GROUND–BASED REMOTE SENSING OF WATER AND NITROGEN STRESS

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ABSTRACT. *A ground–based remote sensing system (Agricultural Irrigation Imaging System, or AgIIS) was attached to a linear–move irrigation system. The system was used to develop images of a 1–ha field at 1 × 1 m resolution to address issues of spatial scale and to test the ability of a ground–based remote sensing system to separate water and nitrogen stress using the coefficient of variation (CV) for water and nitrogen stress indices. A 2 × 2 Latin square water and nitrogen experiment with four replicates was conducted on cotton for this purpose. Treatments included optimal and low nitrogen with optimal and low water. ANOVA was not an adequate method to assess the statistical variation between treatments due to the large number of data points. In general, the coefficient of variation of water and nitrogen stress indices increased with water and nitrogen stress. In fact, the coefficient of variation of stress indices was a more reliable measurement of water and nitrogen status than the mean value of the indices. Differences in coefficient of variation of stress indices between treatments were detectable at 3 m grid resolution and finer for water stress and at 7 m grid resolution and finer for nitrogen stress.*

Keywords. *Remote sensing, Nitrogen, Water, Stress, Irrigation, Cotton, Coefficient of variation.*

This project investigated the feasibility of collecting high–resolution remotely sensed spectral and thermal data using the Agricultural Irrigation Imaging System (AgIIS). The researchers designed and constructed a ground–based remote sensing system (AgIIS) that collected 1–m resolution data for application in precision agriculture.

Spatially variable drying of a field is caused by the spatial variability of soil properties. The coefficient of variation (CV) of remotely sensed indices may be as strong an indicator of plant stress as the mean value of stress indices. The focus of this work is primarily on the variability of stress indices in space rather than the mean values of stress indices.

Others researchers on the project conducted a detailed comparison of mean values of water stress (Colaizzi, 2001) and nitrogen stress indices (Haberland, 2001) with field measured soil water content and leaf tissue nitrogen concentration, respectively.

The objectives of this research were to: (1) demonstrate the feasibility of using the AgIIS system to detect nitrogen and water stress in a cotton field, (2) evaluate the effect of scale on detection of stress and on the variation of stress indices within plots, and (3) evaluate the CV of stress indices as an indicator of plant nitrogen and water stress.

LITERATURE REVIEW

With the advent of the earth resources satellites, the concept of collecting remotely sensed data for management of agricultural products was one of the many applications proposed to utilize this technology (Barnes et al., 1996). Myers (1975) stated, "Remote sensing offers the feasibility of monitoring agricultural areas for rapid and continuous assessment of plants, soil and water resources, and interrelated problems." He further stated, "A successful remote sensing program must be tailored to solve or manage the maximum variety and complexity of applications." Presently, remotely sensed spectral data have primarily been used at the research level. However, it shows potential for managing crop water stress and applying fertilizer.

Major issues associated with remotely sensed systems include resolution and the timeliness of the data. High–resolution data can be costly and time consuming to collect (Moran et al., 1997), but data with low spatial resolution can be less descriptive and thus less useful. Resolution is an issue of scale, and scale is important in management decisions (Woodcock and Strahler, 1987) and must be optimized to provide the best economic return. Data collected on a small scale (high resolution) provide more detail than data collected at a large scale (low resolution), and data collection costs increase as scale decreases (Klopatek and Gardner, 1999). This produces a tradeoff between cost and the value

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of the information such that the optimum system would collect sufficient data for crop management at the least cost.

In addition to scale, the timeliness of delivery of remotely sensed data is a factor. It has been shown that the usefulness of remotely sensed data decreases rapidly as frequency decreases and time from collection increases (Moran et al., 1997). Remotely sensed data are typically obtained through satellite or aerial images and presently takes from three days to several weeks to be post–processed and became available for making management decisions. These timeframes make the information of little use in crop management, and faster delivery of data is essential but prohibitively expensive for growers.

Water management with remotely sensed data is typically based on canopy temperature. Jackson et al. (1981) used remotely sensed temperature data to determine water stress and subsequently developed a crop water stress index (CWSI). Primarily by measuring canopy and air temperatures with a handheld infrared thermometer, a CWSI method to schedule irrigations for an individual field was investigated (Geiser et al., 1982). Moran (1994) also utilized remotely sensed surface temperatures and reflectance data to determine a crop's water status and developed a water deficit index (WDI) to address incomplete canopy cover. Methods for irrigation management that determine crop water stress in Arizona using satellite or aircraft remotely sensed data have been proposed (Moran, 1994).

A good correlation between petiole nitrate content and a spectral index derived from plant reflectance of near–infrared, blue, green, and amber light has been demonstrated for cotton (Sui et al., 1998). A relationship between a reflectance–based index named the canopy chlorophyll concentration index (CCCI)) and N status was demonstrated by Barnes et al. (2000). The CCCI utilizes the normalized red–edge difference to determine the canopy chlorophyll content.

As mentioned earlier, scale is an important consideration in data collection and management. The question of what scale best defines the phenomenon being studied has no easy answer. The problem of scaling from one level to another is not just a simple mathematical process but is more likely a complex exercise (Golley, 1989). Cao and Lam (1997) discussed how to extrapolate the results across scale and resolution.

The problem of scale can be considered two–sided, that is, scale can be too large where local variation is missing, or scale can be so fine that it is difficult to discern what is observed (Meyers, 1997). Scale dependency can cause results to be heterogeneous at one spatial scale and homogeneous at another (Quattrochi et al., 1997). On dealing with the issue of scale, it has been stated that there is no absolute standard for what is a small or large scale; rather, the researcher must ensure that the scale fits the goal of the study (Cressie, 1993).

It is well understood that aggregating data through averaging smoothes the data and reduces the variance. At the uppermost aggregated level, the scale would be one large pixel, one value and zero variance. It has been recommended that when analyzing the differences between scales, the variances at each resolution level can be used to determine how much variation exists as one goes from coarse to fine (Cola, 1996).

Methods

This study used the AgIIS system constructed at the University of Arizona Maricopa Agricultural Center near Phoenix, Arizona, to collect remotely sensed data. The AgIIS system was designed to simultaneously monitor water status, nitrogen status, and crop growth at 1–m spatial resolution. This study used the difference between plant canopy and air temperature (PCT) as an indicator of water stress. The CCCI (Barns et al., 2000) was used as an indicator of nitrogen stress. CCCI values range from 0 to 1, with low values representing lower canopy chlorophyll content and more nitrogen stress.

This section includes discussion of the AgIIS remote sensing system, statistical design and data collection, and soils.

AgIIS System

The AgIIS system consisted of a nadir–looking group of reflectance and infrared sensors that were transported by a self–propelled cart that moved along a track. The track was mounted on a two–span linear–move irrigation system. The linear–move irrigation system (LM) provided a means to precisely control water and nitrogen application. In addition to the LM and cart, infrastructure for the delivery of electricity, water, and nitrogen was installed. The infrastructure and field layout are shown in figure 1, and the rail system is shown in figure 2. Further information on the AgIIS system is contained in Haberland (2001).

The AgIIS system measured incoming and reflected radiation with band–specific optical sensors. Thermal radiation was measured with an infrared thermometer (IRT). The sensor packages were designed and constructed by the USDA–ARS United States Water Conservation Laboratory. The upward and downward sensors consisted of four optical sensors, all nadir–looking from a 4–m height above the ground with a 15° field of view, resulting in a footprint of about 1 m. They were: (1) red (670 nm, maximum chlorophyll absorption), (2) green (550 nm, maximum chlorophyll reflectance), (3) red–edge (720 nm, a dynamic spectral region sensitive to crop stress), and (4) near–infrared (790 nm, sensitivity to canopy density). Each band was filtered to a 10–nm bandpass about the band centers. Only the downward sensor package contained an IRT.

Statistical Design and Data Collection

The field was planted to cotton on 16 April 1999 (DOY 105). A Latin square experimental design was used to compare four treatments with four replicates (rows). Treatment locations are shown in figure 1. The treatments were: (1) low nitrogen and low water (nw), (2) optimal nitrogen and low water (Nw), (3) low nitrogen and optimal water (nW), and (4) optimal nitrogen and optimal water (NW). Water was managed by measuring soil water content with neutron probes and TDR probes. For optimal water, irrigations were scheduled when the soil water content was depleted by 30%. For stressed plots, irrigations were scheduled when the soil water content was depleted by 50%. The water application dates and amounts just prior to the dates of the four selected images used in this analysis are provided in table 1. The total seasonal irrigation, nitrogen application rates, and final lint yields for each treatment are provided in table 2, with seasonal nitrogen application data provided in table 3.

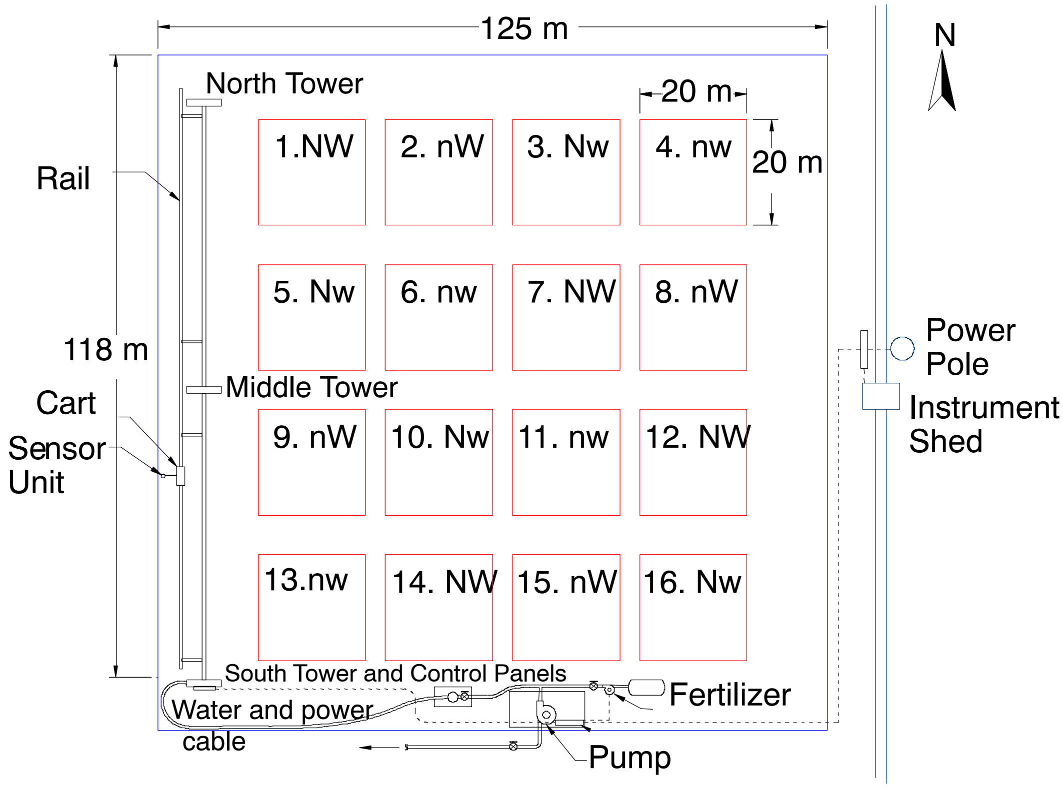

Figure 1. Schematic of Agricultural Irrigation Imaging System (AgIIS) and field layout.

Figure 2. AgIIS cart and rail system mounted on linear–move irrigation system.

Data were collected at solar noon, as this was the optimal time of day and the effects of shadows from the LM and the plants were minimized. Imaging the complete field at a resolution of 1 m took approximately 2.5 hours. The speed of the LM system was adjusted so that 1 × 1 m spatial resolution resulted as the sensor traversed the field. The AgIIS acquired field images as often as three times per week during rapid crop growth. Data from both the upward and downward looking sensors were recorded with Campbell Scientific CR–10X data loggers (Campbell Scientific, Inc., Logan, Utah). The GPS system used in this project was a differentially corrected Trimble AgGPS 132 12–channel receiver (Trimble Navigation, Sunnyvale, Cal.).

Table 1. Previous irrigation for each day of year (DOY) analyzed.

Image DOY	Last Irrigation
181–182	DOY 177, 2.80 cm (1.1 in.), all plots
218	DOY 217, 3.05 cm (1.2 in.), all plots
228	DOY 225, 3.81 cm (1.5 in.), all plots
231	DOY 228, 2.54 cm (1.0 in.), optimal water plots only

Table 2. Total seasonal irrigation, rain, nitrogen application, and final lint yield for each treatment.

Treatment	NW	nW	Nw	nw
Irrigation (mm)	1070	1070	1000	1000
Rain (mm)	150	150	150	150
Nitrogen (kg ha^{-1})	222	112	222	112
Lint (kg ha^{-1})	1200	1380	1250	1360

Table 3. 1999 cotton season nitrogen applications for optimal and low nitrogen treatment plots.

DOY	Date	Optimal N (kg ha^{-1})	Low N (kg ha^{-1})
97	7 April[a]	34	34
148	28 May	29	9
162	11 June	43	26
176	25 June	70	24
197	16 July	46	19
Total		222	112

[a] Nitrogen was applied to the soil as a pre–plant application on 7 April and by fertigation on the remaining days.

The cart ran along the linear move in the north–south direction, and the sensor system was triggered over each crop row: a small cable ran the length of the rail, metal strips attached to the cable were aligned with each row, and a proximity sensor was mounted on the cart and triggered by the strips. The longitude of the cart at the time each image was collected was calculated based on the number of triggers that had been tripped since the cart left the end tower or by interpolation based on the time since the cart left the end tower. The cart started nearly instantaneously at each tower, so the cart speed was constant along the track. A GPS antenna was fixed on the south tower of the linear move and recorded the position of linear move in the east–west direction. The latitude of the cart was calculated based on the position of the GPS antenna at the time the image was collected.

The sensor had a "footprint" (the area of an image) resulting in a data resolution of 1 m^2. However, because the cart and linear were moving, the data were not collected in a symmetrical 1 × 1 m grid. To create a symmetrical 1 × 1 m grid for analysis, an inverse distance weighting (IDW) routine (a power equation in which points within 1 m were given full weight and points 2 m away had 1/4 weight) was used to create 1 × 1 m grids within each plot. An additional routine produced grids from the 1× 1 m grid for the 2 × 2 m through the 10 × 10 m grids.

Access paths between plots were approximately 2 m wide in the north–south direction and approximately 3 m wide in the east–west direction. The access paths provided distinct borders between plots. A handheld GPS was used to determine the path locations. The paths produced edge effects in the plots due to additional light, water, and fertilizer. To remove path and edge effects from the remotely sensed data, a path mask was developed. The width of the mask included the sum of the access path, edge effect buffer, and GPS error. Edge effect widths were 1 m (one row) on either side of the east–west access paths and 0.3 m on either side of the north–south access paths. The GPS error portion of the mask included two averaged standard deviations (1.56 m) of typical GPS location data on each side of the path. Thus, the mask was 8.1 m wide in the east–west direction and 5.7 m wide in the north–south direction, and only 45% of the total field area was included in the analysis. The mask was applied after the inverse distance weighting procedure.

Sixty half–field and full–field images were collected during the 1999 cotton–growing season and resulted in 39 full–field images. To facilitate analysis, a sub–set of the data was selected with the following criteria: (1) one image collected prior to initiation of water treatments, (2) one image that shows visually apparent crop stress after treatments were applied, (3) two images collected when crop stress was not visually apparent, and (4) all images under clear skies. The dates selected to meet this criteria were based upon how the crop was managed and not on the actual soil moisture and plant nitrogen content.

Water treatments were started when the cotton had approximately 50% canopy cover. A pretreatment image that had at least 50% canopy cover was limited to late June and early July. Two half–field images taken on 30 June (DOY 181) and 1 July (DOY 182) were selected and combined for the pretreatment data set (DOY 181–182). Images taken on 6 August (DOY 218) and 16 August (DOY 228) were selected as days with no visual stress, and 19 August (DOY 231) was selected as a day when nitrogen stress was visually apparent in the low nitrogen treatment plots and when data for the entire field were collected. Even though visual nitrate stress was not apparent on other days, measurements showed that there were differences between treatments in petiole nitrate for all days selected for this study (Haberland, 2001).

The primary statistics used in the study were ANOVA F and P (probability) values, means, and CV. The ANOVA F value (test for significance) was used to determine field effects in the Latin square and confirm differences between treatments. The ANOVA F statistic compares the variability between groups to the variability within groups. The F value is significant and the null hypothesis is rejected (treatments are different) if it exceeds a critical F value that is based on the sample size. The P statistic reports the probability that two treatments are from the same population. Means were used for general comparisons, while CV was used as a measure of water and nitrogen stress variability.

Soils and In–Situ Measurements

To determine soil properties, three soil pits were excavated, one each in the southwest, northeast, and southeast corners of the field. The soil in all three pits was a Casa Grande (fine loamy, mixed, hyperthermic Typic Natragrid). Casa Grande soil is a deep, well–drained, slowly permeable soil formed from old alluvium.

Measurement of petiole nitrate was conducted on a weekly basis during the growing season with 30 leaves collected per plot (Haberland, 2001). The fraction of soil moisture depletion (fDEP = 0 at field capacity and fDEP = 1 at the permanent wilting point) was estimated with TDR measurements after DOY 201 (Colaizzi, 2001).

RESULTS AND DISCUSSION

First, the GPS error is assessed. Second, nitrogen and water stress images collected with the AGIIS system are presented. Third, statistical differences between treatments are evaluated. Fourth, the relationship between CV of stress indices and nitrogen and water stress is shown.

GPS ERROR

The GPS antenna was located on the south tower as the linear move traversed the field in an east–west direction collecting 39 days of location data. A regression line was fitted to the points and was assumed to represent the actual east–west position of the GPS antenna. The GPS data were then compared to the regression. The frequency distribution of the GPS data around the regression line, along with the cumulative distribution, is provided in figure 3.

The standard deviation between the regression line and the GPS data was 0.78 m with a standard error of 0.09 m. Two standard deviations (1.56 m) were included in the mask to ensure that pathway and edge effect data points were minimized. Assuming a normal distribution, only about 4% of the remotely sensed readings that occurred in the paths or the edge effect portions of the plots were included in the analysis.

REMOTELY SENSED IMAGES

Images of PCT were generated for 1, 3, 5, and 7 m grids for DOY 231 and are shown in figure 4 with optimal water treatments outlined. The difference in PCT for optimal and low water treatments is readily apparent regardless of scale or nitrogen treatment.

Images of CCCI were generated for 1, 3, 5, and 7 m grids for DOY 231 and are shown in figure 5 with optimal nitrogen treatment plots outlined. The difference between nitrogen treatments is apparent, and scale had minimal effect on visual interpretation of images, as with the PCT data in figure 4. It is also apparent that data collected with AgIIS can be used to produce images and distinguish stressed from non–stressed areas of the field.

It took approximately one year to calibrate and assemble the 1 m resolution data in images. Kriging and other statistical analysis associated with this study took another six months. However, if the analysis of mean and coefficient of variation were automated within a GIS software program, then the data turnaround time could be less than 24 hours. Kriging or other more complicated statistical analysis would have a longer turnaround time.

COMPARISON OF REMOTELY SENSED DATA WITH IN–SITU MEASUREMENTS

The field–measured fDEP and petiole nitrate along with remotely sensed PCT and CCCI values are presented in table 4. There was very little difference between PCT measurements in optimal and low water treatments on DOY 181–182, and there was no TDR in–situ data to compare to the remotely sensed data. Although a theta probe indicated that the soil was dry at 5 cm depth, the plants did not appear stressed. The reason that the plant temperature was high relative to air temperature (PCT in table 3) on DOY 181–182 was that half of the image was soil and soil is much hotter than plants.

The optimal water plots (NW and nW) had greater fDEP (table 4) on DOY 218 than the low water plots because the low water plots had just been irrigated. There was an unexpected negative correlation between PCT and fDEP, and thus PCT was not a reliable indicator of fDEP in the range of fDEP = 0.2 to 0.3. There were minimal fDEP and PCT differences on DOY 228 between treatments. The plants were

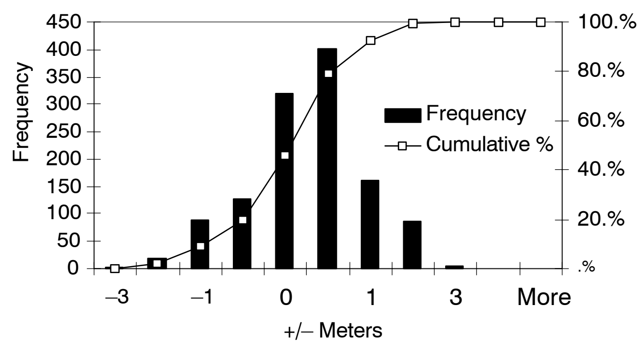

Figure 3. Frequency distribution of GPS latitude from regression line.

Table 4. Treatment means for canopy chlorophyll concentration index (CCCI), petiole nitrate content, difference between plant canopy and air temperature (PCT), and fraction of soil moisture depletion (fDEP) for four field composites, with correlation coefficient.

	DOY							
	181–182		218		228		231	
Treatment	CCCI	PNC[a]	CCCI	PNC	CCCI	PNC	CCCI	PNC
NW	0.57	10,800	0.77	6,000	1.06	4,000	0.96	3,000
nW	0.55	8,200	0.76	1,200	0.87	1,000	0.72	1,000
Nw	0.55	11,200	0.73	4,000	1.06	5,000	1.06	4,000
nw	0.57	7,800	0.69	1,200	0.94	1,000	0.83	500
Correlation	–0.13		0.53		0.93		0.91	
	PCT[b]	fDEP	PCT	fDEP	PCT	fDEP	PCT	fDEP
NW	10.31	n/a	–3.66	0.31	–6.75	0.32	–5.23	0.39
nW	10.1	n/a	–3.97	0.29	–6.79	0.26	–4.99	0.29
Nw	9.74	n/a	–3.21	0.19	–6.64	0.32	–2.15	0.58
nw	9.89	n/a	–2.93	0.21	–6.08	0.32	–2.19	0.57
Correlation	–0.08		–0.83		0.45		0.94	

[a] PNC = petiole nitrate content (mg kg–1).
[b] PCT = $T_s - T_a$ (°C).

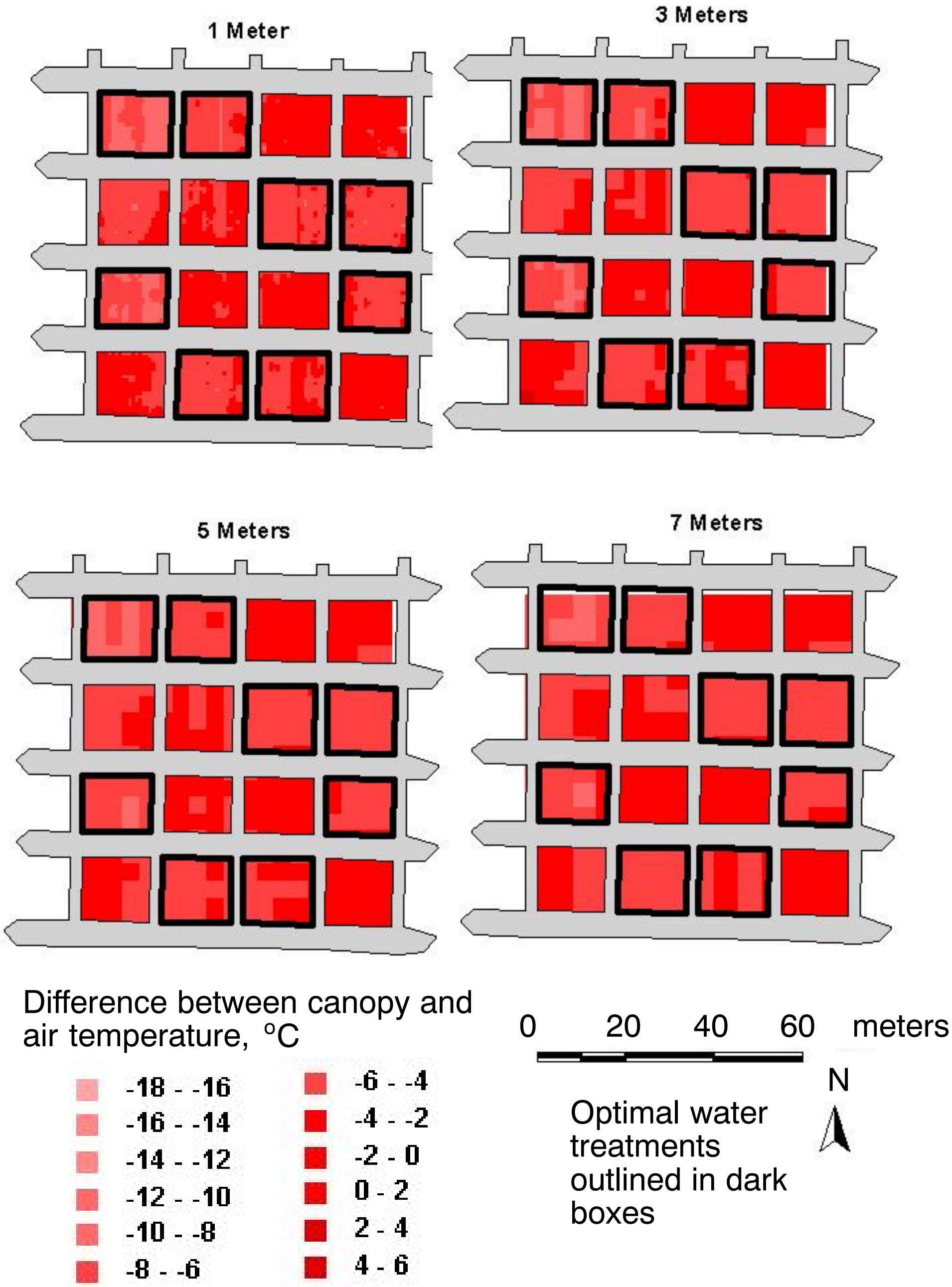

Figure 4. Field images of difference between plant canopy and air temperature (PCT) at four different grid sizes for day of year 231.

both water treatments even though the fDEP was less for the low water plots on DOY 218, and the fDEP was essentially the same for the optimal water treatments. The hotter temperature on DOY 218 could have been caused by incomplete canopy cover on DOY 218 and complete canopy cover on DOY 228. There was a large difference in fDEP on DOY 231 between treatments and a corresponding difference between PCT measurements: the difference between crop and air temperature was greater in the unstressed treatments (adequate transpiration and crop cooling) than in the stressed treatments (transpiration less than maximum). In summary, PCT was a good indicator of plant stress in the case of very high stress, but not in other cases.

There was a difference in petiole nitrate between optimal and low water treatments on DOY 181–182. However, there was no corresponding difference in CCCI between treatments (table 4). A lack of correlation is not surprising with 50% canopy cover because it is likely that the soil reflectance masked differences in leaf chlorophyll concentration. Even with a large difference in petiole nitrate content on DOY 218, there was no corresponding difference in CCCI. One factor that may have limited the effectiveness of the CCCI measurement was that the canopy cover was not quite full on all treatments on this date (Haberland, 2001). On DOY 228 and 231 all the low nitrogen treatment plots (nw and nW) had less petiole nitrate than their counterparts (NW and Nw). There was also a 10% to 20% difference between CCCI readings on the optimal and low nitrogen treatments on these two days. In summary, the CCCI distinguished between nitrogen treatments only in the case of full canopy cover (DOY 228 and 231).

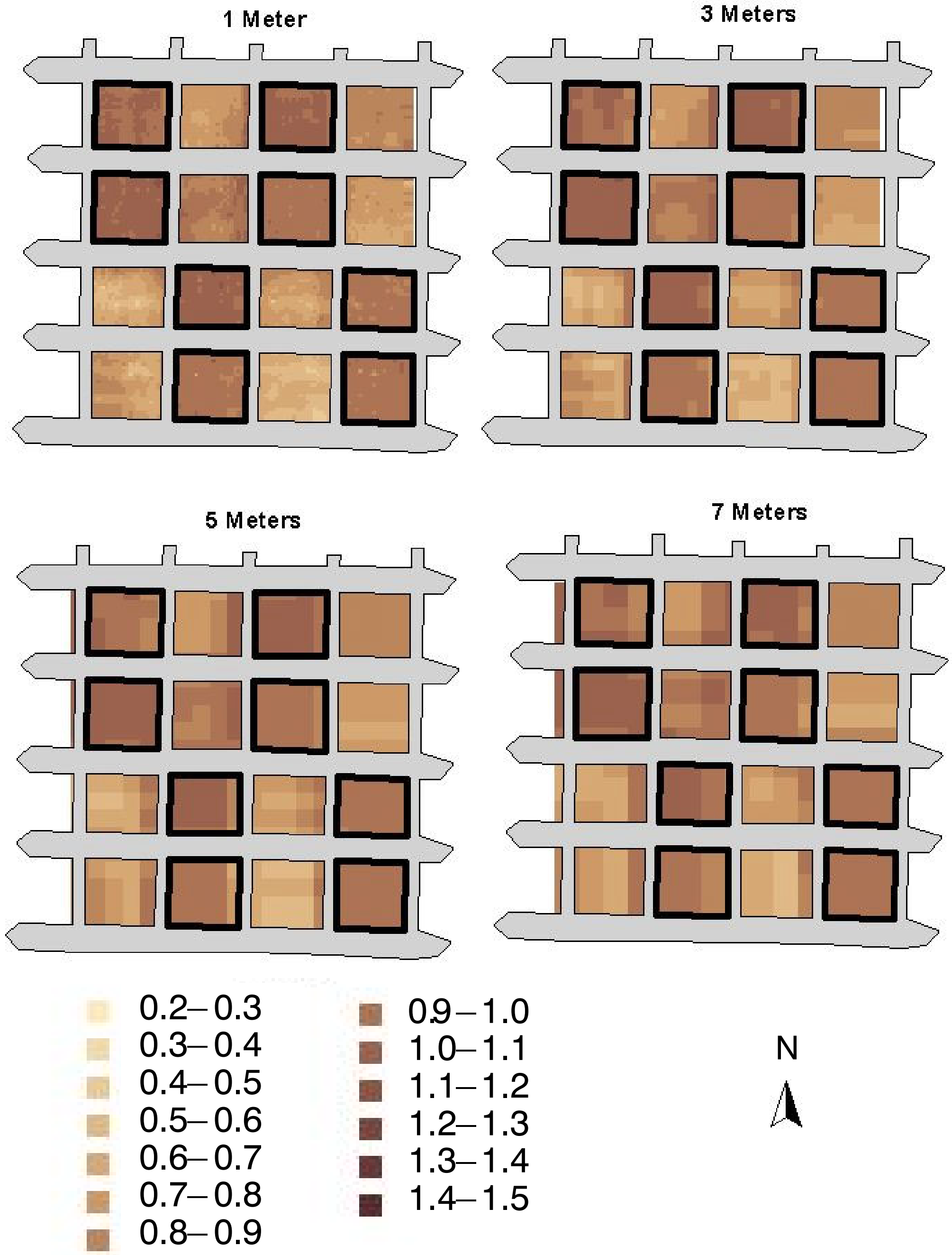

Figure 5. Field images of canopy chlorophyll concentration index (CCCI) at four different grid sizes for day of year.

Latin Square Statistical Analysis

PCT and CCCI data from the 16 plots and 4 selected days were used to determine statistical differences between treatments. ANOVA was performed on the data by treatment and by DOY to determine if treatment effects were significant. Because the experimental design was a Latin square, the ANOVA also provided information on row and column effects. The rows were oriented east–west, and the columns were oriented north–south. The ANOVA results for modeling treatment by row and treatment by column for PCT and CCCI for the 1 × 1 m grids are provided in table 5.

Table 5. ANOVA F statistic for difference between plant canopy and air temperature (PCT) and canopy chlorophyll concentration index (CCCI) for the 1 × 1 m grid.

	Deg. of Freedom	DOY 181–182	DOY 218	DOY 228	DOY 231
PCT					
Treatment	3	37	159	110	2350
Row	3	172	15	15	242
Column	3	2869	427	255	843
CCCI					
Treatment	3	151	3641	4308	10347
Row	3	53	991	372	1697
Column	3	852	3063	1659	595

The PCT and CCCI data showed significant differences between treatments (P > 0.000*x*) at all grid sizes even before treatments were applied (DOY 181–182). Significant P values are common for very large data sets such as the 1–m grids (exceeded 20,000 points). To understand what is occurring, it is often necessary to compare the relative size of the F statistic between the different models (treatment, row, and column effects). It appears that with high–resolution remote sensing data, ANOVA alone may not be sufficient for evaluation of the significance of differences in all cases.

The data in table 5 for DOY 181–182 (no treatment day) show that the column effects greatly exceeded the treatment effects for both PCT and CCCI. For PCT, even the row effects were more dominant than the treatment effects. That the results for the treatments were significant is misleading, as the column effects were the dominant effects and there were no water management differences between treatments. Excavation of soil pits and field observation indicated that there was a slight variation in soil along a southwest to northeast gradient, and the column/row effects for individual plots (Kostrzewski, 2000) supported this variation. It is also possible that the large column effects were caused by the fact that the linear moved across the field in the east–west direction, and data collection was taken over a period of 2 hours. Thus, the column of data at the east end of the field was taken under slightly different environmental conditions than the column at the west end of the field.

Column effects were 2 to 3 times greater than treatment effects for PCT on DOY 218 and 228. Only on DOY 231, when water stress was visually apparent and was high (fDEP = 0.6) on the water–stressed plots, were the treatment effects dominant. This further demonstrates the difficulty in using PCT values for directly determining water stress.

CCCI treatment effects were less than column effects on DOY 181–182, approximately the same as column effects on DOY 218, and much greater than column effects on DOY 228 and 231. This is also in agreement with the average CCCI differences between treatments presented in table 4: treatment effects were dominant only on DOY 228 and 231.

Coefficient of Variation of Remotely Sensed Indices

The effect of grid size and level of stress on the coefficient of variation of remotely sensed data was evaluated. Lower resolution grid cells were constructed based on the mean of the 1 × 1 m grid cells that were contained by the larger cells; this method of averaging is representative of remotely sensed data collection at different spatial scales (2 × 2 m to 10 × 10 m). The determination of the maximum spatial scale that provides sufficient information for assessment of spatial variability should aid in the selection of the appropriate scale of future remote sensing platforms.

The Dunnet (Kuehl, 1994) test was used to determine if there was a statistical difference in average treatment PCT or CCCI values with large and small grid sizes. As expected with the method of constructing grids based on simple averaging, out of 144 comparison tests, not one was significant.

The coefficient of variation of PCT vs. grid size is shown in figure 6 for DOY 181–182, 218, 228, and 231. The four plot numbers that are included in each treatment are also shown in the legend, and the data from the four plots within each treatment were pooled for this analysis. Figure 6 combined with information in table 4 indicates that the coefficient of variation increases with soil water depletion and plant water stress.

On DOY 181–182, CV was low in all treatments at all scales (fig. 6), and CV did not change significantly with scale. For DOY 218, the optimal water plots (NW and nW) had greater fDEP (table 4) than the low water plots (Nw and nw). Three of the treatments had higher CV of PCT in the 1, 2, and 3–m grid sizes on DOY 218: the two optimal water plots (NW and nW) and the optimal nitrogen and low water plot (Nw). Thus, the CV of PCT showed stress in the same plots in which the in–situ measurements indicated stress

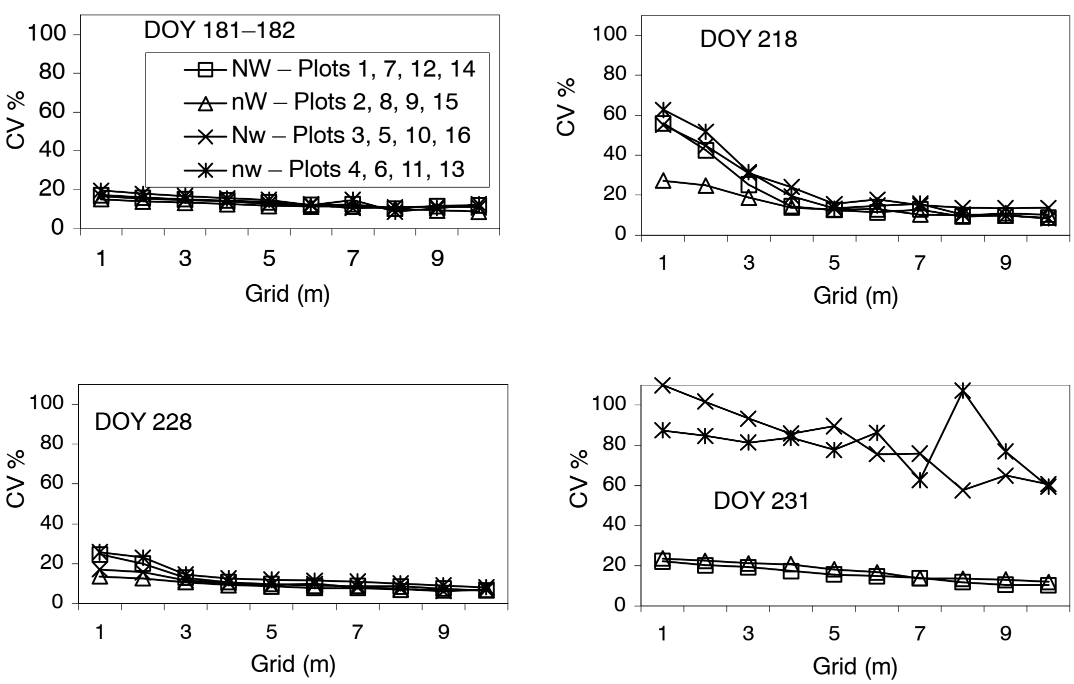

Figure 6. Coefficient of variation of difference between plant canopy and air temperature (PCT) vs. grid resolution.

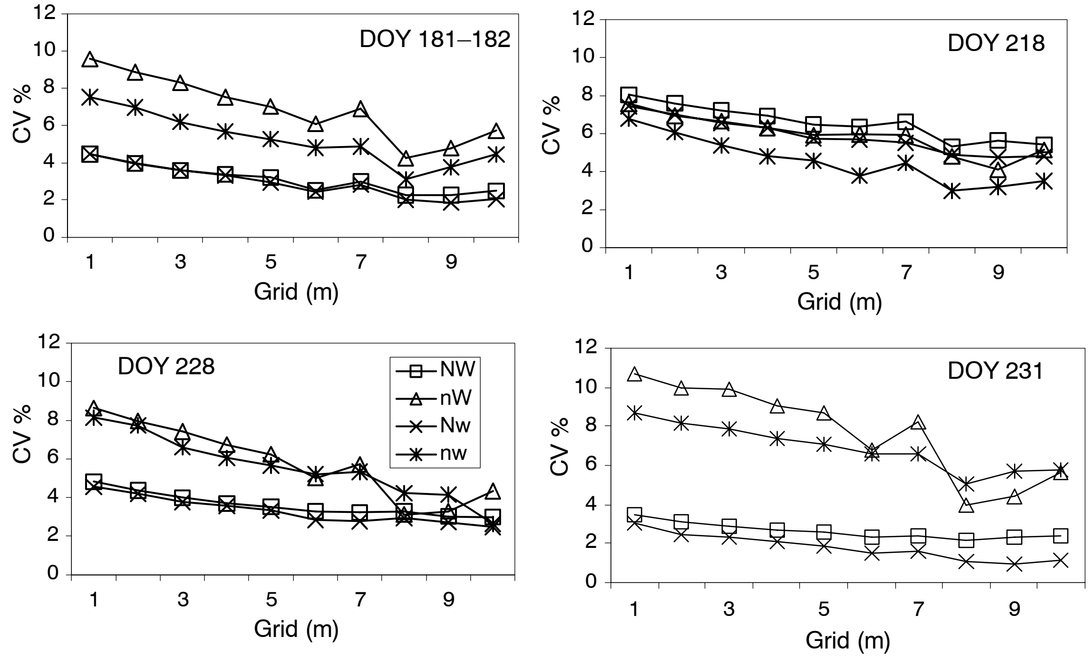

Figure 7. Coefficient of variation of canopy chlorophyll concentration index (CCCI) vs. grid resolution.

(table 4). The increase in CV in the optimal nitrogen and low water plot is possibly explained by the fact that the optimal nitrogen treatments had increased plant biomass and were thus more susceptible to water stress; field biomass measurements indicated that the plants in the nW plots had less biomass than the NW treatments. However, the fDEP values in table 4 do not support the contention that the nW treatment had less fDEP than the NW treatment. On DOY 228, the low nitrogen and optimal water treatment had less fDEP than the other plots (0.26 vs. 0.32) and also had a slightly lower CV than the other plots at the 1 and 2 m grid scales. The low water plots on DOY 231 were stressed beyond the treatment design of a maximum 50% fDEP (table 4). This stress difference is reflected in the CVs in figure 6, in which the CVs for the low water plots are significantly higher for all resolutions. In summary, the CV of PCT shows promise as a reliable indicator of plant water status, even though the mean value of PCT was not.

The CV of CCCI vs. grid size is shown in figure 7 for DOY 181–182, 218, 228, and 231, respectively. The explanation for the fact that the CCCI CVs were much lower than the PCT CVs is unknown. Except for DOY 181–182, with less than full canopy and dominant soil effects, all CVs of CCCI at nearly all grid scales were nearly twice as high in the low nitrogen treatments as in the optimal nitrogen treatments. The CV of CCCI is a more robust indicator of nitrogen status than the mean CCCI.

The fact that CV of CCCI was higher at all grid sizes and CV of PCT was generally higher only at high resolution may be due to either or both of the following explanations: variation of nitrogen occurs over a greater length scale than variation of PCT, and/or there is such a large difference in CV of CCCI between the treatments that it is still apparent at larger scales. If detection of change in CV of PCT is a design criteria for a remote sensing system, then grid scales of 3 m or finer may be acceptable. Likewise, 7 m resolution may acceptable for detection of CV of CCCI. However, it is likely that determination of the minimum acceptable scale is soil dependent and should be evaluated for each soil type.

Conclusions

The mean value of the difference between canopy and air temperature (PCT) was not an effective method to detect water status except in the case of extreme stress on DOY 231. However, the coefficient of variation (CV) of PCT detected small differences in soil water depletion (6% to 10%) in the 20% to 30% soil water depletion range. Except for extreme stress, detection of water status with CV of PCT was only apparent at a scale of 3 m or finer.

Except for DOY 181–182, with less than full canopy and dominant soil effects, all CVs of the canopy chlorophyll concentration index (CCCI) at nearly all grid scales were nearly twice as high in the low nitrogen treatments as in the optimal nitrogen treatments. Differences in CV of CCCI between treatments were generally less at grid scales greater than 7 m.

ANOVA was not an effective statistical method to evaluate differences between treatments because of the large number of data points in each plot.

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