QUANTITATIVE REMOTE SENSING APPROACHES FOR MONITORING AND MANAGING AGRICULTURAL RESOURCES

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MISSION

The ultimate goal of this research is to use remote sensing technology to increase our understanding of processes associated with environmental variability and to provide resource managers with information that will assist them in making tactical and strategic management decisions on farms, rangelands, and natural plant communities. Emphasis will be given to approaches that have potential for operational application, and that also have a strong physical foundation based on quantitative measurements.

correlation with canopy chlorophyll content, reaching a maximum at early stem elongation (Zadoks 30-34) as seen in Figure 2. The CCCIwl correlated well with final harvested grain quality when two rules were applied to the data. First, phenology must be in the milk to early dough stage (Zadoks 70-85). Second, the RVI must be greater than 8.0 for a datum to be included. With results thus constrained, very good correlation with harvested grain quality as measured by protein content was achieved, as shown in Figure 3.

INTERPRETATION: The three-band, planar domain method of determining canopy chlorophyll content appears effective in this first look. If the technique is verified using existing data from other years, work can proceed on developing nitrogen recommendations based on CCCIwe, and on developing grain quality prediction algorithms based on CCCIwl.

FUTURE PLANS: A second set of wheat data containing nitrogen-limited wheat reflectances from the 1996 FACE experiment will be used to verify the efficacy of both CCCIs. Future experiments in wheat will focus on further verification and development of management tools based on remotely sensed information.

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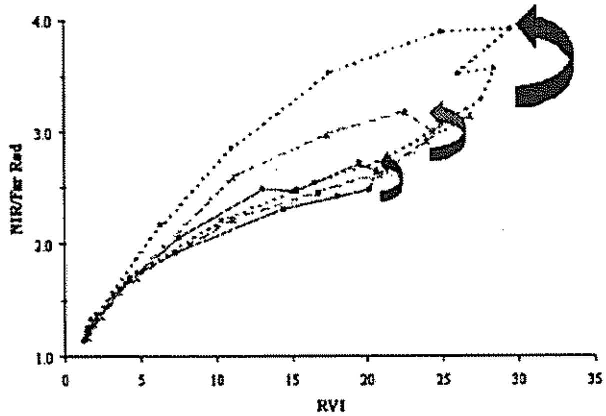

Figure 1. Planar domain of the CCCI applied to wheat. Data from three plots are shown: low nitrogen availability (●), high nitrogen availability (■), and an intermediate level (▲). A shift in the far red band during the late stem elongation and flowering stages of growth resulted in an upward shift in the domain, the location and direction of which is shown by the arrows.

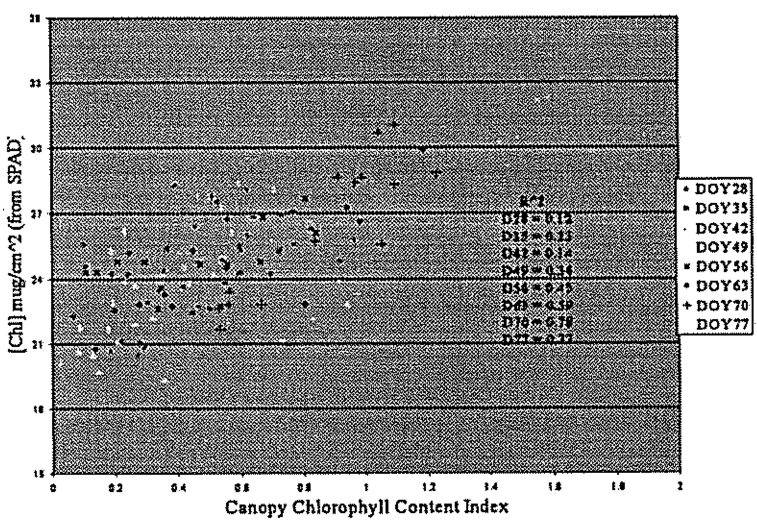

Figure 2. Correlation of chlorophyll content as estimated by SPAD measurement with CCCIwe up to mid stem elongation growth stage.

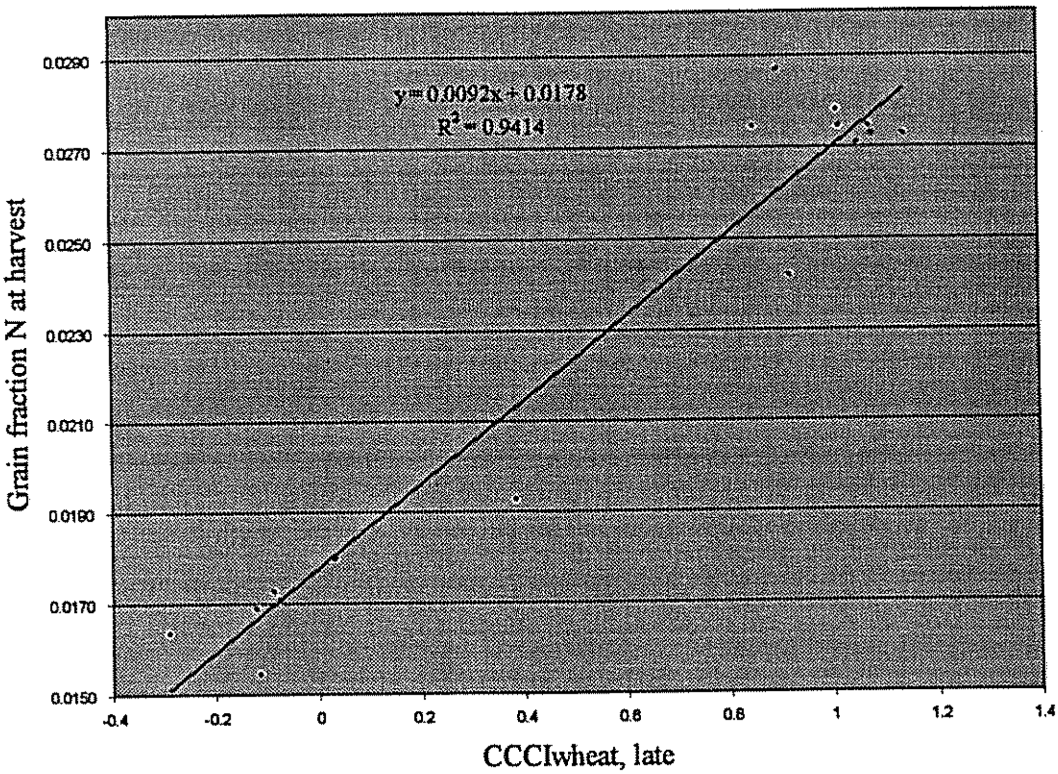

Figure 3. Correlation of grain fraction nitrogen as a measure of protein at final harvest with CCCIwl. Data were constrained to Zadoks growth stage 70 through 85 and Ratio Vegetation Index greater than 8.0.

DEVELOPMENT OF A MODELING AND SENSOR SYSTEM TO PROVIDE INFORMATION FOR PRECISION CROP MANAGEMENT

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PROBLEM: Precision farm management requires timely, georeferenced information on crop and soil conditions. In this management system, the crop is given what it needs based on the current soil and environmental conditions so that economic return (not necessarily yield) is optimized. Cost efficient methods to provide this information are lacking at the present time. The objective of this project is to provide the tools needed to manage crop inputs economically at a very fine scale (potentially as small as 1 m).

APPROACH: To provide real-time management information, a combined sensor- and modeling-based approach has been under development. This project is part of a cooperative study between the U.S. Water Conservation Laboratory, the University of Arizona, Texas A&M University, and the Idaho National Environmental and Engineering Laboratory (INEEL). The project is also enhanced by the participation of two private companies, Valmont, which is providing a linear move irrigation system for the project, and CDS Ag. Industries, which is providing an injection pump.

The project began in 1998 with cotton and barley field experiments during which agronomic and hand-held radiometer data were collected. These data were used to begin formulation of quantitative relationships between spectral response and crop condition. Concurrent with these experiments, a system was developed to allow the linear move irrigation system to serve as a remote sensing platform (named Agricultural Irrigation Imaging System, AgIIS, i.e., "Ag Eyes"). The AgIIS was completed in time for the 1999 cotton season and was able to provide images in the red, green, red-edge, near infrared (NIR), and thermal portions of the spectrum. During the growing season, the AgIIS was used to obtain images at a minimum of weekly intervals, with as many as three images per week during the period of rapid crop development. The reflective bands were calibrated to units of reflectance by using a plywood panel mounted at the center of the linear move. Periodic radiometer measurements of the panel were taken during the season so that its spectral properties were known.

A Latin square experimental design was used during the 1999 cotton season with four treatments: (1) control (WN, optimal conditions); (2) low nitrogen (Wn, 50% optimal plant requirements); (3) low water (wN, decreased irrigation frequency, allowing the plants to become water stressed five times during the season); and (4) low water and low nitrogen (wn). Soil moisture levels were monitored in every plot using a neutron probe at a minimum of weekly intervals (two access tubes per plot). Additionally, two plots were heavily instrumented with TDR probes in four locations at four depths (5, 10, 15 and 20 cm). The probes were used to determine the soil surface moisture content at hourly intervals using an automated data acquisition system. Stem flow gages were also added to these plots to measure the cotton's daily transpiration rate. The plants were sampled weekly for nitrate status, leaf area index (LAI), leaf, stem, and boll dry weights, plant height and percent canopy cover.

FINDINGS: The data collected during this study are being used to examine issues related to geostatistical analysis of spatial variability in crop condition (Kostrzewski, 2000), and improvement of remote sensing techniques to infer crop nutrient and water status. In order to present examples of some the progress made in these areas, three spectral indices will be used: the ratio vegetation index (RVI = ratio of NIR to red reflectance), a planar domain version of the crop water stress index (CWSI) similar to the version developed by Clarke (1997), and the Canopy Chlorophyll Content Index (CCCI; Clarke and Barnes, 1999). For a more complete description of these indices, see Barnes et al. (2001).

Figure 1 shows the seasonal trends in leaf area index and petiole nitrate content based on the treatment averages. The difference in water treatments began on DOY 193, after which point there was a definite slowing of LAI accumulation for the low water treatments (wN and wn). By DOY 236 there is little difference in the LAI between the Wn and wN treatments. There was no clear response in LAI to the N treatments until DOY 215 at which point petiole analysis indicate a significant difference between high and low N treatments.

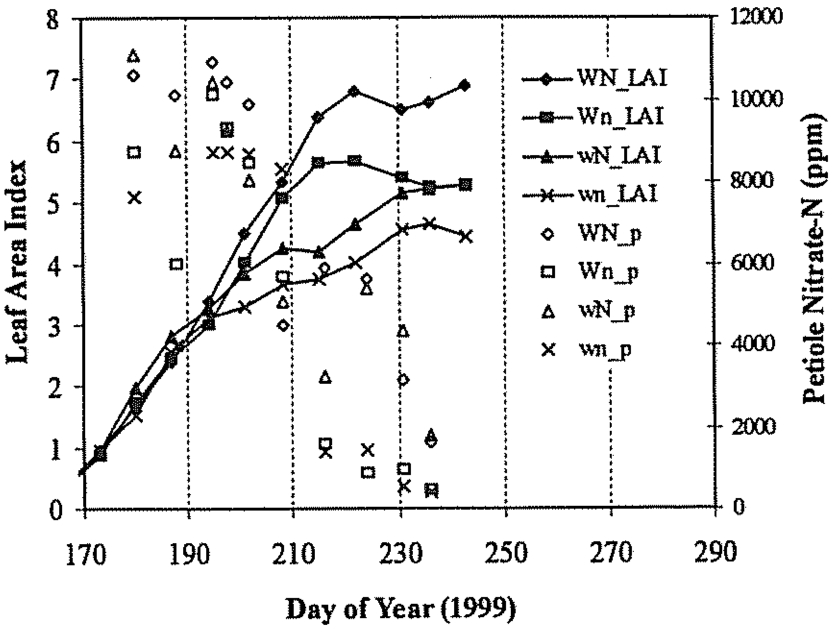

Figure 1. Seasonal trends in treatment average leaf area index (LAI) and petiole Nitrate-N concentration (p).

Figure 2 shows the season trends in the stressed treatment averages (Wn, wN, and wn) relative to the control treatment (WN) for the RVI, (1-CWSI) and CCCI. Note that 1-CWSI is used in computing the ratio to the WN treatment in Figure 2c, because under conditions of low water stress, which was common in the WN plots, the CWSI was approximately 0. The relative differences in RVI follow similar trends as LAI with some exceptions (Figure 2a). The sharp relative decrease in RVI on DOYs 194, 202, and 209 was due to a combination of a wet soil background in the high-water treatments (WN and Wn) and some leaf wilting in the low water treatments due to water stress. Note that from DOY 233 to 259 the RVI for the wN treatment becomes higher than the Wn. This illustrates the difficulty in interpreting the differences of simple vegetation indices as a measure of a single stress. Indices based on combinations of the NIR and red areas of the spectrum are strongly correlated with canopy density; therefore, any stress that alters canopy density will impact these indices.

The CCCI begins to show a clear distinction between the low N treatments (Wn, wn) after DOY 214 (Figure 2b), about the same time the petiole data indicated a strong difference between the high and low N treatments (Figure 1). Unlike the RVI, the CCCIs of the low N treatments are consistently less than the control from DOY 214 to 260. While this index does appear to minimize the impact of canopy density, it was sensitive to changes in the wetness of the soil surface background under partial canopy conditions as indicated by the increase in the index on DOYs 198 and 209. On both of these dates, the soil background in the low water treatments was dry, but wet in the high water plots. This resulted in a false indication that the chlorophyll content was higher in these treatments than the control.

In Figure 2c, the periods after which water was withheld (DOYs 194, 202, 209 and to a lesser extent 231 and 245) are identified by the relative decrease in (1-CWSI) in the low water (wN, wn) treatments. While some of these events also decreased the RVI in the low water plots with respect to the high, the RVI trends are not as related to water treatment levels as those in CWSI later in the season, particularly on DOY 251, after the water treatments were purposely reversed (i.e., water was not applied to the WN and Wn treatments on DOY 250). Also note that on dates after all of the plots were irrigated (e.g., DOY 215), there was little difference in the CWSI between water treatments, unlike the RVI.

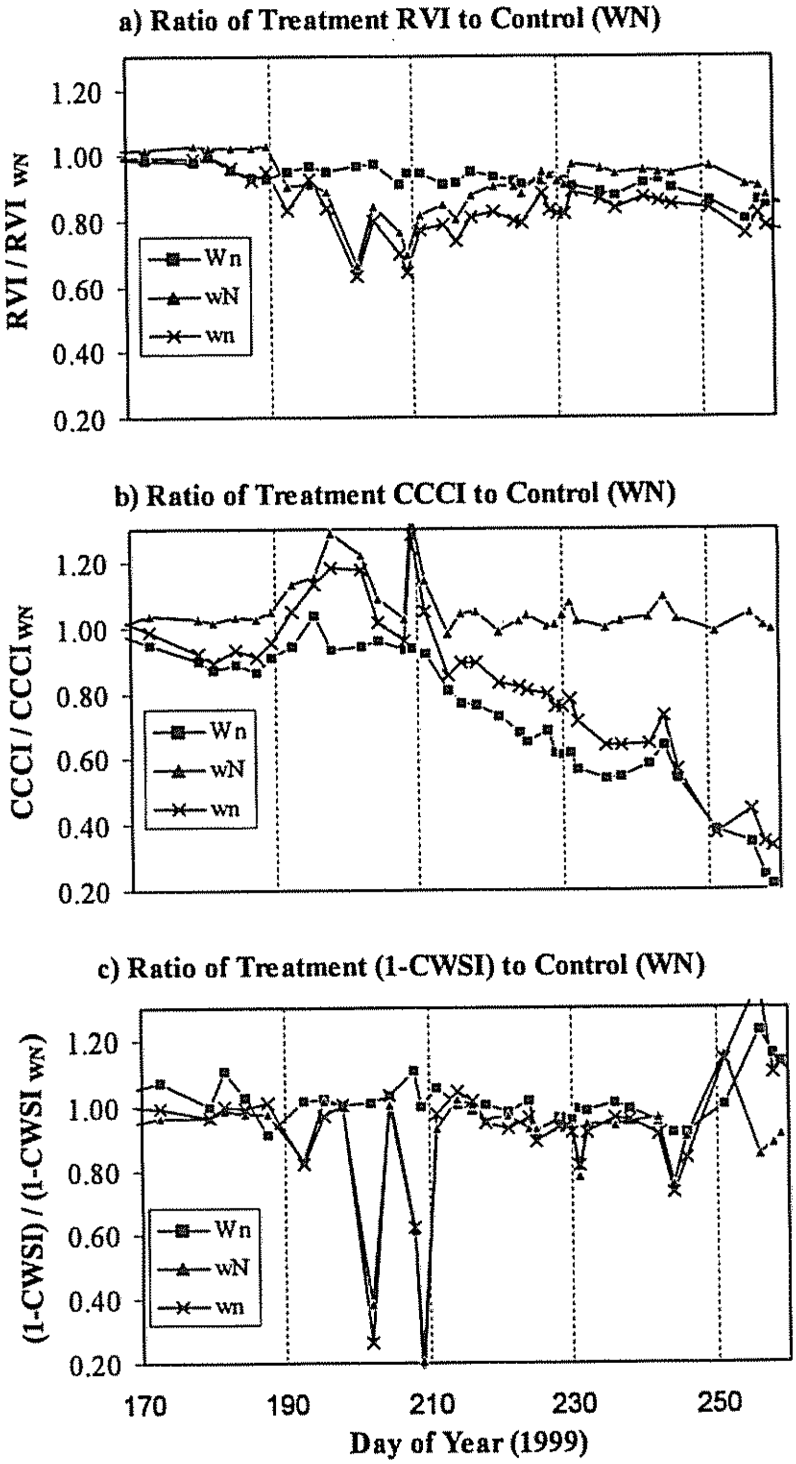

Figure 2. Seasonal trends in the ratio of (a) ratio vegetation index (RVI), (b) 1-crop water stress index (CWSI), and (c) canopy chlorophyll content index (CCCI) in the high water, low N (Wn), low water, high N (wN) and low water, low N (wn) treatments to the respective index in the control treatment (WN).

INTERPRETATION: The system under development will provide farmers and agricultural consultants with a simple, cost effective data source to map spatial variations in crop water and nitrogen levels. These data will have the potential to serve as an integral part of a decision support system for precision crop management.

FUTURE PLANS: Work will continue to integrate the sensor information with simulation models to provide decision support in water and nitrogen management. Related studies will begin during the 2000-2001 growing season using AgIIS to determine the feasibility of remote sensing and modeling technologies to provide information relevant to quality management in broccoli.

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INTEGRATION OF REMOTELY SENSED DATA WITH CERES-WHEAT

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PROBLEM: The development of crop growth models has been progressing since the 1970s and was originally focused on the prediction of average field conditions. More recently tools have been developed to integrate growth models with geographic information systems (GIS) at either regional or field scales. One limitation to simulating spatial variations in crop production is the large amount of input data necessary to accurately characterize the growth conditions. The objective of this study is to determine how remotely sensed observations can be used to improve a growth model's ability to simulate actual field scale variability.

APPROACH: Wheat was selected as the first crop to test methods to integrate remotely sensed observations with crop models due to the extensive growth and remote sensing data set collected during the FACE wheat experiments (Kimball et al., 1999). CERES-Wheat (Ritchie and Otter, 1985) was selected as the crop model to use in this approach because it is a process oriented model capable of simulating different management practices, while maintaining reasonable input requirements that would not prevent its application by a farm manager. Two potential links between CERES-Wheat and remotely sensed data have been identified: the fractionally absorbed photosynthetically active radiation (fAPAR) and crop water status via the crop water stress index (CWSI).

CERES is essentially a radiation use efficiency model, predicting potential carbon accumulation (PCARB, g plant^{-1}) as a function of solar radiation and leaf area index (LAI):

$$\text{PCARB} = 0.5\ \text{SolarRad RUE}\ [1\text{-exp}(-0.85\ \text{LAI})]\ /\ \text{PlantPop} \tag{1}$$

where 0.5 is from the assumption that 50% of the total incoming solar radiation (SolarRad, MJ m^{-2} d^{-1}) is PAR, and PlantPop is plant population (plants m^{-2}). The actual amount of carbon accumulation is then decreased if there is water, nitrogen or temperature stress. The model was modified by replacing the [1-exp(-0.85 LAI)] term in the equation 1 with the remotely sensed estimate of fAPAR. Note that by using "observed" fAPAR, the equation provides an estimate of actual carbon production (i.e., it does not need to be modified to account for stress); however, other stress factors in the model that relate to carbon partitioning will not be influenced by these modifications. The remotely sensed estimate of fAPAR was determined as a function of the normalized difference vegetation index (NDVI) using the approach developed by Pinter et al. (1994).

The model predicts transpiration as a function of either the plant available water in the root zone or atmospheric limitations, whichever is smaller. The potential water uptake by the roots (RWU_L, cm^3 water per cm roots per day) in a particular soil layer (L) is calculated by

$$RWU_L = c_1 \exp[c_2\,(SW_L - LL_L)]\ /\ [c_3 - \ln(RLV_L)] \tag{2}$$

where c_x are empirical constants, SW_L is the soil water content (cm^3 cm^{-3}), LL_L is the soil water content at permanent wilting point (cm^3 cm^{-3}) and RLV_L is the root length density (cm root per cm^3 of soil). If the sum of RWU_L across the soil profile (TRWU, cm) is greater than potential transpiration for the day, RWU_L is decreased so that the water uptake by the plant is equal to potential transpiration. A soil water deficit factor (SWDF1) is then defined as:

$$SWDF1 = TRWU / E_p \tag{3}$$

where E_p is potential transpiration (cm). SWDF1 is essentially equivalent to the definition of (1-CWSI). Therefore, the model was modified when there was a CWSI observation on a given the day and (1-CWSI) was not within 10 percent of SWDF1. The modification was accomplished by solving equation 2 for SW_L and setting the soil water content distribution in the soil profile so that when the total RWU of equation 3 was calculated, SWDF1 would equal (1-CWSI). A limitation to this approach is that when the model is under-predicting plant available water, the amount of water that can be added to the profile will only be sufficient to bring the predicted levels back to the verge of water stress.

FINDINGS: Figure 1 represents the fAPAR determined by remotely sensed estimates and the model's predicted fAPAR for the 1993-94 and 1995-1996 ambient CO2 treatments. The spikes in the model's predicted fAPAR in the 1993-94 season for the dry treatment are due to the water stress factor, which rapidly returns to one after an irrigation. The remotely sensed fAPAR estimates do not respond to rapidly changing stress conditions caused by short-term water stress between irrigations. However, they do reflect the accumulated effects of the water stress in the later half of the season. For the nitrogen stress treatment in the 1995-96 growing season, the nitrogen stress factor does not change as rapidly, indicating the more sustained nature of the stress.

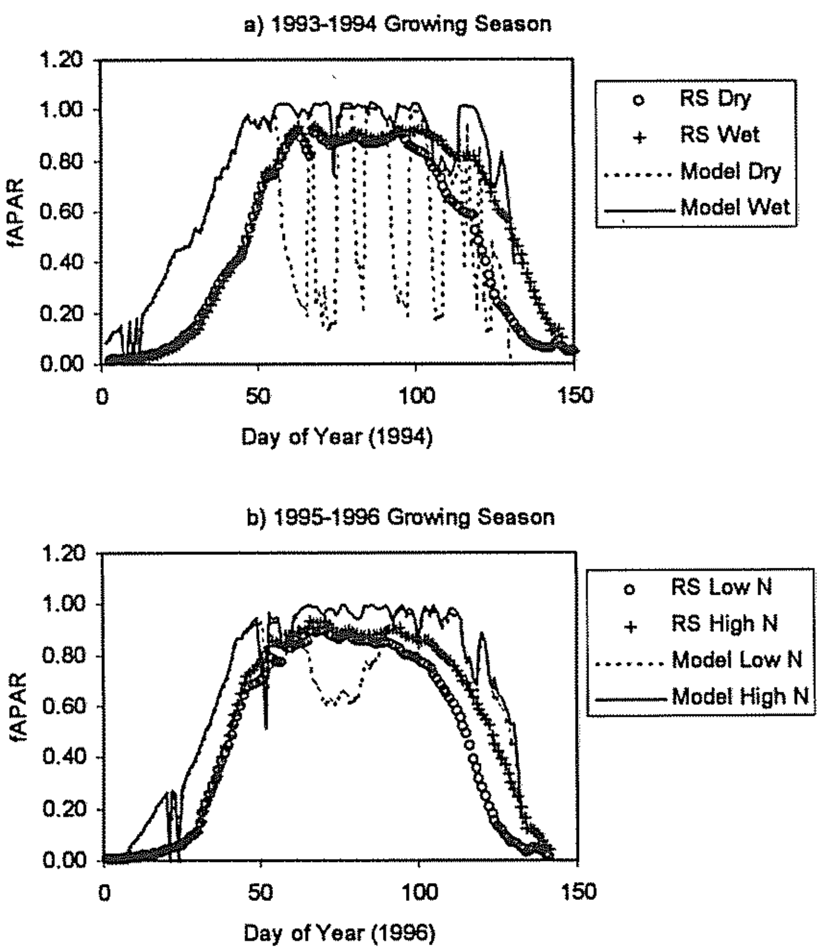

Figure 1. Remotely sensed and model predicted estimates of fAPAR for the 1993-94 (a) and 1995-96 (b) growing seasons.

For water stress, the CWSI is a more appropriate remotely sensed parameter than fAPAR because it is correlated directly with transpiration. In Figure 2, a comparison is shown between observed extractable water in the top

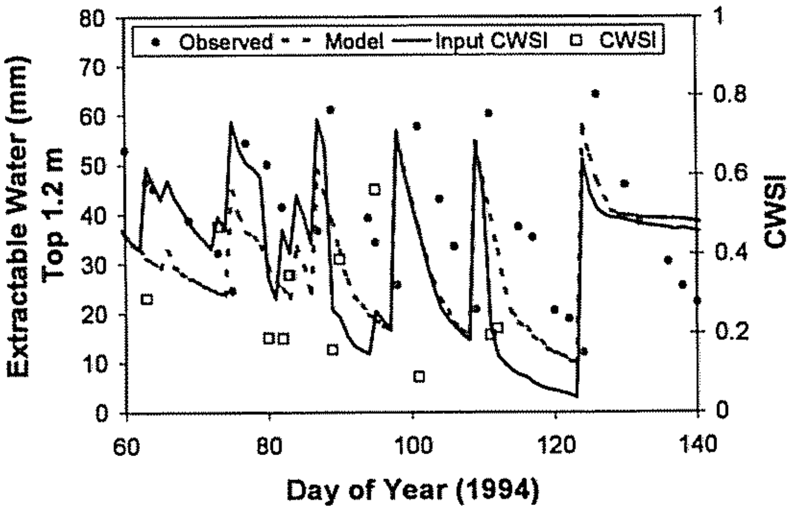

Figure 2. Extractable water in the top 1.2 m of the soil profile as predicted by the model with and without CWSI input. The value of the CWSI input is indicated on the y-axis to the right.

1.2 m of the soil profile with model predictions from CERES with and without CWSI input for the ambient Dry treatment during the 1993-94 season. The squared symbols show when CWSI measurements were made. Early in the season, the CWSI input improved predictions; however, later in the season, CWSI input resulted in under prediction of soil water. This under prediction may have been due to the assumption that the relative distribution of moisture in the soil profile remains unchanged when a CWSI modification is made; however, more investigation is needed. The model alone provided good estimates of soil water content and there were no significant differences in the prediction of yield between the two methods.

Figure 3 shows the results when the 1992-93 ambient Wet treatment was simulated for the first part of the season, and then single CWSI measurements from the Dry treatment were input on selected days and the dry treatment was simulated for the rest of the season. The observed values are for the dry treatment. The different lines indicate the results when the CWSI was input on the day of year indicated. For inputs prior to DOY 90, the CWSI was able to reset soil water to an amount very close to observed. Changes later in the season were not as accurate, but still within 20-mm of the measured value. These test indicate the input of CWSI could be very useful when soil water measurements are not available to initialize the model.

INTERPRETATION: Use of fAPAR estimates from NDVI is best suited for chronic stress conditions (i.e., stress conditions that persist long enough to impact canopy development). Compared to N stress, water stress can develop over much shorter time periods under high evaporative demand, and it can be relieved shortly after an irrigation or rainfall event. Use of the CWSI with the model shows promise as an alternative to measured soil water initial conditions. Dependable methods to forecast yield during the early season would provide a new tool for producers to make informed decisions in the application of precision farming practices. The approaches taken in this study demonstrate that the integration of remotely sensed data and crop models can lead to such a tool; however, improvements in the current methods are needed.

FUTURE PLANS: Further development is need on both approaches, particularly to determine methods to adjust the model's parameters through iteration so that the number of required remotely sensed observations can be minimized.

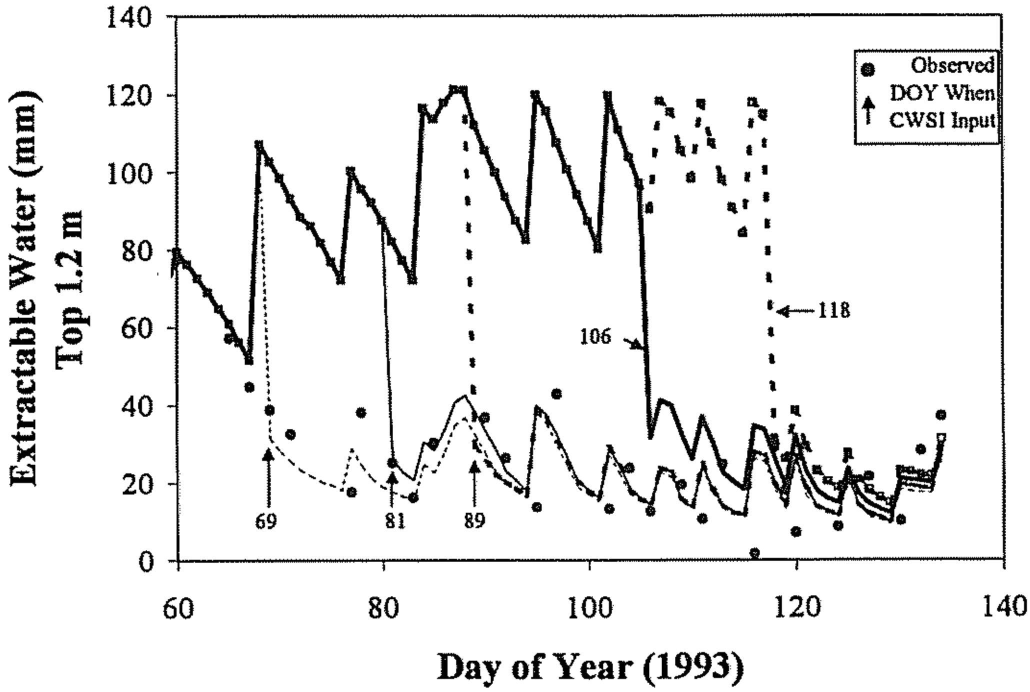

Figure 3. Extractable water in the top 1.2-m of the soil profile predicted by the model when simulating the wet treatment until a day when a CWSI was input and then simulating the dry treatment for the remainder of the season. The observed data points are for the dry treatment.

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