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PHYSIOLOGY

Application of Remote Sensing to Strategic Questions in Cotton Management and Research

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INTERPRETIVE SUMMARY

Remote sensing can be a relatively inexpensive source of data for site-specific crop management and for addressing research questions concerning spatial variability of fields. Many of the potential research and management applications of remote sensing are tactical; that is, they involve responses to particular conditions or situations that arise during the course of the season. Examples include insect pest management, weed management, and irrigation scheduling. Other potential applications, however, involve strategic questions: that is, information concerning the integrated whole of the crop production system.

Tactical questions often involve determining how a field is changing: for example, detecting an emerging pest infestation. Detecting change with remote sensing involves collecting images frequently and comparing them with previous images. This can be fairly costly for two reasons. First, a relatively large number of images must be collected. Second, the images must be calibrated (i.e., an absolute standard must be set for data within the image) so that values from a location in one image may be compared with values from the same location in other images. Calibration of a remotely sensed image is generally accomplished by laying out large panels of known properties that then appear in the image.

In the case of strategic questions addressing spatial variability, however, one is interested in comparing one part of a field with another. Strategic questions, even those that involve the behavior of the field over the entire season, may often be answered by measuring the properties of the field relative to each other. There are two potential sources of simplification in addressing these questions. One is that fewer images may be necessary than with tactical questions, and the other is that it may not be necessary to calibrate the images. If either of these situations proves true, then considerable financial savings may be possible, as images can be costly to collect and calibration panels can be costly to purchase and maintain. The objective of this paper is to determine whether such savings are possible when addressing certain strategic questions in cotton production.

There are two questions associated with this objective: (i) the question of whether calibrated images can be used, and (ii) the question concerning the number of images required. This paper uses two methods to address these questions. The question of whether a calibrated image is necessary is addressed using mathematical analysis, and the question concerning the number of images is addressed using the statistical method of longitudinal data analysis. Both methods analyze data in the form of the normalized difference vegetation index (NDVI), a numerical index of the intensity of infrared and red reflected light in the image. The NDVI is the most common numerical index for multispectral data. The results presented in this paper indicate that uncalibrated data can be used to measure spatial patterns in field variability but not to measure changes over time or between fields. Moreover, NDVI patterns in mid- to late season display a high level of temporal autocorrelation, so that relatively few images may

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Abbreviations: NDVI, normalized difference vegetation index; WSREC, University of California West Side Research and Extension Center.

be needed to obtain information about patterns of spatial variability within the field during this period. Both of these results imply that considerable financial savings may be possible when using remote sensing to address strategic research or management questions in cotton.

ABSTRACT

Remote sensing can be a relatively inexpensive source of data for site-specific crop management. Many potential applications of remote sensing are tactical, in that they involve responses to particular conditions or situations that arise during the course of the season. Other potential applications, however, both in research and in management, involve strategic questions that concern the integrated whole of the crop production system. Strategic decision making generally occurs before the season begins. The use of remotely sensed images in addressing strategic vs. tactical questions differs in that strategic questions may involve patterns of spatial variability only and tactical questions may involve temporal as well as spatial variability. This difference may have several practical consequences. In the strategic use of remote-sensing data, extreme speed in the delivery of the image or image data after acquisition may be unnecessary. Speed may be necessary for tactical management uses. Using remote sensing in strategic situations may not require calibrated image data and may not require as many images. If true, this could result in considerably lower data-collection costs. The objective of this research was to seek answers to two questions: (i) can uncalibrated data be used for strategic management? (ii) what is the inter-temporal relationship among sequences of images? Analyses of chronological sequences of images of irrigation and N stress indicate that uncalibrated data are useful for addressing strategic questions that involve spatial variability of crop status and that locations within the field are highly autocorrelated, so that relatively few images are necessary to determine crop spatial reflectance properties.

Remote sensing is increasingly identified as a relatively inexpensive source of data for site-specific crop management (Moran et al., 1997). Many of the potential applications described in the literature thus far are tactical; that is, they involve responses to a particular condition or situation that arises during the course of the season. Tactical applications include insect pest management (Fleischer et al., 1997), weed management (Johnson et al., 1997), and irrigation scheduling (Brusch, 1989). Other potential applications, both in management and in research, involve strategic questions or decisions concerning the integrated whole of the crop production system. Strategic decision making generally takes place before the season begins. Strategic management decisions include variety selection, soil reclamation, and irrigation system design. An example of a strategic research question that involves commercial fields is that of how to identify the factors underlying observed spatial variability in yield (Plant et al., 1999). The very making of a yield map must generally be considered a strategic action because the yield information comes too late to affect current yield and must be used to improve economic yield in future harvests.

In both tactical and strategic crop management and research, the use of remotely sensed multispectral data from the visible and near infrared range of the electromagnetic spectrum generally involves the use of vegetation indices: that is, algebraic combinations of the major spectral bands. By far the most commonly used vegetation index is the normalized difference vegetation index, or NDVI (Tucker, 1979). Many of the commonly used vegetation indices have similar responses to vegetation characteristics, and indeed several are algebraically related to each other and to the NDVI (Perry and Lautenschlager, 1984). Wiegand et al. (1991, 1994) studied the relationship of a number of vegetation indices with cotton (*Gossypium hirsutum* L.) grown in salt-affected soil and found a significant relationship between yield and seasonal accumulated NDVI (i.e., the sum of daily NDVI values). (They also found a significant relationship between yield and other accumulated indices). Plant et al. (2000) observed a positive relationship between yield in cotton and NDVI-days (defined in the Theory section below).

There is a subtle but very important difference in the way vegetation index data are used to address strategic vs. tactical questions. Tactical questions often involve change detection: that is, the comparison of values of a pixel or set of pixels obtained at different times. For example, in the case of infestations by arthropod pests, such as mites, damage to leaves is an indication of the presence of an infestation, and an unexpected change in vegetation index at particular locations in the field may signal an infestation at those locations. In strategic questions, on the other hand, the focus is often on the overall spatial configuration of the field. Specific comparisons between consecutive remotely sensed images are less important than the patterns of the images and the spatial variability at different locations in the field. A second, practical difference between tactical and strategic use of remotely sensed data is that tactical use generally requires a very short time between acquisition and delivery of the images, whereas this rapid turnaround is less important in strategic management.

As with any source of data, one of the key questions in gathering remotely sensed images is how to minimize the cost of data collection by avoiding unnecessary expense. One major expense associated with remote sensing of agricultural fields involves the use of calibration panels, large panels coated with a material of known reflectance properties. These panels are placed in the field in such a way that they are visible in the image. Because it is unlikely that the reflectance properties of these panels will stay fixed for long under the dusty conditions associated with agricultural production, expense is incurred both in the purchase and the maintenance of these panels. A second cost is the acquisition of the images themselves. In assessing strategic questions, acquiring a large number of images may be redundant. If the extent and structure of temporal autocorrelation are known, then considerable savings can be realized by acquiring images only when they are needed.

The object of this paper is to address these issues of operation and cost for strategic cotton management and research. The first issue to be considered is that of calibration and correction of the remotely sensed data used in computing vegetation indices. This issue is addressed here in an entirely theoretical manner and is derived from earlier empirical results of Plant and Munk (1999a) and Plant et al. (2000). The second issue is the estimation of the extent and structure of spatial autocorrelation. This is addressed with the use of the data set analyzed by Plant et al. (2000) that consists of a set of replicated experiments in which the treatment factor was either water or N stress and the response factors were yield and NDVI. The research questions addressed in the earlier paper were: (i)what is the relationship between vegetation indices and yield? (ii) what is our ability to detect N and water stress? These two questions were investigated and described with the use of classic analysis of variance (ANOVA) techniques. In the present paper, we use methods of longitudinal analysis (Diggle et al., 1994; Hand and Crowder, 1996) to analyze the temporal autocorrelation structure of the data. This approach generally involves analyzing the relationships between each individual plot rather than aggregating plots by treatment. Graphical analysis of normalized data is used to visualize the temporal relationships between plots, and rank correlation coefficients are computed to quantify temporal autocorrelation.

MATERIALS AND METHODS

The data analyzed in this paper are the same as studied by Plant et al. (2000). Data collection methods are discussed in detail in that paper. Chronological sequences of false color infrared aerial photographs were taken of replicated field experiments on cotton conducted at five sites in 1997 and four sites in 1998. One of the 1997 sites and two of the 1998 sites were located on plots of approximately 85 by 325 m at the University of California West Side Research and Extension Center near Five Points, CA (36.3° N lat; 120.1° W long). The soil at this location is relatively uniform and is classed as a Panoche clay loam (fine-loamy, mixed, superactive, thermic Typic Haplocambids). The other sites were located on commercial cotton fields in the San Joaquin Valley in California. These fields were generally about 700 by 700 m in size. The experimental trial areas were generally 150 m wide and covered the entire length of the fields. The treatment in each experiment involved either N or water stress. The variety of cotton in all trials was Acala Maxxa. With the exception of the specific stress treatments, each field was maintained for optimum yield using University of California management methods described in Hake et al. (1996).

False color infrared aerial photographs were taken of the sites with Kodak 2443 Aerochrome II infrared film. Photographs were taken from an altitude sufficient to include the entire field in the image (~850 m at the University of California West Side Research and Extension Center site and ~1500 m at the commercial fields). In 1997 the photographs were taken on 28 July, 13 August, 26

August, 15 September, and 30 September. In 1998 fields were photographed on 30 June, 14 July, 29 July, 11 August, 25 August, 14 September, 1 October, 15 October, and 30 October. Photographs were taken at midday, and skies were generally cloud-free. (During those months cloud cover is rare in the San Joaquin Valley.)

The N stress experiments were part of an ongoing fertilizer rate study. All of these experiments were identical in design. Total soil N level in the upper 0.6 m was measured just prior to fertilization and sufficient N fertilizer was applied to bring available soil N to the treatment levels, which were 55, 110, 165, and 220 kg ha^{-1}, respectively. Where residual soil N exceeded 55 kg ha^{-1} no fertilizer was added to the 55 kg ha^{-1} treatment. In one experiment (Fresno County) in 1998, the highest rate used in treatment was 190 kg ha^{-1}. Each treatment was replicated four times in a randomized complete block design. Aerial photographs were taken of three experimental N sites in 1997 and three different sites in 1998.

Two of the experiments in 1997 and one in 1998 involved water stress. The treatments in 1997 were the dates of the final irrigation. One experiment was conducted at the University of California West Side Research and Extension Center. This involved four final irrigation dates (18 June, 21 July, 8 August, and 29 August). The experiment was laid out as a split plot with four replications in which final irrigation date was the main plot factor and variety was the subplot factor. Only results from the Acala Maxxa plots are discussed here. There were four replications. Each plot consisted of six 1.02-m rows. The second experiment was located in a commercial cotton field. The experiment involved three final irrigation dates (11 August, 25 August, and 5 September). It was laid out as a randomized complete block with four blocks and four treatments per block (there were two treatments on 5 September in each block). The field was maintained according to normal commercial production practices. The 1998 irrigation experiment was conducted at the University of California West Side Research and Extension Center. The treatments were the number of times the field was irrigated: either zero, once, two or three times at evenly spaced intervals. (There is negligible precipitation in the San Joaquin Valley during the summer and early fall.) The spring of 1998 was unusually rainy; in most years a crop could not have been grown without any irrigation. The experiment was laid out as a split plot in which number of irrigations was the main plot factor and variety was the subplot factor. As before, only the results of the Acala Maxxa treatment are discussed. There were three replications.

Positive images of false color aerial photos were scanned at 600 dpi with an Agfa Argus II scanner (Agfa, Ridgefield Park, NJ), which separated the bands into TIFF image files. These files were imported into the Idrisi geographic information system (Clark Univ., Worcester, MA) and georegistered. Georegistration was carried out using reference points obtained with a Trimble Pro-XL global positioning system (Trimble Navigation, Sunnyvale, CA). During georegistration the images were resampled so that the number of image pixels per crop-row width had the integer value nearest to that of the original image. This was done to simplify extraction of plot data from the image. Data were analyzed with Idrisi, Microsoft Excel (Microsoft Corp., Redmond, WA), and Minitab (Minitab Inc., State College, PA). In analyses of plot data, only the values from the middle rows of cells from each plot were used so that edge effects and mixed pixels could be avoided. Normalized difference vegetation index (NDVI) was computed on a cell-by-cell basis according to the formula

$$NDVI = \frac{IR - R}{IR + R} \qquad [1]$$

where IR is the near infrared (~700 to 800 nm) digital number value of the cell and R is the red (~600 to 700 nm) digital number value.

One objective of this report is to show that uncalibrated images may be used in the application of remotely sensed reflectance images to strategic questions in crop management. The second objective is to use the temporal autocorrelation structure of the images to estimate how many such images are necessary and when they should be collected. The first objective is addressed mathematically in the theory section with the methods of Perry and Lautenschlager (1984) to show that, for management purposes, the calibrated and uncalibrated images provide equivalent information. Also in the theory section, the crucial question for determining whether two images provide equivalent information is shown to be whether or not the rank order of data values from one image is the same as the rank order of data values from the other image. In other words, NDVI from two images of the same crop taken at different times provide equivalent information if the rank order of these NDVI values is the same. Accordingly, the second objective was addressed graphically and statistically using a method described by Diggle et al. (1994) and Hand and Crowder (1996). The method is concerned with determining how rank order changes in successive data sets and considers each individual plot result separately, rather than aggregating by treatment as is done in ANOVA. The graphical method entails normalizing plot values and then plotting these normalized values as a collection of curves. The changes in rank order can then be visualized by observing how many times the curves cross each other. The statistical method is to analyze the rank correlation coefficients of the data on each date.

THEORY

The primary purposes of this section are the consideration of errors associated with data calibration and the determination of the extent to which errors induced by uncalibrated data affect the use of these data in analyses intended for strategic applications in site-specific cotton management and research. All analyses carried out in this paper involve the NDVI computed in Eq. [1]. Thus, the issue that needs to be discussed is the effect of errors on this quantity. Similar analyses could, however, be carried out on any mathematically defined vegetation index.

The fundamental data used in the computations of Eq. [1] are the IR and R values on the right hand sides of these equations. These are represented in an image on a pixel by pixel basis as digital numbers: that is, as integers taking on values that can theoretically range between 0 and 2^N - 1, with N being the number of bits. Generally $N = 8$, so that $2^N - 1 = 255$. Here 0 represents the minimum measurable radiation in that spectral band and 255 represents the maximum measurable radiation. Because these are measurable quantities, we denote them as IR_m and R_m. These quantities are assumed to represent the *true* aggregated reflectance values (measured on the same scale) of the crop surface represented by that pixel, which we denote IR_t and R_t. Similarly, we denote the NDVI computed from the *measured* and *true* values by NDVI_m and NDVI_t,respectively. The issue addressed in this section is the extent to which NDVI_m represents NDVI_t.

In 1997, the photographs of the fields were made in rapid succession at two aperture settings. Plant and Munk (1999a) computed NDVI values for the same location using data from these paired photographs. They found that NDVI varied by as much as 30% due to different responses in the red and infrared digital number values related to changes in aperture. Plant et al. (2000) calibrated sequences of images of individual fields based on pseudo-invariant objects and plotted NDVI values computed from calibrated images against those computed from uncalibrated images. Simple linear regression of NDVI from calibrated images against the NDVI from uncalibrated images yielded relationships with an r^2 valueof at least 0.96. Paris (1998) points out that digital number values from field images contain a component from scattered radiation as well as one from reflected radiation. Based on these observations, we assume that the relationship between measured and true digital number values in any given image may be written as

$$\begin{aligned} R_m &= aR_t + c \\ IR_m &= bIR_t + c \end{aligned} \qquad [2]$$

Two simplifying assumptions are implicit in these equations. The first is that the response in the measured value to changes in the true value may be represented as multiplication by a constant. Secondly, the level of scattered radiation is assumed to be the same in both the red and infrared bands. Both of these assumptions have limitations. For example, the measured value may saturate at high levels of radiation, and the level of scattering may be different between red and near infrared bands. Plant and Munk (1999a) and Plant et al. (2000) provided empirical evidence in support of these assumptions, and each assumption should be considered as a first approximation. Of course, the values of a, b,and c will, in general, be different in different images.

In addressing the effect of image-induced errors on NDVI values, we will use the concept of equivalence developed by Perry and Lautenschlager (1984). They defined two vegetation indices as being equivalent if they led to the same decision (ignoring random error effects). Perry and Lautenschlager formalized this definition by saying that two indices are equivalent if there is an invertible, i.e., one-to-one and onto (Rudin, 1976), relationship between them. In our notation, this means that every value of NDVI_m corresponds to one and only one value of NDVI_t. In the same way, we will say that NDVI measures are equivalent if they lead to the same decisions, as indicated by the existence of an invertible relationship between NDVI values computed from them.

In the case where $c = 0$, the question of equivalence is a special case of a relationship demonstrated by Perry and Lautenschlager (1984). They showed that if the measured NDVI is defined by (in our notation)

$$NDVI_m = \frac{aIR_t - bR_t}{aIR_t + bR_t}, \tag{3}$$

then NDVI_m is equivalent to the ratio IR_t/R_t. They demonstrated Eq. [3] by showing that if the transformation $T(y)$ is defined by

$$T(y) = \frac{\frac{a}{b}(1+y)}{1-y}, \tag{4}$$

then $T(\mathrm{NDVI}_m) = IR_t/R_t$. Because this relationship is true for any a and b, it is true for $a = b = 1$. Thus, NDVI_m and NDVI_t are both equivalent to IR_t/R_t. Because equivalence is a transitive relationship (Rudin, 1976), this implies that NDVI_m is equivalent to NDVI_t for $c = 0$.

For the general case $c \neq 0$, i.e., the case of background scattering radiation, we can also show that NDVI_m and NDVI_t are related by an equivalence relation. Indeed, if the formulas for IR_m and R_m given in Eq. [3] are plugged into Eq. [1] and the resulting function is differentiated with respect to c, we get

$$\frac{\partial NDVI_m}{\partial c} = \frac{-2}{(aIR_t + bR_t + 2c)^2}. \tag{5}$$

Because the right-hand side of Eq. [5] is strictly negative, NDVI_m is monotonic in c. Therefore, for any fixed a and b, there is a one-to-one and onto relationship between NDVI_m and NDVI_t. Thus, they are equivalent.

Plant et al. (2000) employed NDVI-days extensively in their analysis of remotely sensed data. This quantity is defined as the integral of NDVI over time and may be estimated according to the trapezoidal rule as

$$NDVI - days = 0.5\sum_{j=1}^{n-1}(NDVI_j + NDVI_{j+1})(D_{j+1} - D_j), \tag{6}$$

where NDVI_j is the NDVI value on day j and D_j is the number of elapsed days on day j. NDVI-days may be considered as a remote sensing analogy to degree-days. Although we do not employ NDVI-days in the present paper, this quantity has been used in other studies concerned with strategic questions in crop production (e.g., Wiegand et al., 1991; Denison et al., 1996). It is, therefore, worthwhile to consider whether this measure is affected by using uncalibrated images.

Under our assumptions, the measured values $\mathrm{NDVI}_{m,j}$ in the equation are given by

$$NDVI_{m,j} = \frac{IR_{m,j} - R_{m,j}}{IR_{m,j} + R_{m,j}}, \tag{7}$$

where

$$R_{m,j} = a_j R_t + c_j$$
$$IR_{m,j} = b_j IR_t + c_j. \tag{8}$$

The subscripts j are added to the coefficients in Eq. [8] to indicate that the relationship between measured and true NDVI may be different on different days. Nevertheless, because NDVI-days are linear in the individual NDVI_j terms, when Eq. [6] is differentiated with respect to any of the c_j, the result is the same as Eq. [8]: i.e.,

$$\frac{\partial NDVI - days_m}{\partial c_j} = \frac{-2}{(a_j IR_t + b_j R_t + 2c_j)^2}. \quad [9]$$

Once again, this is monotonic in c_j.This effect can be seen in Fig. 1a, which shows the trends of NDVI vs. date for an irrigation trial conducted at the University of California West Side Research and Extension Center in 1997. A drop in NDVI occurs across all plots on 18 August. This drop is almost certainly an artifact. That is, the true reflected NDVI of the crop probably did not decrease on this date and then subsequently return to a higher level. Instead, changes in factors such as the intensity of radiation, the processing of the film or other factor changes probably caused the measured NDVI on this day to be relatively lower than on the other days. Without calibration these changes are impossible to correct. Yet, because the measured drop occurs in all measurements taken on that date, the values of NDVI-days, which represent the areas under the curves, are all affected in the same way; therefore, their order relationship is not affected.

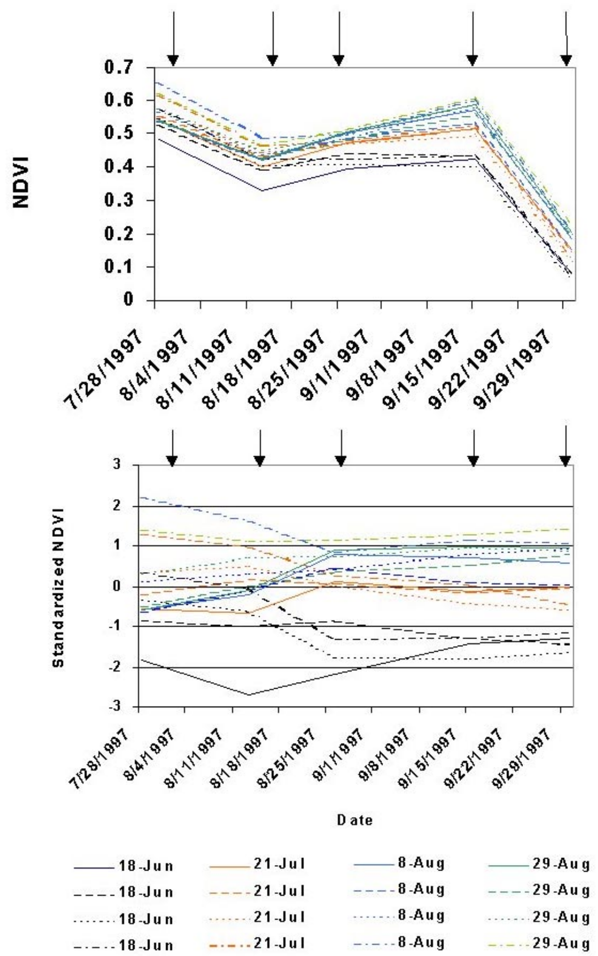

Fig. 1. (a) Average plot--normalized difference vegetation index (NDVI) vs. date for each of the individual plots in the irrigation experiment conducted at the Univ. of California West Side Res. and Ext. Ctr. in 1997. The treatments, distinguished by color, are date of last irrigation. The individual plots are distinguished by form of curve. Arrows indicate dates on which photographs were taken. Note that all curves tend to move up and down together. **(b)** Standardized values of the same data shown in Fig. 1a. The data were standardized by subtracting the daily mean and dividing by the daily standard deviation. The curves tend to sort themselves out after 25 Aug. and remain in the same order.

We intuitively summarize this section as follows. When considering an individual image, changes in the relative magnitude of the infrared and red bands or the addition of background scattering affect the computation of NDVI in a complex way. However, if the true NDVI in one pixel is larger than that in another pixel, then the measured NDVI will also be larger. As a result, estimates of relative levels in the same image remain valid, but nothing can be said about the change in NDVI within a pixel from one image to the next without calibration. Similarly, in the case of NDVI-days, all of the values that make up the contribution of an image to the value of NDVI-days increase or decrease together. Consequently, comparisons of order relationships (that is, which parts of the field have high NDVI and which have low) within a single field in a single season can be made without calibration. On the other hand, in order to compare two different fields or a single field between different years (i.e., to achieve some absolute measure of NDVI), calibration must be carried out.

RESULTS

Irrigation Experiments

In order to address the questions of how many images are necessary for strategic analysis and when these images should be taken, it is necessary to examine the level of consistency of the relationship, over the course of the season, between vegetation indices computed for different stress treatment levels. Figure 1a shows a plot of a typical NDVI time course for an experiment. This figure

Table 1. Spearman rank correlation coefficients (ρ) between dates in 1997 for the plot--normalized difference vegetation index (NDVI) data of Fig. 1.

	28 July	13 Aug.	26 Aug.	15 Sept.
13 Aug.	0.89***			
26 Aug.	0.27	0.54*		
15 Sept.	0.36	0.62**	0.97***	
30 Sept.	0.36	0.61**	0.94***	0.98***

*, **, *** Significant at the 0.05, 0.01, and 0.001 probability levels, respectively.

Table 2. Correlation coefficients (*r*) of plot--normalized difference vegetation index (NDVI) values with plot yield for each date for the 1997 data of Fig. 1.

	28 July	13 Aug.	26 Aug.	15 Sept.	30 Sept.
r	0.38	0.59**	0.80***	0.84***	0.84***

, * Significant at the 0.01 and 0.001 probability levels, respectively.

describes the irrigation trial conducted at the University of California West Side Research and Extension Center in 1997. The treatment was date of last irrigation. The colors represent different treatments and the form of the curves (i.e., solid, dashed, etc.) distinguishes plots within treatments. The intent of figures such as this is to allow one to focus on the overall behavior of the collection of plots rather than on the behavior of any individual plot (Diggle et al., 1994; Hand and Crowder, 1996). Based on the results of the theory section, one of the most important pieces of information for our purposes is the extent to which individual plots change their rank order (i.e., cross each other). Diggle et al. (1994) suggest that this is most easily visualized by plotting curves of data that have been standardized by subtracting the daily mean and dividing by the daily standard deviation. Figure 1b shows the same data as Fig. 1a but is standardized in this way. The plot values have assumed a reasonably consistent rank order by the date of the first aerial image, and this tendency increases as the season progresses.

Examination of the standardized NDVI data in Fig. 1b indicates that rankings are fairly dynamic prior to late August and are fairly stable after that. Table 1 shows the Spearman rank correlation coefficients (Steel and Torrie, 1980) between dates for the individual plot-NDVI values in the experiment. It is evident that the last three images present almost exactly the same information. Table 2 shows the correlation coefficients of the plot NDVI values with plot yield. The first two dates have only a small correlation; the last three dates have essentially the same information. In summary, the same strategic information on overall plot response to treatment could have been gained from a single aerial photograph taken some time after 26 August: in other words, taken at any time after the final stress effects from the irrigation treatment became established.

The second irrigation experiment performed in 1998 at the University of California West Side Research and Extension Center yielded essentially the same results. The treatment was number of irrigations and only the 0-irrigation treatment showed a significant effect (Plant et al., 2000). Figure 2 shows a plot of standardized NDVI vs. date for all the plots. There is a considerable amount of crossing of curves prior to approximately mid-August. After that point the curves tend to stay in order until around mid-October, at which time there is again considerable rearranging. Table 3 shows Spearman rank correlation coefficients among plots for each of the dates with the middle date (25 Aug.). Although all correlation coefficients are significant (the 18 June coefficient is barely so), the pattern of coefficients follows that of Fig. 2, with the middle dates being most highly correlated.

The experiments at the University of California West Side Research and Extension Center, while highly informative, do represent an important deviation from normal practice in commercial fields. Water stress differences in commercial fields ordinarily are influenced by soil textural or topographical differences within the field, rather than to differences in irrigation timing. The third field in the irrigation component of our study, a commercial field in Fresno County, had a high level of spatial variability in soil properties (Plant and Munk, 1999a; Plant et al., 2000). In particular, each experimental plot in this field, with plots running

Table 3. Correlation coefficients for the plot--normalized difference vegetation index (NDVI) data shown in Fig. 2. The first row of the table contains the Spearman rank correlation coefficients (ρ_s) of plot NDVI values on the given date in 1998 with plot NDVI values taken on 25 Aug. The second row contains the correlation r_y of plot NDVI values on the given date with plot yield.

	18 June	14 July	25 July	11 Aug.	25 Aug.	14 Sept.	1 Oct.	15 Oct.	30 Oct.
ρ_s	-0.15	0.69**	0.65**	0.90***		0.73**	0.80***	0.93***	0.59*
r_y	-0.20	0.74**	0.81**	0.84**	0.87***	0.85**	0.86***	0.80**	0.63*

*, **, *** Significant at the 0.05, 0.01, and 0.001 probability levels, respectively.

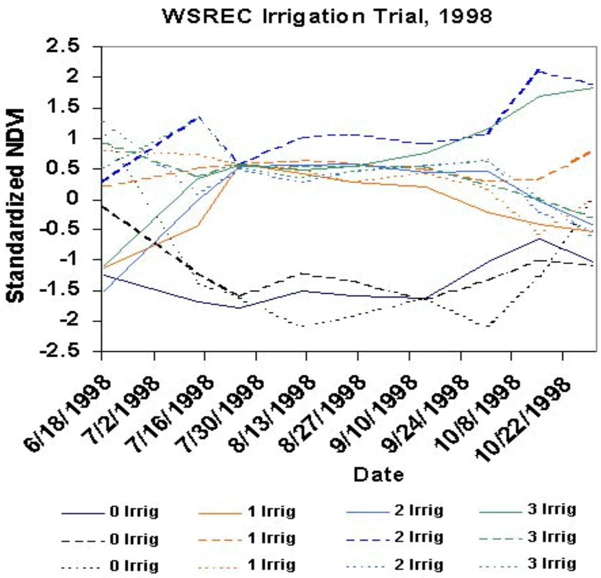

Fig. 2. Standardized normalized difference vegetation index (NDVI) values vs. date for each of the individual plots in irrigation experiment conducted at the Univ. of California West Side Res. and Ext. Ctr. (WSREC) in 1998. The treatments are number of irrigations. As with Fig. 1, colors distinguish treatment levels, curve forms distinguish plots, and arrows indicate date of photographs. Note that the treatments tend to be in the same order from one date to the next during the middle of the season, but not the beginning or end.

east-to-west, had a sandy area on the east side and heavier soil on the west side. The treatment effect in this experiment was date of last irrigation, and

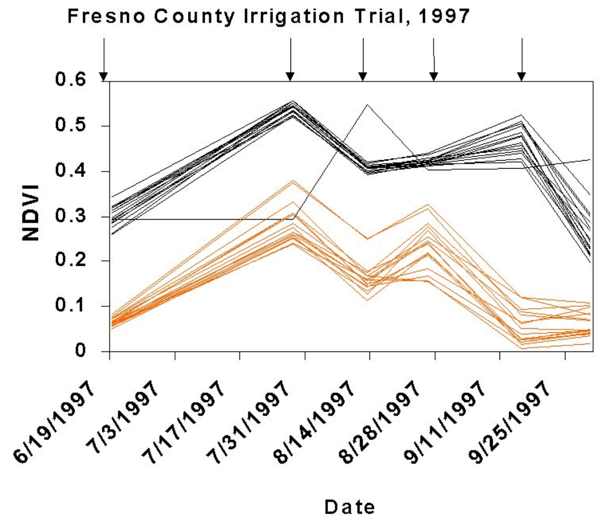

Fig. 3. Normalized difference vegetation index (NDVI) values for all the plots in an irrigation experiment in which the east side of the plots was in sandy soil and the west side was in loamy soil. The NDVI values from the east side are shown in red, and the values from the west side in black.

there were no significant differences in yield or NDVI between treatments (Plant and Munk, 1999a). Figure 3 shows NDVI data from the east and west sides of the field for each of the 16 plots. Aside from one apparent outlier, there is an evident pattern to the data. The eastern (sandy) side of the field has a consistently lower NDVI, and at the end of the season the dramatic drop in NDVI characteristic of all these data sets occurs earlier on the east side. This is consistent with the assumption

Table 4. Spearman rank correlation coefficients (ρ_s) for plot--normalized difference vegetation index (NDVI) values in the 1998 N experiments with the plot NDVI values on the median date for that year (25 Aug.) and correlation coefficients r_y of plot NDVI with plot yield.

	18 June	14 July	25 July	11 Aug.	25 Aug.	14 Sept.	1 Oct.	15 Oct.	30 Oct.
WSREC [*] ρ_s	0.12	0.98***	0.65**	0.94***		0.99***	0.87***	0.19	0.12
WSREC r_y	0.33	0.55*	0.47	0.48	0.56*	0.56*	0.58*	-0.15	-0.12
Fresno ρ_s	-0.10	-0.27	0.51*	0.76***		0.93***	0.84***	0.90***	0.87***
Fresno r_y	0.17	0.09	0.49	0.42	0.34	0.25	0.34	0.31	0.15
Kings ρ_s	0.75***	0.54*	0.90***	0.83***		0.99***	0.85***	0.67**	0.54*
Kings r_y	0.02	0.32	0.16	0.26	-0.19	-0.03	0.01	0.32	0.26

*, **, *** Significant at the 0.05, 0.01, and 0.001 probability levels, respectively.
[*] WSREC, University of California West Side Research and Extension Center.

Table 5. Spearman rank correlation coefficients (ρ_s) for plot--normalized difference vegetation index (NDVI) values in the 1997 N experiments with the plot NDVI values on the median date for that year (28 Aug.), and linear correlation coefficients r_y for plot NDVI values with plot yield.

	28 July	13 Aug.	28 Aug.	15 Sept.	30 Sept.
Fresno ρ_s	0.80***	0.98***		0.64**	0.42
Fresno r_y	0.84***	0.74**	0.73**	0.60*	-0.06
Madera ρ_s	0.79***	0.88***		0.80***	0.45
Madera r_y	-0.49	-0.48	-0.59**	-0.53*	-0.31

*, **, *** Significant at the 0.05, 0.01, and 0.001 probability levels, respectively.

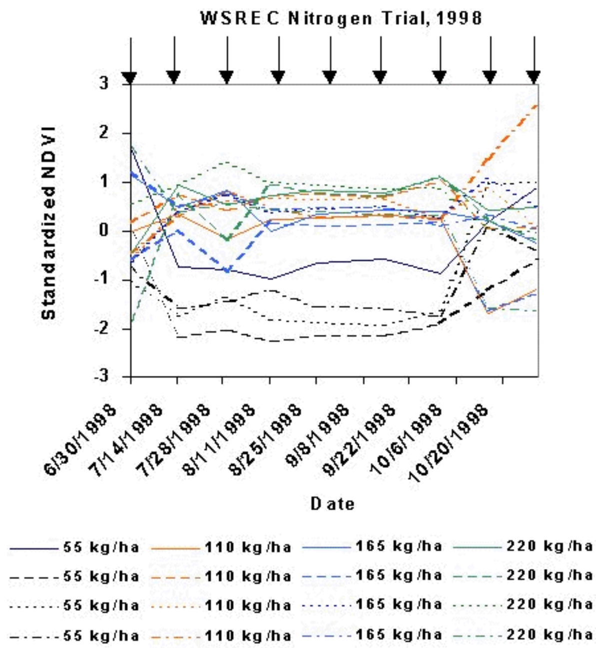

Fig. 4. Standardized normalized difference vegetation index (NDVI) values vs. date for each of the individual plots in the N experiment conducted at the Univ. of California West Side Res. and Ext. Ctr. (WSREC) in 1998. The treatments are total N rates.

that the lower water-holding capacity of the sandy soils led to reduced vegetative growth and earlier senescence. The means of the east and west side NDVI values (with the apparent outlier removed) were significantly different on each date.

Nitrogen Experiments

Plant et al. (2000) presented an extensive statistical analysis of the means of the N experiments as they relate to yield. In summary, their analysis indicated that NDVI is a conservative predictor of N stress in that no significant yield differences existed between N treatments without corresponding significant differences in NDVI. On the other hand, there were significant NDVI effects not matched by a significant yield effect (although in each such case there was a nonsignificant yield trend). Figure 4 shows standardized NDVI vs. time for a typical experiment that was conducted in 1998 at the University of California West Side Research and Extension Center.

Tables 4 and 5 show the Spearman rank correlation coefficients of NDVI at each date with the chronologically median date for that year, and the correlation coefficients of each date with yield. In many cases, the individual NDVI values have no significant correlation (or even a negative correlation) with yield; however, NDVI values taken during the middle and, in some cases, late season have strongly significant serial autocorrelation, even when they do not correlate with yield.

DISCUSSION

The mathematical argument in the theory section is intended to show that NDVI values computed from uncalibrated data are valid representations of spatial variability, although they cannot be used to estimate intertemporal variability. The advantage of a mathematical demonstration is its complete generality. Assuming that the relationships given in Eq. [2] are valid (or are close approximations), then the mathematical formulas hold for any set of NDVI data. The reason is that these relationships are a mathematical property of the NDVI formulas, rather than a physical property of the electromagnetic spectrum or a biological property of cotton. This conclusion from the theory section justifies the use of uncalibrated image data to address the second objective of the study, the determination of trends in spatial ordering of the data from image to image.

One striking result of our experiments is the strong level of serial autocorrelation of NDVI values during the mid- to late season. In virtually all cases there was little difference in the rank order of plot NDVI values in images taken between first flower and cutout. In both irrigation and N stress experiments, the serial correlation tended to break down at the beginning and, sometimes, at the end of the season. This finding indicates that if the only objective is a survey of field variability for strategic management, then a few images taken during mid- to late season should suffice. Images taken earlier in the season may have less direct value because the canopy is not fully developed. Those taken at the end of the season may be more influenced by the distribution of senescence. However, such images may have other value: for example, early-season images may relate to variations in soil properties, and late-season images may be used to indicate the need for defoliation by showing areas of green vegetation (Plant and Munk, 1999b).

To be of use in strategic management, the daily NDVI values should provide a significant prediction of yield variability. We do not address this question in the present paper, but other studies have demonstrated such a relationship (Wiegand et al., 1991, 1994; Plant et al., 2000). However, the spatial distribution of NDVI cannot be used blindly as an indicator of the spatial distribution of yield. The NDVI is primarily a measure of vegetation, rather than one of reproductive material. It should be considered as one component of a suite of spatial measurements. Depending on the specific question being addressed, these measurements may include soil properties (e.g., electrical, physical, and chemical properties), ground-based scouting for pests and disease, plant mapping, and yield itself. The advantage of aerial images is that they provide, at relatively low cost, a high-resolution measure of the vegetative condition of the crop. When used in conjunction with other crop data, this information can provide essential knowledge about the factors underlying observed spatial variability in yield (Plant et al., 1999).

Statistics texts and monographs uniformly discourage the use of time-by-time analysis, such as that used here, to study longitudinal data (Diggle et al., 1994; Hand and Crowder, 1996). One of the primary themes of this paper is that this form of analysis is, nevertheless, appropriate for our data. The reason is that the data, because they are uncalibrated, are not really a true longitudinal data set, but rather a series of *snapshots* for which the relative rather than the absolute positions are of primary importance. For that reason a time-by-time analysis captures the essential features of the data. A secondary theme of this paper is to show that such data have value in addressing strategic management and research questions for cotton production.

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