi-collinearity testing was undertaken by calculating the “tolerance” and “VIF” (variance inflation factor) using the “Collinearity Diagnostics” module in SPSS. Tolerance is an indication of the percent of variance in the predictor that cannot be accounted for by the other predictors, values less than 0.1 was set as the threshold to flag possible collinearity present. VIF is the inverse of the Tolerance and therefore a value of greater than 10 was set as the indicator to investigate influences of Collinearity. The Collinearity Diagnostics module was also used to calculate the Condition Index as it is possible to have tolerance and VIF values which suggest no collinearity but it may be picked up in the Condition Index. A Condition Index value greater than 15 suggests a possible multi-collinearity problem, a value of greater than 30 suggests a serious multi-collinearity problem is present. Specific testing found multi-collinearity present between the predictor variables.

To address concerns over the presence of multi-collinearity, a partial least squares (PLS) analysis was conducted using the R package version 2.1-0 (Wehrens and Mevik 2007). PLS is a predictive technique which can handle many independent variables, even when these display multi-collinearity. PLS models the association between blocks of observed variables using latent variables (R Development Core Team 2007). Wavelengths found to be significant at the 1% (important) and 0.1% (very important) level were identified from this analysis. The coefficient of determination (R^2) was calculated for up to 10 components for each data set (i.e. each measurement date, all data combined and all data combined using measurements within a normal irrigation range for leaf water potential defined as $>2.5\text{MPa}$).

As each component of a PLS analysis may use a number of weighted individual band widths it was desired to know which individual bands widths/centres (predictor variables) were most significant at accounting for variability in the independent variable (i.e. leaf water potential). Therefore a listing of all the bands from the PLS analysis which had “important” and “very important” significance were listed and the median (centre) for consecutive significant bands were found. These bandwidths were then re-analysed using a step-wise multivariate regression in SPSS 15.0 for Windows and the “Collinearity Diagnostics” testing conducted to identify multi-collinearity. The strength of the relationship (R^2) was calculated for a model with up to five parameters.

Re-analysis of the data using a customized statistical package such as “The Unscrambler” (CAMO, Oslo) which is specifically designed for the analysis of hyperspectral data would be appropriate but was not able to be conducted for this season..

3.0 Results and Discussion

3.1 Yield and Water Use

The site was picked on the 26th and 27th April 2007. The yield results for each treatment are shown in Table 4. Gross Production Water Use Index (GPWUI = Yield ÷ Total Applied Water) for each variety is shown below in Table 5. It should be noted that the calculated total applied water applied value includes irrigation plus estimated effective rainfall plus the soil moisture reserve (starting soil moisture – final soil moisture at harvest).

Table 4. Yield (bales/ha) for each treatment

	71 B	80 B	43 B
A (Early)	12.4	11.5	11.7
B (Commercial)	11.6	10.6	11.0
C (Late)	10.6	9.8	10.0
Single skip		7.8	

Table 5. GPWUI (bales/ML) for each treatment

	71B	80B	43B
A (Early)	1.66	1.54	1.60
B (Commercial)	1.63	1.43	1.50
C (Late)	1.47	1.33	1.36
Single Skip		1.39	

3.2 SDS

The aim of the SDS work was to investigate if threshold levels of daily contraction could be found and used for commercial irrigation scheduling in cotton. Work conducted in the previous season under a lateral machine for a single crop variety across three irrigation treatments showed promising results and the potential to develop a crude threshold DCA level for irrigation scheduling using stem diameter sensors. However, the data from this year's (2006/07) trial relating the DCA data against measures of LWP and also against imposed soil moisture and climatic conditions showed no significant correlation between DCA and either LWP, soil moisture or climatic conditions.

One reason for the lack of a significant DCA and LWP relationship may have been that this trial only had access to nine stem diameter sensors and hence, there was only a single sensor in each nine irrigation strategy by crop variety treatments. However, it may also have been because the measurements were principally taken later in the season when there was likely to have been a significant plant conditioning effect and hence, a difference in daily contractual amplitude between plants exposed to a different irrigation history (levels & frequencies of stress). Differences in both DCA and LWP responses between the crop varieties are also likely to be a major factor.

Visual interpretation of the DCA data does provide some indication of the crop stress prior to an irrigation event. However, the lack of significant quantitative relationships between the DCA and LWP in this trial suggests that it may be impossible to identify a specific generic DCA threshold value for cotton that is consistent across crop varieties and irrigation management strategies.

3.3 Hyperspectral Analysis

A low level of strength was found in the linear relationships between the selected wavelength(s) and leaf water potential (Table 6) with many of these relationships non-significant, even at the $P < 0.05$ level. The analysis of the hyperspectral data collected during this season suggests that many published ‘water reflectance bands’ are not suitable for the prediction of cotton stress (i.e. leaf water potential) under irrigated conditions. This may be due to previous work being conducted on a wider range of soil moisture conditions which are outside the range normally found in irrigated cotton fields. Alternatively the poor predictive capability may be due to differences in the way the spectral signature is collected. Spectral signatures in this work were based purely on crop canopy reflectance whereas in some of the work published by others there may be a significant effect of the background in the signature where this is included in the field of view. Hence, it may be that other studies have captured an architectural change in the leaf canopy which is related to moisture stress (e.g. leaf wilt).

Table 6. Linear correlations between selected spectral bands/indices and leaf water potential for the 2006/07 field trial

	Reference	29/01/07		09/02/07		26/02/07		ALL DATES	
		R ² (%)	Sig.	R ² (%)	Sig.	R ² (%)	Sig.	R ² (%)	Sig.
NDVI	Bajwa, 2006	15.0	0.035	10.4	0.088	2.8	0.361	16.2	<0.001
GNDVI	Bajwa, 2006	2.1	0.442	3.0	0.369	25.8	0.003	6.4	0.016
R750	Wanjura, 2004	23.1	0.007	0.2	0.823	14.4	0.032	8.2	0.006
R880	Wanjura, 2004	17.9	0.02	0.6	0.679	5.4	0.201	10.7	0.002
R810	Bowman, 1989	18.9	0.016	2.2	0.439	3.3	0.32	8.6	0.005
DETAR (1)	Detar, 2006	21.6 ^{MC}	0.038	13.0 ^{MC}	0.165	10.3 ^{MC}	0.208	18.2 ^{MC}	<0.001
DETAR (2)	Detar, 2006	22.2	0.084	38.6 ^{MC}	0.006	11.2 ^{MC}	0.335	19.2 ^{MC}	<0.001
Water Absorption		12.2	0.059	1.3	0.557	3.6	0.299	4.0	0.057
Water Band		24.0	0.006	0.4	0.74	5.2	0.208	17.5	<0.001

^{MC} signifies possible multi-collinearity exists

The PLS regression analysis (Table 7) identified a number of wavebands as “very important” (significant at 0.1% level) or “important” (significant at 1% level). From the analysis conducted varying strengths of relationship were found between the predictor (i.e. waveband centres) and leaf water potential. From the list of very important and important correlations, a short list of the most promising wavebands was developed. This list was developed based on the range of bands consistently found to be significant in the PLS analysis (Table 7 & 8) and those previously identified by other workers (Table 3). All correlations of the most promising bands were found to be highly significant ($P < 0.01$) except the one parameter model on 26/2/07 which was only significant at the $P < 0.05$ level. However, when the tests for multi-collinearity were conducted based on the Tolerance level, VIF and Condition Index, all parameters failed one or more of the threshold levels set signifying multi-collinearity was still present (Table 8). Hence, when the data was compiled across all sampling dates and

assessed in terms of robust bandwidths (Table 8) a substantial proportion of the variation in plant water potential which could be measured was able to be explained by the selected radiometric bands. This suggests that the selected radiometric bands could be used to identify moisture stress and potential be used in developing appropriate irrigation schedules. However, it should be noted that all of this work was conducted on a single crop variety and further work is required to identify if these relationships hold across a broader range of crop and operating conditions.

Table 7. Partial least squares linear regression for selected bands and leaf water potential

Parameters	29/01/07			09/02/07			26/02/07		
	nm	R ² (%)	Sig.	nm	R ² (%)	Sig.	nm	R ² (%)	Sig.
1	710	39.3 ^{MC}	<0.001	339	39.1 ^{MC}	<0.001	739	18.5 ^{MC}	0.014
2	710,474	70.1 ^{MC}	<0.001	.	.	.	739,979	34.9 ^{MC}	0.002
3	739,979,748	45.0 ^{MC}	0.001
4	979,748	41.4 ^{MC}	<0.001
5

^{MC} signifies possible multi-collinearity exists

Table 8. Stepwise multivariate regression for the promising reflectance bands and the LWP

Parameters	All data			All data <2.5MPa		
	nm	R ² (%)	Sig.	nm	R ² (%)	Sig.
1	470	13.3	<0.001	422	13.2	0.001
2	470,751	39.1 ^{MC}	<0.001	422,710	39.9 ^{MC}	<0.001
3	470,751,980	59.9 ^{MC}	<0.001	422,710,934	44.0 ^{MC}	<0.001
4	470,751,980,662	63.2 ^{MC}	<0.001	422,710,934,806	48.0 ^{MC}	<0.001
5	470,751,980,662,804	65.4 ^{MC}	<0.001	422,710,934,806,656	54.3 ^{MC}	<0.001

^{MC} signifies possible multi-collinearity exists

As is the case with all plant based sensors when used as a tool for irrigation scheduling, the values obtained need to be correlated with the soil water (potential) data and that of evaporative demand. Only with robust correlations between the sensor response and both the soil and environmental conditions is it possible to define an appropriate trigger for irrigation scheduling in any crop. However, an alternative is to implement irrigation strategies based on a range of threshold values for the plant monitoring sensor and evaluate the resulting yield and quality characteristics. A third method is to assess the response to imposed 'water conditions' is in terms of a physiological response such as photosynthetic rate and assimilate production. However, a reduction in the rate of photosynthetic rate may not inhibit the yield potential of the crop. In the case of irrigation strategies such as deficit irrigation there may in fact be an increase in yield response and a reduction in water use and/or water use efficiency.

5.0 Conclusion

This field trial evaluated both the use of stem diameter sensors and hyperspectral sensing within an irrigated cotton crop. The SDS data was obtained across a several crop varieties and irrigation management strategies and suggests that it may be difficult to identify a single threshold trigger for irrigation based on daily contractual amplitude. Hyperspectral data was obtained on three dates for a single crop variety and related to leaf water potential data. Many of the reflectance bands used to predict water stress in other crops were found to be ineffective for cotton. However, a multivariate step-wise regression using up to five bands within the 422 to 980 nm range was found to explain between 54 and 65% of the variation in leaf water potential. This suggests that it may be possible to develop a low-cost radiometric sensor for the non-destructive sensing of crop water stress in cotton. Future research in this area should focus on confirming the utility of the specific radiometric bands identified in this study and if appropriate develop a low cost radiometric sensor. Such a sensor could be integrated with the currently plant vision sensing equipment (e.g. McCarthy et al 2007) to enable the top fully expanded leaf to be identified and the radiometric reflectance measured.

References

- Bowmann, W. D. (1989) The relationship between leaf water status, gas exchange, and spectral reflectance in cotton leaves. *Remote Sensing of the Environment*, 30, 249-255.
- Browne, R. (1986) The role of the pressure chamber technique in irrigation practice. *Irrigation '86*. Toowoomba, Irrigation Association of Australia.
- McCarthy, C., Hancock, N. and Raine, S. (2006). On-the-go machine vision sensing of cotton plant geometric parameters: first results. 13th Annual Conference on Mechatronics and Machine Vision in Practice. 5-7th December 2006, Toowoomba.
- McCarthy, C., Hancock, N. and Raine, S. (2007). Automated machine vision sensing of plant structural parameters, Biological Sensorics: Critical Technologies for Future Biosystems, 15-17 June, Minneapolis. American Society of Agricultural and Biological Engineers, St Joseph.
- Meron, M., Grimes, D.W., Phene, C.J. and Davis, K. R. (1987) Pressure chamber procedure for leaf water potential measurements of cotton. *Irrigation Science*, 8, 215-222.
- R Development Core Team (2007). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL <http://www.R-project.org>
- Wanjura, D.F. & Upchurch, D.R. (2004) Spectral reflectance estimates of cotton biomass and yield. *Beltwide Cotton Conferences*. San Antonio.
- Wehrens, R. and Mevik B. (2007). PLS: Partial Least Squares Regression (PLSR) and Principal Component Regression (PCR). R package version 2.1-0. <http://mevik.net/work/software/pls.html>