IRRIGATED CROP MANAGEMENT UTILIZING REMOTE SENSING

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PROJECT SUMMARY

We propose to conduct agricultural water management research using remote sensing approaches with the following objectives: (1) Develop and critically assess methods for using reflected solar and emitted thermal energy to quantify temporal and spatial variations in crop response to water, nutrients, and pests. Special emphasis will be placed on developing algorithms that perform reliably regardless of plant phenology and biomass, and thus can be used for crop management purposes throughout the entire growing season. (2) Develop and improve irrigation scheduling methodologies that are responsive to actual crop evapotranspiration (ET) and irrigation requirements. Multispectral vegetation indices will be used to develop and test real time, basal crop evapotranspiration coefficients (K_{cb}) which are expected to provide significant improvements of actual crop ET prediction for use with irrigation scheduling procedures for cotton and wheat. (3) Develop methods for using remotely sensed observations in precision management of water, nutrients, and pests in irrigated crops. Remote data will be tested as a means to direct an efficient sampling routine. It will also be used in conjunction with simple and process-oriented crop growth and management models to provide spatial information needed to run the models with a minimum amount of input. Research accomplished during this project will result in improved methods for quantifying actual crop water and nutrient needs, as well as methods to detect water, nutrient, and pest related stresses. This will enable growers to make better informed, within-season management decisions about the need to irrigate, fertilize, or control pests on an "as needed" basis within their farms or fields and particularly in situations where variable rate technology is in use.

OBJECTIVES

1. Develop and critically assess methods for using reflected solar and emitted thermal energy to quantify temporal and spatial variations in crop response to water, nutrients, and pests.

   Spectral reflectance and thermal emittance properties of soils and plants will be used to detect environmental stresses that limit productivity of agricultural crops. Traditional vegetation indices such as the NDVI will be combined with other spectral information that is less sensitive to canopy biomass in order to reduce problems associated with partial canopy conditions and enable identification of water and nutrient related stresses throughout the entire growing season.

2. Develop and improve irrigation scheduling methodologies that are responsive to actual crop evapotranspiration and irrigation requirements.

   Basal crop coefficients (K_{cb}) will be derived from multispectral vegetation indices then refined to provide improved water management capabilities within the framework of accepted FAO-56 irrigation scheduling procedures. A two-dimensional Crop Water Stress Index (CWSI) which accounts for partial canopy conditions will be used to more accurately quantify real-time crop water use and map its spatial variability throughout the entire growing season.

3. Develop methods for using remotely sensed observations in precision management of water, nutrients, and pests in irrigated crops.

   Statistical and image analysis procedures will be used with multispectral reflectance and thermal emittance imagery of agricultural fields to guide efficient sampling ground procedures, define management zones, and generate maps of crop density and conditions related to water, nutrient, and pest stresses. Indices related to crop nutrient status, transpirational potential (*i.e.* K_{cb}), and water stress (CWSI) will be integrated into process-oriented crop models to predict spatial and temporal variability in plant response across a field and provide a framework for precision management of water and nutrients.

NEED FOR RESEARCH

Description of the Problem to be Solved

Industrialized nations are poised on the threshold of dramatic changes in the way natural resources are surveyed, monitored, and managed. Growers are being encouraged to increase their productivity per unit of land and water in order to feed a hungry world. Agricultural resource managers are recognizing within-field variability in potential productivity and seeking ways to customize their growing practices to exploit that variability (National Research Council, 1997). Environmental guidelines mandate more efficient and safer use of agricultural chemicals. As a result, today's farmers require an increasing amount of information on field and plant conditions to manage their crops in a sustainable and environmentally sensitive manner and still make a profit. Not only does this information need to be accurate and consistent, but it also needs to be available at temporal and spatial scales that match the farmer's capability to vary water and agrochemical inputs (*i.e.,* precision crop management).

A large body of research spanning the past three decades has demonstrated the potential for remote sensing (RS) to deliver this type of spatial and temporal information on soil and crop response to dynamic environmental conditions and management. Now, when combined with extraordinary advances in precise global positioning satellite (GPS) devices, microcomputers, geographic information systems (GIS), and enhanced crop simulation models, farmers can use remote sensing from ground, aircraft, and satellite platforms to monitor and manage their crops on a routine, cost-effective basis. The successful application of RS technology to agricultural resource management requires a basic understanding of how changes in plant growth, form, and function affect spectral reflectance and thermal emittance properties of crops in the field.

Beyond this fundamental requirement however, a number of significant problems still need to be overcome before RS will be able to deliver on promises made to consumers and agriculture towards the end of the last century. How, for example, can signals associated with plant water-, nutrient-, and pest stress conditions be discerned for certain when scenes are composed of varying amounts of plant and soil components? What is the best way for RS to provide additional spatial and temporal information needed to improve the performance of existing irrigation scheduling and crop growth simulation algorithms? These are research issues that are becoming more important as precision agriculture assumes a greater role in producing America's food and fiber. They are also examples of the problems that we propose to explore in this project's research plan. One has only to look at the somewhat disappointing failure rate among of commercial remote sensing ventures to recognize that this is high risk research that is best addressed through a long-term national research program.

Relevance to ARS National Program Action Plan

This project relates broadly to several components within the National Program for Water Quality and Management by providing approaches for monitoring the response of soils and crops to management practices and environmental conditions, for detecting the occurrence of growth-limiting plant stresses, and for quantifying biophysical processes such as evapotranspiration (ET) and absorption of solar energy used in photosynthetic pathways.

Objective 1 relates to the Irrigation and Drainage Management Component, Problem Area (PA) 2.1, Economical Irrigated Crop Production, Goal 1 - Develop water, pest, and nutrient management practices and technologies that protect the environment and improve the economic benefits of irrigation and drainage. Objective 1 also has linkages with National Program (NP) 204 Global Climate Change, and NP 305 Crop Production.

Objective 2 relates to PA 2.3, Water Conservation Management, Goal 1 - Develop technologies to quantify and control a broad range of water supplies and uses, and Goal 2 - Develop cultural and management practices for agriculture, turf, and urban landscape plantings that maximize the return for irrigation water used.

Objective 3 relates to PA 2.2, Precision Irrigated Agriculture, Goal 1 - Develop precision agricultural irrigation systems that incorporate water management strategies and remote sensing technologies into site-specific management for the production of agronomic and high-value crops, and PA 2.3, Water Conservation Management, Goal 3 – Develop improved agricultural practices and systems that mitigate the adverse effects of irrigation on water quality and the environment. Objective 3 also has links to NP 207, Integrated Agricultural Systems.

Potential Benefits

Research conducted in this project will result in improved methods for quantifying crop water, nutrient, and pest related stresses and actual irrigation water requirements. This will enable growers to make better informed, within-season management decisions regarding irrigation timing and delivery volumes, fertilizer needs and pest control on an "as needed" basis within their farms or fields. Farmers will be able to initiate remedial actions that will maximize economic benefits and minimize detrimental environmental impacts. Incorporating RS soil and plant information into crop irrigation, growth simulation, and management models will provide spatial information that is needed to use these models on a finer spatial scale for describing within field variability and will increase their utility for precision agriculture approaches such as generating variable rate fertilizer application maps. In addition, the enhanced models will add predictive capabilities to somewhat less frequent remote observations, an important benefit in regions where cloud cover interferes with regular satellite or aircraft coverage.

Anticipated Products

This project will result in new and improved RS approaches for identifying different types of plant stress and quantifying their intensity, regardless of plant biomass or phenological stage. Products for scheduling the timing and amounts of irrigation and fertilizer applications are also anticipated. Multispectral, real time crop coefficients for determining the seasonal course of actual crop ET will be developed for cotton, wheat, and alfalfa. The project will also lead to new methods for combining the spatial information from RS and the predictive capabilities of crop management models, and provide specific approaches for utilizing RS capabilities in the emerging field of precision agriculture.

Customers

Stakeholders who will benefit from the research include growers; crop, soil, and irrigation consultants; cooperative state extension personnel; commercial providers of RS products; and commercial entities and governmental agencies that control or regulate water supplies. Algorithms developed during the course of this research will have a direct bearing on yield prediction, and thus have potential use for agencies such as NASS or FAS who forecast yields over broad geographic regions. NASA and commercial RS providers will be active partners in developing practical farm management and regulatory applications of RS imagery.

SCIENTIFIC BACKGROUND

Objective 1 – Crop Response

The theoretical basis for using RS in agricultural resource monitoring has been established in numerous laboratory and field investigations over the past four decades (Monteith, 1959; Gates et al. 1965; Knipling, 1970; Gausman and Allen, 1973; Bauer, 1975; Jackson, 1982; Asrar et al. 1989). These studies have shown vegetation to be rich in spectral features that might be used for identification and stress assessment purposes (Gates et al., 1965; Gausman and Allen, 1973). Healthy, green vegetation has low reflectance and transmittance in the visible regions of the spectrum (400 to 700 nm) due to strong absorptance by plant pigments. However, a number of different types of stress often cause chlorophylls to decline, allowing expression of other pigments (*e.g.* carotenes and xanthophylls), broadening the green reflectance peak (~550 nm) towards the red, and producing a characteristic chlorotic appearance (Adams et al. 1999). In the near-infrared (NIR, 700 to 1300 nm), green leaves typically display high reflectance and transmittance, since there is very little absorptance by photosynthetic pigments and considerable scattering by mesophyll cells. When plants are stressed, NIR reflectance decreases, albeit proportionately less than the visible increases. The abrupt "red edge" transition normally seen between visible and NIR in vigorous vegetation shifts towards shorter wavelengths and then disappears entirely in senescent vegetation. Optical properties of leaves in a third region of the solar spectrum, the middle- or short wave-infrared (SWIR, 1300 to 2500 nm), are strongly absorbed by water but reports in the literature suggest there is insufficient variation over biologically significant ranges of plant water content for the practical use of the SWIR as a diagnostic tool (Bowman, 1989). Energy in the thermal infrared (TIR) atmospheric “window” (~8 to 14 :m) has proven very useful in assessing water status. It is controlled primarily by latent and sensible energy fluxes at the surface of soils and plants and is somewhat decoupled from their optical properties (Jackson, 1982). Physical and biological stresses that interfere with transpiration result in elevated plant temperatures.

Compared with plants, spectral signatures of most agricultural soils are relatively simple. Nevertheless, the reflectance of soils contributes significantly to the total surface reflectance, especially early in the season when plants are small. Agricultural soils generally exhibit gradual increases in reflectance throughout the visible and NIR (Condit, 1971; Stoner and Baumgardner, 1981). High moisture and organic matter contents cause lower reflectances while smooth surfaced soils tend to be brighter. Occurrence of specific minerals in the soil have been associated with unique spectral features (*e.*g., higher red reflectance in the presence of iron oxides). The SWIR spectra of soils display more structure than those observed in shorter wavelengths but seem dominated by moisture content and litter amounts.

From a RS perspective, crops represent a complex mixture of soil and vegetation components that vary dynamically over the season. It is readily observable that overall scene reflectance and emittance change markedly as the vegetation component increases from planting to harvest. Less obvious, but not less important, spectral properties of underlying soils vary with moisture content, tillage, and litter fall and decomposition. Spectra of plant components change with age of tissues, stage of growth, and architectural arrangement of organs. Apparent spectral properties are also strongly affected by illumination and viewing angles, row orientation, topography, meteorological phenomena, and other factors that are not directly related to the plants (Jackson et al., 1979; Pinter et al., 1983, 1985, 1987; Qi et al.,1995). The real challenge for agricultural RS is to be able to separate spectral signals originating with a plant response to a particular stress from normal plant biomass or the background “noise” that is introduced by exogenous non-plant factors.

Estimating Green Biomass, fAPAR, and K_{cb}: When the goal is simply to determine how much green plant material is present, vegetation indices (VIs) computed as differences, ratios, or linear combinations of reflected light in visible or NIR wavebands usually provide very good, season long performance (Tucker, 1979; Richardson and Wiegand, 1977; Jackson and Huete, 1991). The simple ratio (NIR/Red) and normalized difference vegetation index [NDVI=(NIR-Red)/(NIR+Red)] have gained wide acceptance for estimating plant cover, green plant biomass, and leaf area index. Soil adjusted VIs such as SAVI and modified SAVI have been developed that minimize variation in soil reflectance (Huete, 1988; Qi *et al.*, 1994). Of particular interest, VIs can also provide a remote estimate of the fractional amount of solar energy captured by the canopy for potential use in photosynthesis (fAPAR) for use in plant modeling studies (see scientific background in Objective 3) as well as a basal crop coefficient (K_{cb}) used in irrigation scheduling algorithms (Bausch and Neale, 1989; Choudhury et al., 1994; also refer to Objective 2 below).

Detecting Crop Stress: Wideband VIs are often used in a relative sense to provide maps of "crop vigor" for management purposes (Blackmer et al., 1996). For the most part, however, VIs lack diagnostic capability for determining why biomass is at a certain level or for identifying a particular type of stress. Inadequate nitrogen fertilizer, for example, can result in the same NDVI as that from a sparse canopy caused by low seeding rate or drought. To a certain extent, diagnostic ambiguity can be reduced by including reference strips that are known to have sufficient N supplies within the field (Blackmer et al., 1995). But in practice, such comparisons are expensive to implement and difficult to achieve without incurring a cumulative bias in the signal from the reference strip. A definitive solution that uses an absolute measure instead of a relative comparison is more desirable and practicable.

There are a number of different strategies for accomplishing this goal. One is to look for spectral features that are uniquely associated with a particular stress. Those that alter the ratio between chlorophyll and accessory pigments should be clearly detectable with high resolution spectroradiometry (*viz.* Maas and Dunlap, 1989; Buschman and Nagel, 1993). Many indices based on narrow band spectral features sensitive to pigment concentrations have been proposed to identify specific nutrient and water stresses (Gamon et al., 1990, 1992, 1997; Fernandez et al. 1994; Filella et al. 1995; Yoder et al., 1995; Gao, 1996; Peñuelas et al., 1997a, b, c; Peñuelas and Filella, 1998; Blackburn, 1998; Adams et al., 1999, 2000). Usually these techniques compare the reflectance or absorptance signal at a pigment-sensitive wavelength with that in a region that is less affected by the stress. Many of these indices are also correlated with green biomass and, thus, cannot be applied uniformly throughout the entire growing season. At present, quantitative research on plant stress effects on narrow band features is still in its early stages - detailed spectral signatures of major crops grown on different soils and exposed to various management regimes and environmental conditions have not been thoroughly investigated. It is, however, expected to lead towards new approaches for using spectral signatures to unambiguously identify different types of plant stress throughout the entire growing season. In fact, the SPAD meter (Minolta Corporation) and The Observer (Spectrum Technologies, Inc.) are commercial examples of handheld devices that are used to infer N concentration in single leaves or canopies based on the differential absorption of light in relatively narrow far red and NIR wavelength intervals (Wood et al 1993; Blackmer and Schepers, 1995; Whaley, 2001). New NASA satellite sensors such as MODIS and ASTER and aircraft sensors (*e.g.* AVIRIS, HYDICE) have been deployed to exploit the expanded source of information in narrower wavebands.

In addition to traditional remote sensing methods, advances in consumer electronics and the merging of photography and videography with computer technology have produced low cost camera systems that produce high quality digital images. Adamsen et al. (1999) and Kawashima and Nakatani (1998) have developed methods to assess the greenness of plants using images from digital camera equipment. Methods of estimating flower numbers have been developed using digital images (Adamsen et. al. 2000). Advances in low light video cameras have been achieved by increasing the sensitivity of the cameras in the NIR region of the spectrum. Along with tight integration of the cameras to computers, this opens the way for inexpensive devices that can produce images with good resolution in the NIR region when coupled with appropriate filters.

Hyperspectral reflectance data offer additional strategies for identifying and quantifying plant stress. Red edge position, peak characteristics, and spectral derivatives have been proposed and tested with varying degrees of success to monitor nutrient stress in plant canopies (Horler et al., 1980, 1983; Demetriades-Shah et al., 1990; Masoni et al., 1996). Neural net analysis, fuzzy analysis, and partial least squares regression analysis are powerful approaches for capturing complex functional relationships between spectra and plant properties that cannot be envisioned via usual regression techniques (Kimes et al., 1998; Jones et al., 2000). In theory, a library of spectral features could be used to make predictions regarding plant vigor, nutrient content, or pest infestations. In still another approach, linear unmixing techniques (McGwire et al. 2000) use a spectral reference library of predetermined "pure" spectral signatures (endmembers), to decompose multispectral and hyperspectral images into their component features (*e.g.* sunlit and shaded soil, healthy and stressed plant areas). Such models can be inverted to extract the amount of the whole scene that is associated with a particular stress signature. If the images are georeferenced, the stressed area can be precisely located in the field for directed sampling, traditional pest scouting, or variable rate fertilizer applications. Spectral mixing models also provide insight into how spectral properties of soils and individual plant components (leaves, stem, fruiting structures, etc.) measured with an integrating sphere or handheld spectroradiometer in the field can be scaled up to full canopy or field levels and realistically be compared with imagery acquired from aircraft or satellite sensor systems.

Crop Water Stress: Functional relationships between the TIR and plant water status have been used to define a crop water stress index (CWSI) based on canopy temperature and meteorological conditions (Idso et al., 1981; Jackson et al. 1981). One limitation of this technique is that actual plant temperature is needed, and thermal influence of the background soil can result in an erroneous estimate of water stress. Moran et al. (1994) and Clarke (1997) refined the CWSI for use under partial canopy conditions by including an estimate of percent crop cover from a vegetation index (Fig 1). In this 2-dimensional planar domain approach, the method of Idso et al. (1981) is used to predict crop canopy temperature under well-watered and water-stressed, full cover conditions (points 1 and 2, respectively in Fig. 1) and predictive equations or actual surface temperatures of a dry bare soil are used to determine point 4. Fractional vegetative cover is estimated from the NDVI using reflectance (**D**) of a 10 nm wide, NIR (790nm) and red (670nm) band:

$$NDVI = \frac{\rho_{790nm} - \rho_{670nm}}{\rho_{790nm} + \rho_{670nm}}. \qquad (1)$$

Based on the points labeled A, B, and C in fig. 1, the CWSI for a particular percent cover was calculated as:

$$CWSI = \frac{C - A}{B - A}. \qquad (2)$$

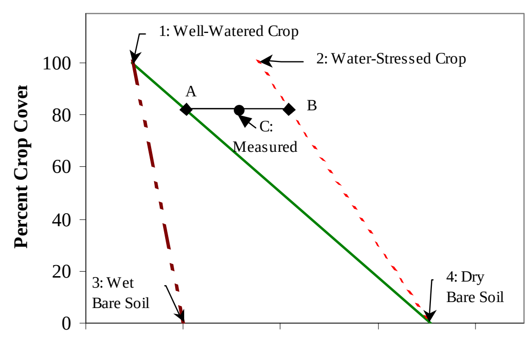

Figure 1. Diagrammatic representation of a 2-dimensional Crop Water Stress Index that compensates for varying amounts of plant cover.

Where points A and B represent the surface minus air temperature difference at a particular percent cover for a non-stressed and completely stressed crop, respectively, with a dry soil background. Points to the left of the line formed between points 1 and 4 represent a moist soil background. Since this would likely indicate a recent irrigation, no water stress is assumed under these conditions. Point C was determined based on the measured NDVI and surface – air temperature difference. From eqn. 2, a CWSI of 0 corresponds to a well-watered crop with a dry soil background, while 1 represents a water-stressed crop. The 2 dimensional CWSI has not yet been validated for quantifying plant stress during stand establishment and maturity. Establishing it as a reliable water stress index that works throughout the entire season will pave the way for its acceptance as an irrigation scheduling practice in production agriculture.

Crop Nutrient Stress: An analogous 2-dimensional index, the Canopy Chlorophyll Content Indes (CCI) that compensates for partial canopy conditions has been developed by the USWCL team for assessing the nutrient status of a cotton canopy (Fig. 2). The NDVI (eqn. 1) is used to estimate percent cover and a normalized difference red edge index (NDRE)

$$NDRE = \frac{\rho_{790nm} - \rho_{720nm}}{\rho_{790nm} + \rho_{720nm}} \qquad (3)$$

represents a spectral signal sensitive to chlorophyll pigments. Maximum and minimum chlorophyll-content limits of NDRE were defined as linear functions of NDVI and shown as solid and dashed lines on Fig 2. The CCCI was then derived using the same form as the CWSI (eqn. 2). Note that unlike the CWSI, a CCCI of 0 will typically represent a condition of crop stress (low chlorophyll content) and 1 will correspond to high chlorophyll, low stress conditions. Further testing is expected to confirm that the CCCI will be positively correlated with chlorophyll content and independent of green plant biomass during a significant portion of the growing season. Data sets will also be examined to determine if the CCCI is sensitive to the amounts of N present in storage organs of plants.

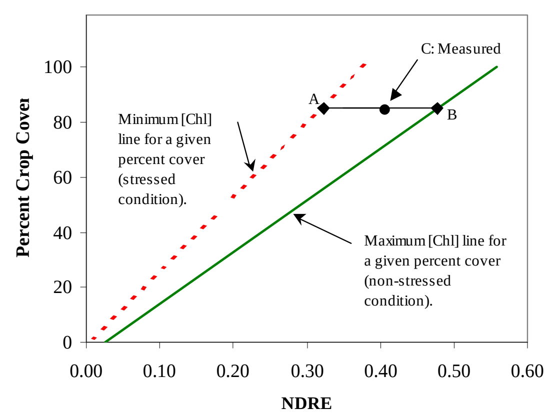

Figure 2. Diagrammatic representation of a 2-dimensional Canopy Chlorophyll Concentration Index (CCCI) that compensates for varying amounts of plant cover.

Search for Related CRIS Projects

A search of the CRIS database for "remote sensing" revealed 105 active projects within ARS and another 292 outside of ARS. Narrowing the search further to include only those projects researching areas of plant stress (i.e.,. drought, water stress, nitrogen, nutrient management, pest, insect, arthropod, weed, or disease) revealed 63 ARS and 125 non-ARS projects. A substantial amount of ARS RS research on plant response is being conducted at laboratories identified under the **Water Resource Remote Sensing Applications Initiative** mentioned above. Our research is unique in that we recognize the confounding effects of plant biomass and phenology on remote sensing techniques and to a large extent, strive for approaches that will be useful throughout the entire growing season.

Objective 2 – Irrigation Scheduling

A fundamental requirement for accurate irrigation scheduling is the determination of the actual crop evapotranspiration (ET_c) for each day during the growing period. Past and present research of ET_c is abundant and has provided a wealth of sound theoretical knowledge, as well as major advancements in methods for estimating daily crop evapotranspiration (Doorenbos and Pruitt, 1977; Jensen et al., 1990; Allen et al., 1998). Although a number of techniques are available for estimating daily ET_c for irrigation scheduling, the crop coefficient (K_c) approach has emerged as the most widely used method (Jensen and Allen, 2000). The K_c is an empirical ratio of ET_c to a reference crop evapotranspiration (either grass or alfalfa). Standardized equation forms for computing reference ET with meteorological data have been developed, which are now highly recommended (Allen et al., 1994, Allen et al., 1998; Walter et al., 2000). A K_c curve, constructed for a crop growing period, attempts to relate the daily water use patterns of a specific crop to that of the reference crop. The K_c curve can be susceptible to inaccurate predictions of total daily ET_c, particularly for days following wetting events when the soil is not completely shaded by the crop canopy. This is because the K_c curve attempts to account for the time-averaged contributions of both crop basal ET_c (primarily transpiration) and soil evaporation following wetting events. The effects of soil evaporation on total ET_c can be calculated more accurately by using a dual crop coefficient procedure (Wright, 1982). In the dual procedure, K_c is partitioned into a separate coefficient to predict evaporation from wet soil (K_e) and a separate K_{cb} to predict the basal component of ET_c under a dry surface soil condition. Information on crop coefficients for important agricultural crops is abundant in the literature. The recently published Food and Agriculture, Paper No. 56, (FAO-56) on Crop Evapotranspiration (Allen et al., 1998) presents comprehensive procedures for constructing either the single K_c or dual (K_{cb}) daily crop coefficient curves, for use with the recommended standardized grass reference evapotranspiration (ET_o), for a large number of common agricultural crops. Two recent studies have shown that the FAO-56 dual crop coefficient procedures can adequately predict crop ET_c of cotton and grain sorghum grown in small research plots (Hunsaker, 1999; Tolk and Howell, 2000).

However, the crop coefficient curves presented in FAO-56, and generally those included with most state-of-art irrigation scheduling programs, are time-based and therefore lack the flexibility required to capture abnormal crop development and water use patterns caused by weather anomalies, insect damage, disease, or other influences (Bausch and Neale, 1989). Furthermore, using crop coefficient curves from the literature will usually require some form of locality adjustment, unless specifically developed for the particular location. Determination of actual ET_c under conditions when limitations (e.g., water, nutrient, crop density, and pest) on crop growth are encountered is particularly difficult using conventional crop coefficient procedures. Within a given irrigated cropping system, occurrences of spatially and temporally variable crop water fluxes are often created by a variety of factors, for example, non-uniformities of water application, soil water holding characteristics, nutrient availability, stand density, and micro climatic conditions. Because a crop coefficient curve is designed to estimate the ET_c under optimum agronomic conditions, the effects of spatial and temporal variations of water use within a field or area cannot be adequately accounted for in irrigation scheduling decisions.

Remote sensing techniques offer a means to overcome many of the shortcomings of conventional crop ET estimation by providing real-time feedback of daily crop water use as influenced by actual crop developmental patterns, local atmospheric conditions, and field spatial variability. Such information when obtained on a timely basis could enable growers to more adequately assess whether changes in irrigation management strategies are warranted; e.g., changing irrigation frequency to avoid critical soil water deficits or improving irrigation system uniformities to provide sufficient water at lower ends of fields. A technique for determining total daily ET_c directly using one time-of-day RS measurements was introduced by the USWCL in 1983 (Jackson et al., 1983). Later, Inoue et al. (1994) developed a new concept for applying the technique for estimating actual transpiration and demonstrated that the method may give reliable transpiration estimates. The one-time-of day RS technique for estimating water use appeared promising at the time. However, development of the method for irrigation scheduling purposes has not been practical due to the requirement of daily ground and RS measurements and the inability to obtain reliable ET estimates on cloudy days.

Recognizing that the seasonal trajectory of multispectral VIs was very similar to the time course of wheat crop coefficients, USWCL RS scientists proposed their potential use for this purpose more than 20 years ago (Jackson et al. 1980). Implementing VI-based crop coefficients within irrigation scheduling procedures could potentially be more successful and far-reaching than other RS methods, because of the widespread familiarity and use of the crop coefficient methodology. In addition, VI data can be routinely measured either on the ground, in the air, or by spacecraft. Determining daily crop ET with VI-based crop coefficients would require frequent, but not daily, VI measurements, since the smooth general shape of the crop coefficient curve over a growing season would allow data to be extrapolated over a short period of perhaps two or three days. The VI-based crop coefficient concept of Jackson et al. (1980) later was proven a viable approach for corn in Colorado by Bausch and Neale (1987) and Neale et al. (1989). Bausch and Neale (1989) and Bausch (1995) then incorporated VI-based crop coefficients for use in existing irrigation scheduling algorithms for corn and reported improvements due to better estimation of water use and more appropriate timing of irrigations. Only limited research has been conducted to expand the development of VI-based crop coefficients for other crops, although simulation studies suggest that VIs could be used to obtain crop coefficients for several other important agricultural crops (Choudhury et al., 1994).

Search for Related CRIS Projects

A search of the CRIS system for “remote sensing” and “evapotranspiration” or “evaporation” revealed 32 active projects coded under these topics, twenty of which are within ARS. Of the 32, about 12 projects (6 within ARS) address the application of RS and ET technologies for irrigated crop water management. Only two projects pertain specifically to the development and use of multispectral crop coefficients for improving on-farm irrigation scheduling, although several projects are attempting RS approaches for assessing temporal and spatial differences in evapotranspiration. Research on multispectral VI crop coefficients for orchard and vegetable crops are being planned by the ARS facility in Parlier, California. There is also continued research of VI-based crop coefficients by ARS in Fort Collins for crops grown in Colorado. Development of VI-based crop coefficients for use in the FAO-56 dual crop coefficient procedures is unique to this project, as is the development and application of the 2-dimensional CWSI as reliable tools for assessing crop water stress and guiding irrigation scheduling decisions.

Objective 3 – Precision Agriculture

Three levels of complexity will be pursued in adapting remotely sensed data for use in precision farm management: (1) directed sampling (i.e., use of a single image to spatially interpolate crop attributes measured at locations identified by analysis of the image); (2) combination of simple empirical models (e.g., based on growing degree-days) and remotely sensed data to estimate crop water and nutrient status; (3) integration of remotely sensed data with process-oriented growth models. Note that in this section the background information for levels 2 and 3 are combined under the sections on growth models and approaches to integrate remotely sensed data with these models.

Directed Sampling

Rather than relying on a specific spectral response to a particular soil property, the concept of "directed soil sampling" has been developed (Pocknee et al., 1996). The idea is to first acquire imagery of a bare soil field and then take soil samples from areas in the image with distinct spectral features. Correlations or classification schemes are then developed between the spectral classes or reflectance levels and soil properties of interest. Pocknee et al. (1996) found this method worked well for mapping soil phosphorus, but performed poorly for soil pH. Directed soil sampling can often provide soil maps of similar or better accuracy than those derived from interpolation techniques such as kriging or distance-weighted interpolation with even fewer soil samples (Thompson and Robert, 1995; Barnes and Baker, 2000). A similar approach can be used over fields with a crop present by collecting soil samples and plant material for analysis over areas with similar spectral classes (Yang and Anderson, 1996; Barnes and Baker, 2000). Statistical methods have been developed to assist in the process of selecting sample sites based on the observed spatial variability in soil electrical conductivity within a field to allow the most accurate interpolation (Lesch et al., 1995); however, these methods have not been tested with multispectral data. While directed sampling has been found useful in mapping variations in soil and crop properties, Barnes and Baker (2000) found that a number of interfering factors can compromise such an approach.

Crop Growth Models

Crop growth models have been developed with various levels of sophistication (Penning de Vries et al., 1989). First level models only respond to variations in temperature and radiation.

Level 2 models include some type of soil water balance to integrate moisture stress into the growth predictions. Level 3 models add simulation of the effects of nitrogen availability, while level 4 models address additional stresses such as weed pressure and insect infestations. All growth models require some level of calibration before they can be applied with confidence (Kenig et al., 1993) because a purely deterministic model has yet to be developed. Most process-oriented growth models predict the level of photosynthesis based on weather conditions, photosynthetically active biomass and the availability of resources such as water and nitrogen. Photosynthesis is then partitioned between maintenance and growth respiration based on the crop's predicted development stage (see reviews by Jones and Ritchie,1990; and Hoogenboom et al., 1992). The output from several models have been incorporated with economic and decision support tools in order to enhance their use in farm management decisions. For example, a Decision Support System for Agrotechnology Transfer (DSSAT) has been developed to automatically search for agricultural management optimization strategies based on various objective functions (Tsuji et al., 1994). DSSAT incorporates models of cereal, legume and root crops into a common system and uses an internationally standardized format for data input and predictive output (IBSNAT, 1986). Linkage with GIS has allowed crop models to be applied to regional studies (Lal et al., 1993).

With the increased use of geospatial tools in farm management, efforts began to adapt crop models to predict within field production variability. The earliest efforts, as reviewed by Sadler and Russell (1997), focused on running the models at grid points or management zones within a field. The results for this approach has had mixed success in adequately describing spatial variability in crop development and the input data requirements were dramatically increased. Another approach has been to form a hypothesis as to the parameters in the model most closely associated with the major source of yield variability. The model is then run and used to identify parameters until the error between simulated and observed yields are minimized (Paz et al., 1998). If the major source of yield variability is temporally constant, this procedure then provides a set of spatially associated input parameters for use in future growing seasons.

Integration of Remotely-Sensed Data and Growth Models

Limitations to the use of yield maps for model calibration are that they do not provide a means to assess a model's performance or supply inputs during the growing season and all sources of variability are integrated in the yield response. For example, from a yield map alone it is not possible to determine if a relative decrease in production is related to insect damage, soil properties or weeds. Remotely-sensed data have the advantage of determining spatial variability in crop canopy density during the season. While it may not always be possible to determine the source of variability solely from imagery, field scouting can reveal the source near the time it occurs.

The potential for the integration of remotely sensed data with growth models was suggested over 20 years ago (Wiegand et al., 1979). Maas (1988) identified four approaches for the integration of models and remotely sensed data that can further be reduced to two basic methods: (1) input a remotely estimated state variable (e.g., LAI) directly into the model at each time step or forcing agreement at selected times during the season, and (2) adjustment of the model's initial conditions and/or parameters until the model's predictions are in agreement with remotely sensed estimates. Moulin et al. (1998) provided a review of several of the integration approaches that have been recently developed. Such approaches have been adapted for simple, empirical models (Potdar, 1993; Raun et al., 2001) to the integration with more process-oriented models. Raun et al. (2001) developed a yield forecast model based on early season NDVI and growing degree-days for real-time application of nitrogen. Moran et al. (1995) used remotely sensed estimates of ET and LAI in the real-time calibration of a simple alfalfa and water balance model. This is a unique approach, in that the alfalfa model's predictions are compared to the remotely-sensed estimates and then the model is iteratively adjusted until both estimates are in agreement. Lo Seen et al. (1995) investigated methods to integrate remotely sensed measurements into a grassland production model. The grass production model is a simple level 2 model, modeling growth and the water budget. The analysis of several vegetative indices derived from AVHRR data found that the NDVI and Soil Adjusted Vegetation Index (SAVI) were capable of tracking vegetation development. Barnes et al. (1997) demonstrated the feasibility of inputting remotely sensed estimates of LAI at select times during the season to allow the CERES-Wheat model to predicted nitrogen limited conditions when data was not provided to the model to indicate N deficiency. Similarly, Barnes et al. (2000) also found that the CWSI has potential to adjust the soil-water content predictions of CERES-Wheat to account for water limited conditions. Jones and Barnes (2000) adjusted the soil water holding capacity parameters in the cotton model CALGOS until the model was able to correctly predict LAI during the season for two soil types.

Search of Related CRIS Projects

There is a large number of CRIS projects coded for "remote sensing" and crop modeling – 23 ARS and 18 non-ARS. Of these 41 projects, 26 were not related directly to crop management (i.e., they were focused on prediction of large area yields, water quality parameters, or climate change). The remaining 15 that did have a similar scope to this objective were primarily projects in the Midwest and Eastern United States in non-irrigated conditions and for usually directed towards different crops (primarily corn and soybeans).

National Collaboration

All objectives for this project relate directly to the Water Resource Remote Sensing Applications Initiative in NP201 which will develop cost-effective methods to assess soil, water, and plant conditions and technologies for improved management at field, farm, and watershed scales. The Initiative's research is geared towards providing timely RS solutions to water quantity and quality problems impacting production agriculture, ecology and the environment. We envision all aspects of our research as being complementary to ARS research at Beltsville MD, Bushland TX, El Reno OK, Florence SC, Fort Collins CO, Parlier CA, Kimberly ID, Lubbock TX, Shafter CA, Tucson AZ, and Weslaco TX. Although collaboration with these research groups is not essential in order to complete the research described herein, collaborative interactions will serve to accelerate development, broaden regional applicability, and improve robustness of methods that are useful for major US cropping systems. Under the coordination of National Program Leadership, ARS scientists doing remote sensing research are expected to convene biennially to discuss methods, problems, and research findings of mutual interest.

APPROACH AND RESEARCH PROCEDURES

The overall goal of this project is to develop and test remote sensing approaches that will prove useful in short- and long-term management of agriculture resources. As stated above, the proposed research is organized into three objectives, crop response, irrigation scheduling, and precision agriculture, each of which are described below:

Objective 1 - Crop Response

Develop and critically assess methods for using reflected solar and emitted thermal energy to quantify temporal and spatial variations in crop response to water, nutrients, and pests.

Hypotheses for Objective 1:

1. Environmental stresses that limit productivity of agricultural crops can be detected and quantified by means of observable changes in their spectral properties.

2. Identification of water and nutrient related stresses during periods when plants do not completely cover the soil surface can be improved by combining traditional vegetation indices such as the NDVI with spectral information that does not vary as much with canopy biomass.

Experimental Design

During the initial phase of this project, we plan to develop and refine remote approaches for monitoring crop response using full-season data of numerous RS, soil, and agronomic measurements acquired during previous USWCL experiments in alfalfa, cotton, wheat, and vegetables (*e.g.,* Barnes et al 1996, 2000; Moran et al., 1989,1995; Hunsaker et. al., 1994, 2000; Kimball et. al., 1994, 1999; Pinter et al. 1994, 2000). We will develop a detailed knowledge base of plant spectral reflectance and emittance characteristics for crops growing under optimum water and nutrient conditions. The RS data will be transformed into wide- and narrowband reflectance factors, multispectral vegetation indices, physiological reflectance indices, and other spectral features which, based on RS team experience and reports in the literature, appear most sensitive to plant growth and stress parameters. Correlations between these spectral indicators will identify those which contain redundant information and those which contain unique information. Regression techniques will be used to identify functional relationships between RS signals and properties related to normal and stressed vegetation properties. Emphasis will be placed on further testing and validation of 2-dimensional CWSI and CCCI indices for estimating water and nutrient stress in cotton and wheat throughout the entire growing season, including the stand establishment phase when early detection of stress can have a large influence on a grower's ability to achieve maximum economic yield. Hyperspectral approaches for identifying stress will be explored using neural net, fuzzy analysis, partial least squares regression, and linear mixture modeling techniques.

New experimental data will be obtained from a series of intensive, season-long, interdisciplinary field plot experiments in cotton and wheat. Data from these experiments will serve as a mechanism for evaluation, refinement, and validation of RS irrigation scheduling and crop modeling techniques. Recognizing the limited human resources for this project, these experiments will be coordinated and conducted by the entire RS team in a concerted effort to meet many of the various goals sought under each of the three primary project objectives. We also plan to be opportunistic in our research. For example, if a proposed Free Air CO_2 Enrichment (FACE) experiment in alfalfa is funded by NASA, we intend to make regular RS observations on alfalfa exposed to different CO_2 and water stress treatments, while cooperators obtain agronomic, physiological, and other measurements.

Small Plot Procedures: Upland cotton (*Gossypium hirsutum* L.) and spring wheat (*Triticum aestivum* L.) will each be grown for two seasons in small (1.5 ha), level basin fields at The University of Arizona Maricopa Agricultural Center (MAC) during 2002 and 2003 (cotton) and 2003-04 and 2004-05 (wheat). Each experiment will include a two by three factorial consisting of two nitrogen levels (high and low) and three plant population densities (standard practice, high, and low). The experiments will also include two additional treatments both managed at high nitrogen and standard plant density. The latter two treatments, as well as irrigation scheduling procedures for all treatments, will be described later in the Approach and Procedures section under Objective 2. All treatments will be replicated four times in plots approximately 15 by 30 m. For the cotton studies, seed from a full season, commercial cultivar will be sown on raised, east-west oriented beds spaced 1.02m apart during the normal April planting window. For wheat, seed from a locally adapted cultivar will be sown on the flat during the normal December planting window. The three plant populations will be achieved using precision planting equipment and seeding rates corresponding to 2x, 1x, and 0.5x the recommended rates for each crop. The high N treatment will be managed according to recommended MAC farm nitrogen practices for the crop to achieve full yield potential while the low N treatment will receive an amount calculated to reduce yield by about one-third.

Meteorological Data: Hourly and daily weather data are available from the automated Arizona Meteorological Network (AZMET). The AZMET weather station at MAC is located over a well-irrigated grass plot, less than 1 km away from the small plot basins. Data from this station will be used to calculate the FAO-56 reference ET_o needed for irrigation scheduling as described in Objective 2, Goal 2. Portable weather stations will provide backup weather data in the field. Micrometeorological sensors (*e.g.,* thermocouples, psychrometers, pyranometers, net radiometers, IRTs, etc.) will be deployed in specific plots as needed to achieve specific objectives and for comparison with AZMET station data.

Soil Measurements: The concentrations of nitrate and ammonium throughout the rooting zone will be determined in 300 mm increments before and after the cropping cycle and as needed during the growing season. All plots will receive sufficient N and P to meet recommended preplant requirements. Neutron scattering access tubes and time domain reflectometry (TDR) probes will be installed in each plot to measure soil water status during the season. Irrigation to plots will be provided through a metered, gated-pipe irrigation system (see Approach Objective

2). A salinity map of the field will be made using a tractor-mounted EM-38 system. Data from this map will be used to guide soil sampling. Soil will be analyzed for salinity, moisture and texture as well as other soil properties that may have contributed to variability of EM-38 data.

Plant Measurements: Relevant agronomic parameters (*e.g.,* stand density, phenological development, biomass, leaf area index, and final yield) will be evaluated from destructive sampling at appropriate intervals throughout the season. The nitrate content of the petioles of cotton and the lower 50 mm of stem tissue from wheat will be determined and compared with SPAD readings throughout the growing season. Plant water status will be assayed periodically using pressure bomb, porometry, and stem flow techniques. Plant area index will be monitored at 1-2 week intervals with a LAI-2000. Estimates of fAPAR will be determined using a line quantum sensor or inferred from VI-based relationships developed in previous experiments (Pinter et al., 1994).

Remote sensing: Measurements will be made at the whole canopy level from planting until harvest using (1) wideband radiometers (visible and NIR), (2) high resolution spectroradiometers (visible, NIR, SWIR) region (~350 to 2500nm), and (3) infrared radiometers (10-12 μm). Reflectance and transmittance measurements will be made at the single leaf level using an artificial light source, an external integrating sphere, and high resolution spectroradiometers. Temporal trends in broad-band reflectance factors, multispectral vegetation indices, hyperspectral features (*e.g.* spectral derivatives, red edge position), and canopy temperatures will be critically examined at the single leaf and canopy level for information that can be used to quantify plant water, nutrient, and pest stress. Advances in sensor technology and emergence of new techniques (*e.g.* appropriately filtered, 3-CCD digital cameras) may provide additional opportunities for obtaining spectral data.

Team Responsibilities

Research conducted under Objective 1 (Crop Response) will be under the direction of Paul Pinter. Each scientist will assume responsibility for measurement and analysis of one or more unique aspects of the experiment in which he has expertise. Integration of the various parts and collaboration between team members will be necessary to achieve the stated goals. Paul Pinter for example, will coordinate biological measurements and be responsible for developing relationships between wide- and narrow-band spectral reflectances and various agronomic, biophysical, and stress-related responses of the plant canopy. Ed Barnes and Tom Clarke will focus their attention on measuring necessary parameters and refining and validating the 2-dimensional CWSI and CCCI indices described earlier. Glenn Fitzgerald brings special skills in mixture modeling and image analysis to bear on analyzing the high resolution image and radiometric data obtain from the field experiments and correlating them with specific plant stresses. Doug Hunsaker will be responsible for measuring soil moisture levels and along with Bruce Kimball will evaluate evapotranspiration by various methods. Floyd Adamsen contributes expertise in analysis of digital imagery plus broad experience in managing nutrients in agricultural systems. Gary Wall will be responsible for measuring and interpreting whole plant water relations within the context of irrigation treatments.

Contingencies

As in most scientific research, both positive and negative findings will be useful in delineating realistic opportunities and limitations for using RS in crop management. We recognize that a number of exogenous factors affect remotely acquired reflectance and emittance data although they are not related to soil or crop properties of interest. (*e.g.*, illumination and sensor viewing direction, clouds, droplets of precipitation on vegetation, etc.). Bidirectional models of canopy reflectance will be examined to determine their utility for normalizing data to standard conditions. Thermal indices for evaluating soil water content are likely not to provide useful information when evaporative demand is low, and the CCCI might not be sensitive to plant-stored N. Thus special attention will be paid to defining conditions under which the indices do not perform as expected and guidelines will be developed to minimize their impact. If simple reflectance-based indices of crop vigor do not provide sufficient detection resolution for a particular plant stress or distinguish between different stresses, multivariate analysis incorporating hyperspectral reflectance or wideband thermal data will be used to improve performance.

Collaborations

Necessary (within ARS) - Susan Moran at Tucson AZ (Remote estimates of ET, instrumentation, and calibration). Scientists at a number of ARS locations are actively pursuing spectral reflectance techniques for detecting nutrient stress (Beltsville MD, Fort Collins CO, Lincoln NB), water stress (Bushland TX, Florence SC, Lubbock TX) and salinity stress (Riverside CA). Project scientists anticipate discussing research approaches, comparing techniques, and continued interaction with these related projects. As mentioned above under National Collaboration, ARS also recently brought together these and other ARS scientists who are involved in various aspects of remote sensing research. Bi-annual meetings, workshops, shared resources, and joint publications with this group will increase awareness of other projects and new avenues of cooperation will evolve.

Necessary (external to ARS) - Jiaguo Qi with Michigan State University (BRDF and calibration issues)

Objective 2 – Irrigation Scheduling

Develop and improve irrigation scheduling methodologies that are responsive to actual crop evapotranspiration and irrigation requirements.

Hypotheses

1. Multispectral crop coefficients will provide improved irrigation scheduling and water management capabilities as compared to more traditional crop coefficients that are usually based on time or thermal units after planting.

2. Multispectral crop coefficient models used in conjunction with the 2-dimensional CWSI, can accurately quantify real-time crop water use and its spatial variability.

Experimental Design

Research under Objective 2 is expected to expand the development of remote sensing measurement tools and procedures for guiding irrigation scheduling so that they match actual crop and environmental conditions more closely. We have divided this research into three goals. Goal 1 will be to develop working basal crop coefficient models based on multispectral VIs for primary crops grown in the region - alfalfa, cotton, wheat, and grain sorghum. For Goal 2, small-plot field studies will be undertaken to examine and validate the VI-based crop coefficient models for scheduling proper irrigation amounts to cotton and wheat. In conjunction with the VI-based crop coefficients for irrigation scheduling, we will refine and validate use of the 2-dimensional CWSI for determining appropriate irrigation timing for cotton and wheat. The small-plot experiments will also be designed to include the necessary data for field validation of the one time-of-day direct RS technique for determining actual crop evapotranspiration. Goal 3 will be to evaluate the use of multispectral crop coefficients and thermal indices to provide detailed information about spatial variations of crop water use within large surface-irrigated fields. Such information would ultimately allow growers a means to more adequately appraise the water needs and irrigation requirements within their fields.

Goal 1. During the first year of the project (2001 to 2002), we will analyze and develop initial multispectral basal crop coefficient models and related algorithms using data from past experiments conducted by the USWCL, in which both ET and reflectance measurements were made for crops grown under well-watered and well-fertilized conditions (e.g., data from Hunsaker et al., 1994; Kimball et al. 1994; and Pinter et al., 1992, 1994, for cotton: and from Hunsaker et al., 1996, 2000; Kimball et al. 1999; and Pinter et al., 2000, for wheat). The K_{cb} values for these initial models will be derived following procedures similar to those developed by Hunsaker (1999).

Goal 2. Field demonstration and validation of the VI-based K_{cb} models for irrigation scheduling will take place during the two-year, small-plot experiments planned for cotton (2002 and 2003) and for wheat (2003-2004 and 2004-2005). General experimental design procedures, treatments, and description of field measurements for these studies are described above in Objective 1. All experiments will include six treatments used to test VI-based K_{cb} under three plant densities (high, standard, and low) and two soil nitrogen levels (high and low). These experiments will also include a control treatment, grown under a standard plant density and a high nitrogen application, in which irrigation scheduling will be determined using the dual crop coefficient procedures recommended by FAO-56 including the daily basal crop coefficient curve for the crop recommended in FAO-56. A final treatment (water-stressed), also grown under a standard plant density and a high nitrogen application, will be included in each experiment to provide data needed for assessing the suitability of the 2-dimensional CWSI as a reliable indicator of the effects of water stress on actual ET_c reductions, and as a practical irrigation timing tool. Irrigation scheduling for the water-stressed treatment will follow the same procedures as that for the control treatment, with the exception that three irrigations during the season will be delayed to impose greater soil water depletion and water stress on the crop. Irrigation for the six VI-based K_{cb} treatments will be scheduled using the dual crop coefficient procedures of FAO-56. However, for these six treatments, the multispectral K_{cb} model will be used to determine the daily K_{cb} of each treatment using reflectance field measurements. For determining the irrigation amounts for all treatments, the soil evaporation component of total crop ET will be estimated using the explicit procedures of FAO-56, including their recommended soil evaporation drying parameters for the specific soil type used in the field studies. Plots within several treatments will be monitored to effectively evaluate the direct measurement of ET_c using the one time-of-day RS technique.

Irrigation scheduling based on remote vegetation indices may be less successful early in the season when plants are small, during cloudy weather, or when the water holding capacity in the rooting zone is limited. Thus, during the first-year experiment for each crop, we may find it necessary to periodically update the K_{cb} for some treatments if the initial VI-based K_{cb} model is determined to be performing poorly. Such adjustments would be made on the basis of actual ET_c determined by frequent soil water content measurements. The second-year experiment for each crop will serve to confirm whether or not the original K_{cb} model, or perhaps a refined K_{cb} model - i.e., a model based on data from the past experiments combined with additional findings from the first-year experiment of this study, accurately predicts ET_c under all conditions imposed on treatments. Performance evaluation of the K_{cb} models will be primarily based on comparison of the model-predicted ET_c against actual ET_c determined by detailed soil water content measurements, but will also include evaluations based on actual crop performance as determined from measurements of crop growth during the growing period and final yields. In all experiments, performance of the multispectral K_{cb} model for the treatment under standard plant density and high nitrogen will be compared to that of the control treatment to assess whether the multispectral crop coefficient model provides significant improvement over the FAO-56 K_{cb} curve for irrigation scheduling.

Although not necessary to complete the research outlined here, mutual exchange of multispectral K_{cb} development techniques and/or data is expected to occur with the ARS investigators in Fort Collins (D. Heermann, W. Bausch), Kimberly (J. Wright), and Parlier (T. Trout), who have completed or are planning to conduct similar research. If the FACE alfalfa field experiment is funded by NASA during this project's time-span, we plan to utilize the experiment as a means to field-test the alfalfa K_{cb} model that will be developed in Goal 1 of this objective.

<u>Goal 3.</u> Evaluation of VI-based crop coefficients and thermal indices as tools to detect and quantify field-scale spatial variability of crop water use will be undertaken in 2002 during studies planned on a large, production-size cotton field, described below in more detail in objective 3. After the first aerial image (figure 3) of the field is made at about 35-50% crop cover, the directed sampling approach described in objective 3 will be used to identify three distinct areas within the field at which ET_c rates are potentially different (e.g., high, medium, and low rates). Neutron access tubes and TDR probes will then be installed within each of the three identified areas to measure soil water content. During the course of the season, additional aerial images of the field will be obtained at the end of each irrigation cycle, just before the next irrigation is applied. Thus, measurements of VI and thermal indices will be provided during the

course of the growing season at the three identified areas. Predicted cumulative ET_c over each irrigation cycle during the remainder of the season will be calculated using measured VI data to develop a time-averaged K_{cb} curve over each irrigation cycle for each area. The K_{cb} model developed in the small-plot studies for cotton will be used to determine the K_{cb} values. Thermal indices obtained from the images will also be used to detect differences in crop water status. Measurements of soil water made during irrigation cycles will provide data to quantify differences in actual crop water use among the areas, as well as information on the actual soil water status within the areas.

Team Responsibilities

Research under Objective 2 will be largely under the direction of Doug Hunsaker. He will be responsible for detailed elements of experimental design; measuring, and analyzing soil water contents; estimating ET; and scheduling specific irrigation events. Doug Hunsaker and Paul Pinter will be responsible for developing multispectral K_{cb} values for cotton, wheat, and alfalfa from historic USWCL data sets. Floyd Adamsen will measure and analyze soil and plant nitrogen concentrations. Tom Clarke will handle micrometeorological measurements. Ed Barnes and Glenn Fitzgerald will provide support in image collection and analysis. Bruce Kimball and Gary Wall will provide expertise in determining ET and measuring plant water relations, respectively.

Contingencies

The initial multispectral K_{cb} models developed in goal 1 will be tested during the cotton and wheat small-plot irrigation scheduling experiments. As mentioned under goal 2, these initial K_{cb} models may not perform well under certain conditions during the season and it may be necessary to occasionally adjust the K_{cb} for some treatments during the season. Furthermore, the initial spectral K_{cb} models for cotton and wheat will be developed from past studies in which the crops were grown under sub-surface drip irrigation. Thus, there may be transferability problems associated the models when applied to surface irrigated systems. In the event that the initial K_{cb} models for either or both crops are deemed to be completely inappropriate, we would plan to conduct the second-year experiment with a redeveloped model. In this event, the model would be highly dependent upon the data obtained from the first-year experiment. For the field plot experiments, there is a slight possibility that abundant rainfall may preclude the development of a highly water-stressed treatment.

Collaborations

ARS locations presently engaged in research activities related to irrigation scheduling and the development of crop coefficients include Bushland TX, Fort Collins CO, Kimberly ID, Parlier CA. While formal collaboration is not essential for conducting research under this objective, we interact with the scientists at these locations via the ARS Remote Sensing Workshops. We also work closely with national scientists involved in this area through representation (D. Hunsaker) on the ASCE Committee on Evapotranspiration in Irrigation and Hydrology.

Objective 3 – Precision Management

Develop methods for using remotely sensed observations in precision management of water, nutrients, and pests in irrigated crops.

Hypotheses

1. The statistical sampling approach developed by Lesch et al. (1995) for EM-38 salinity maps can be adapted for multispectral and TIR imagery to generate maps of crop density and conditions related to water, nutrient, and pest stresses.

2. The spatial extent and location of management zones identified from RS imagery will not be consistent during the growing season.

3. Techniques developed under Objectives 1 and 2 (*i.e.*, VI-based crop coefficients, improvements in the 2-dimensional CWSI, and estimation of nitrogen status from the CCCI) can be used to quantify natural variability in crop condition in a production field.

4. The combination of a growing degree day parameter with the CCCI will allow accurate determination of crop nitrogen status throughout the growing season with a single set of calibration coefficients.

5. Integration of the CCCI, multispectral K_{cb}, and 2-dimensional CWSI will provide a comprehensive water and nitrogen management method for crop management purposes.

6. RS estimates of crop water condition, nitrogen status, and fAPAR can improve the ability of process-oriented crop models to predict spatial variability across a field or farm.

Experimental Design

Directed Sampling

At the same time as the cotton field plot studies in 2002 (Objective 2, Goal 2), a separate experiment will be conducted in a commercial sized cotton field to develop methods for using remote imagery to optimize field sampling. Aerial imagery will be acquired at planting and then at approximately two-week intervals once the crop has reached ~35 to 50% cover. We intend to use an imaging system having visible, NIR, and thermal capabilities that was designed and assembled by RS Team scientists and deployed successfully over MAC fields during early June 2001 when cotton plant cover was <10%. Examples of imagery obtained with this system are shown in figure 3.

Consistent spatial and temporal performance of RS approaches to directed sampling or precision agriculture requires careful calibration of imagery. Our protocol therefore, includes coincident ground-based radiometric observations of 8 by 8 m canvas calibration tarps (fig. 3b and Moran et al. 2001) and other specific areas with the field. These observations are used to convert red and NIR images to reflectances from which a meaningful vegetation index such as the NDVI (fig. 3d) can be calculated. Thermal scanner performance is verified in a similar fashion using calibrated handheld infrared thermometers. The day following image acquisition, sample locations within the fields (*i.e.* ESAP points in fig. 3a) will be identified from the imagery using statistical procedures developed by Lesch et al. (1995). These procedures were originally developed for use with ground-based soil conductivity sensor data, but we have adapted them for use with a vegetation index derived from the red and NIR data. In this sampling approach, a minimum set of calibration samples are selected based on the observed magnitudes and spatial locations of the data, with the explicit goal of optimizing the estimation of a regression model (i.e., minimizing the mean square prediction errors produced by the calibration function). The regression model is then used to extrapolate predictions at all remaining (i.e., non-sampled) areas. Once the sampling points have been identified, plant and soil samples will be collected at each location using differentially corrected GPS receivers. Gravimetric moisture content and particle size distribution will be determined from the soil samples and petiole nitrate levels, LAI, biomass, growth stage, insect damage, etc. will be identified from the plant samples. Additional locations will be randomly sampled for later comparison with the methods used to classify the imagery. Two Bowen ratio stations will be installed in the large cotton field to measure ET_c continuously during the experiment. These data will be used to (1) determine what crop characteristics can be accurately interpolated using NIR, red and thermal data, (2) examine the temporal dynamics of spatial variability during a growing season, and test other approaches developed for the field plot studies identified in objectives 1 and 2 in a production-sized agricultural field.

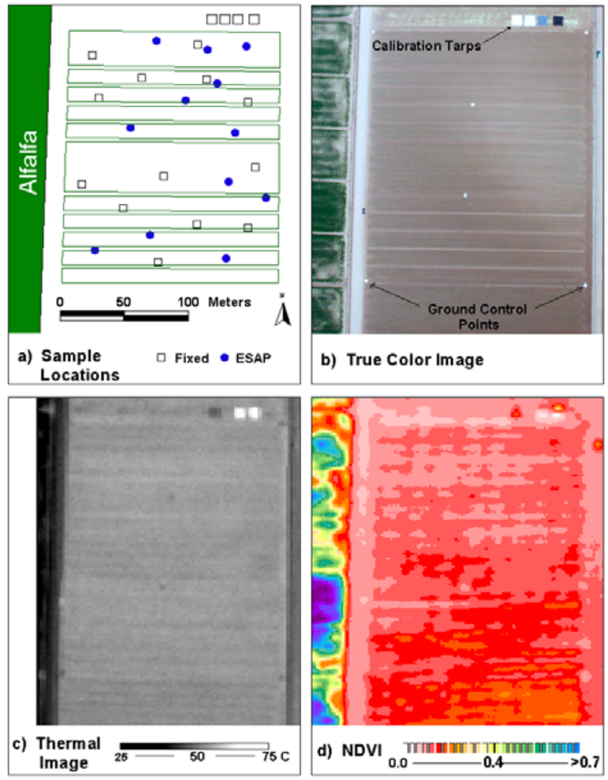

Figure 3. Images acquired at MAC with the USWCL sensor system at ~1045h on 6 June 2001 showing: a) cotton field with fixed- and statistically-selected (ESAP) sampling locations, b) color image from a Nikon digital camera, c) radiometric surface temperatures (grayscale) from an Inframetrics Model 760 thermal scanner, and d) color-enhanced NDVI from a Dycam Agricultural Digital Camera. All images were georeferenced with ERDAS Imagine using ground control points (fig. 3b). Thermal and NDVI data were calibrated using coincident radiant temperature and reflectance factors, respectively, measured with ground-based radiometers over calibration tarps and field targets.

Empirical Model Development

Secondly, procedures to integrate a simple growing degree-day parameter with the CCCI will be investigated to determine if this approach can yield acceptable predictions of nitrogen levels throughout the growing season with one set of calibration parameters. Data from previous cotton (Barnes et al., 2001) and wheat experiments (Kimball et al., 1999) will be used to formulate the calibration relationship, and then data from the small plots studies proposed under objective one will be used for validation and refinement. The next step will be to integrate this model with the water use estimates described in objective 2 to formulate a simple nitrogen and water management model driven by RS data. Additionally, for the data sets collected under objective 3, linear mixing models will be used to determine whether for additional components (e.g., shaded and sunlit soil) improves the 2-dimensional CWSI and CCCI approach.

Integration with Process-Oriented Models

Three cotton models will be investigated for integration with remotely sensed data: CALGOS (Marani et al., 1995); GOSSYM (Baker et al. 1983); and CPM (Cotton Production Model, V.R. Reddy, ARS, Beltsville MD). CALGOS was developed specifically for arid conditions; however, only limited calibration of the model for different varieties has been accomplished. GOSSYM has undergone much development in humid regions. CPM offers more mechanistic handling of energy and water relations, but it is still early in the development stages, and as with CALGOS only has parameters for a limited number of cotton varieties. The primary model for use with wheat will be the generic CERES distributed with DSSAT 3.5 (Tsuji et al., 1994). This model is chosen as it is a member of the DSSAT family and has undergone extensive validation around the world. It also contains the ability to simulate both water and nitrogen use.

For both crops, similar approaches will be used to integrate multi-spectral data obtained during the course of the growing season to provide “mid-course” corrections to the predictions of the growth models. Previous studies by the investigators have found RS estimates of leaf area index (LAI) to be useful in model adjustments (wheat, Barnes et al., 1997; cotton, Jones and Barnes, 2000). In addition to LAI, remotely sensed estimates of fAPAR will be used in the adjustment procedures, as this estimate has been found to be more robust than LAI for different solar zenith angles and crop conditions (Pinter et al., 1994). Further study will also be given to the use of the CWSI to evaluate the model’s estimate of crop water status (Barnes et al., 2000).

The first procedures to be developed will be based on the assumption that the resources limiting growth below potential after accounting for climatic conditions are known (e.g., water and nitrogen). Once identified, the model’s initial conditions and parameters related to the limiting resources will be adjusted iteratively in order to provide a match between the model’s prediction and remotely sensed estimate. Rather than assuming the model is “wrong” and the remotely sensed estimate “right,” uncertainties will be assigned to both estimates. In the case of remotely sensed data derived from empirical relationships, the prediction interval could be used. Ideally, the model’s prediction interval can be established if previous year’s data is available with field observations; however, in an actual application to farm management, such data may not always be available. Therefore, other numeric techniques such as fuzzy number theory will be evaluated to describe uncertainties and define approaches to weight these uncertainties so that the best estimate of actual conditions is determined using information from both the model and RS estimates.

The application of these procedures to cotton will begin by evaluating the three models to simulate existing cotton data sets collected at MAC. A total of seven seasons of growth data are currently available for this site (Pinter et al., 1994 - 3 seasons; Barnes et al., 2001 - 2 seasons and two years of unpublished data). Data collected during the experiments discussed in objective 2 will be critical for validation of the procedures. For wheat, four seasons of data are available (Kimball et al., 1999) for evaluation of the integration procedures as will be the data collected under objective one in the wheat experiments.

Team Responsibilities

The field and modeling research conducted under Precision Agriculture - Objective 3 will be carried out under the direction of Ed Barnes who will be responsible for day to day operation and coordination of the project, scheduling the field cultural activities, image analysis, GPS georeferencing observations, and model integration. Glenn Fitzgerald and Tom Clarke will be responsible for preparing the sensor package used in the aircraft, collecting, and downloading and analyzing image data. Glenn Fitzgerald will provide expertise in spectral modeling approaches used to scale single leaf and canopy component spectral properties up for comparison with larger scale aircraft and satellite imagery. Tom Clarke and Paul Pinter will coordinate the vicarious ground calibrations at time of overpass. Paul Pinter will provide and interpret RS data sets from previous USWCL experiments that will be used in model integration, and coordinate biological observations during the experiments. During the directed sampling experiment, Doug Hunsaker will quantify soil texture and soil moisture parameters while Floyd Adamsen will be responsible for measuring and analyzing soil and plant nutrient concentrations.

Contingencies

In the event that the statistical sampling procedures developed by Lesch et al. (1995) for use with EM-38 derived salinity maps do not provide satisfactory results when adapted for use with a vegetation index, unsupervised classification techniques will be used with a maximum likelihood decision rule to define spectral classes in the field. Samples will then be taken from areas representing each spectral class similar to the procedures used by Yang and Anderson (1996). In certain situations, such as early season nutrient stress detection mentioned in Objective 1, remotely sensed data may not be able to improve a model's performance. When reliable techniques cannot be developed using RS data for within season adjustment of crop models, efforts will focus on characterizing the input information needed by the models (e.g., spatial extent of soil types, zones having similar crop response from previous seasons’ imagery, etc.). In the event other scientists at the USWCL decide to continue development of the $COTCO_2$ model (Wall et al., 1994), this model will be added to the suite of cotton models evaluated for potential integration with RS data. In the event NASA funds an alfalfa study, further refinement of the PROBE model (Moran et al., 1995) will take place.

Project scientists are mindful of scaling issues encountered when quantitative techniques based on ground measurements are implemented at the field and farm level using aircraft or satellite data. Recent addition of a new team member (G. Fitzgerald) and his specialized skills in spectral mixing models are expected to provide additional insight into how spectral properties of soils and individual plant components (leaves, stem, fruiting structures, etc.) measured with an integrating sphere or handheld spectroradiometer can be scaled up to full canopy or field levels and realistically compared with imagery acquired from aircraft or satellite sensor systems. Spectral unmixing techniques can be used to address the disaggregation approach. We have also specified the technical requirements and recently contracted for the purchase of a hyperspectral imaging system utilizing liquid crystal tunable filters which is expected to provide an additional investigative approach for this research.

Remotely acquired data are also inherently discontinuous in time. Simple averages of occasional canopy reflectance factors or midday temperatures are not likely to be the best approach for crop management. It is for this reason that we believe the combination remote sensing and modeling approach mentioned in Objective 3 will be so powerful. Mechanistic models, governed by physical processes, driven by more or less continuous meteorological parameters, and occasionally given a reality check, tune-up, or re-parameterization with remote observations will likely provide an effective way to use remotely sensed data for management purposes.

Collaborations

Necessary (within ARS) - Scott Lesch (ARS, Riverside CA) will provide assistance in efforts to adapt his statistical methods to determine within field sample locations with electrical conductivity data to reflectance-based indices.

Necessary (outside ARS) - The integration of RS and crop simulation models will be investigated in cooperation with Dr. J. Alex Thomasson, University of Mississippi with ARS in Stoneville MS. Dr. Thomasson has compiled a team of scientist engineers, an economist and extension specialist to assist in development of these approaches for cotton, including Dr. James McKinnon with ARS who was one of the original developers of GOSSYM. Shared data sets between the two locations will allow evaluation of the techniques under diverse growing conditions. David Jones, University of Nebraska, Lincoln will provide technical expertise on the application of fuzzy number theory to describe uncertainties.

Project scientists recognize that official involvement with the regional committee - NCR 180 “Precision Agriculture” would also be very beneficial to our program. There are a number of participating states that have a large irrigated agriculture component and thus are dealing with many of the same precision agriculture management issues. In particular, NCR 180 is addressing the need for quality, timely, and readily available remote images for scouting field problems, predicting yields, monitoring crop quality, making management decisions, and identifying crop management zones. We presently interact with several of the active members of this committee, and plan to participate in their annual meetings. Another potential point for cooperation involves the Ag 20/20 Project which is a partnership between NASA, CSREES, and various national commodity groups. We have used their listing of top management requirements for cotton and wheat to help focus our research on areas that commodity groups think are most important. Our current projects do not meet the criteria for formal involvement in Ag 20/20 (*e.g.* commercially available imagery, large scale fields, yield monitors), but their objectives and goals are very similar to our own and we intend to remain peripherally involved with that project.

Physical and Human Resources

The USWCL in Phoenix has adequate laboratory, calibration, and office spaces for conducting this research. In addition to high speed internet and network connections, personal computers are well-equipped with up-to-date word processing, spreadsheet, graphics, and presentation software. Scientists have ready access to SAS statistical analysis software and image processing/analysis packages from ESRI (ARC INFO and ARC View), ERDAS, and ENVI. Specific RS equipment consists of handheld, fixed-mount, and imaging infrared thermometers; an extended-area, black body IRT calibration device; wide- and narrowband radiometers; two portable, high resolution fiber optic spectroradiometers with dedicated field computers and an external integrating sphere; $BaSO_4$ and Spectralon field calibration panels; and digital cameras with visible (Nikon) and red and NIR (Agricultural Digital Camera, Dycam, Inc.) capabilities. The lab shares 4%, 8%, 48%, and 64% canvas calibration tarps with the ARS, Southwest Watershed Research Center in Tucson. The RS team has two differentially corrected GPS units and an Agricultural Irrigation Imaging System (AgIIS, Barnes et al. 2001) on a linear move irrigation boom. The USWCL also has the necessary neutron scattering and TDR equipment for monitoring soil water contents, EM-38 for remote estimates of soil texture and conductivity, and Giddings tractor-mounted hydraulic soil sampler with rotary head, flow meters, and flumes for irrigation measurements. There are leaf area meters, balances, refrigerated spaces, and drying ovens for agronomic measurements, SPAD chlorophyll meters, a plant canopy analyzer and linear PAR sensor for characterizing canopy properties, and pressure bombs, leaf psychrometers, and stem flow gages for determining plant water status. We also have standard micrometeorological instrumentation, 2 Bowen ratio towers, and data loggers for use in this project. A soil mechanics and analytical chemistry lab are available at the USWCL for determining chemical and physical properties of soil and plant samples.

The USWCL maintains an ongoing research support agreement with the Maricopa Agricultural Center (MAC), 30 miles south of Phoenix, which is an 1800-acre agricultural research and demonstration facility of The University of Arizona. The MAC facility is fully equipped and staffed for managing a variety of crops simultaneously. It has ready access to irrigation water from the local Irrigation and Drainage District. Field plot experiments will be conducted on the research portion of the facility, whereas large-scale experiments will be conducted on commercial-sized fields available on the demonstration portion. Pending funding approval, all of the USWCL facilities will be relocated to MAC on or about 2005.

The experiments we propose to satisfy goals in each of the three objectives will be planned and executed by the entire RS team consisting of 4.0 Category 1 SYs, 1.0 Category 3 SY, and 3.7 technicians. Dr. Pinter will take the lead role in the Crop Response Objective, assisted by Drs.

Fitzgerald, Barnes, and Wall, Support Scientist Tom Clarke (0.4), and 1.5 FTE technicians. The Irrigation Scheduling Objective will be lead by Dr. Hunsaker with assistance from Drs. Pinter, Barnes, and Fitzgerald, and Kimball, Support Scientist Tom Clarke (0.3), and 1.3 FTE technicians. Leadership in the Precision Agriculture Objective will rest with Dr. Barnes, with help from Drs. Pinter, Fitzgerald, Kimball, Adamsen, Support Scientist Tom Clarke (0.3) and 0.9 FTE technicians. Technical assistance will be supplemented during the field season by temporary employees.

Milestones and Expected Outcomes

<table>
<tr><th rowspan="2">Date</th><th colspan="3">Research Objective or Area of Study</th></tr>
<tr><th>1. Crop Response</th><th>2. Irrigation Scheduling</th><th>3. Precision Agriculture</th></tr>
<tr><td>Oct. 2001</td><td colspan="3">Scheduled Starting Time for Project</td></tr>
<tr><td>Jan. 2002</td><td>· Concept paper on two dimensional indices (CCCI, WDI) written and submitted to journal (Clarke, Barnes, Pinter)
· Manuscript on fAPAR and spectra from prev. FACE Expts. written and submitted to journal (Pinter)
· Data from 2001 LiMIE Broccoli experiment used to confirm CCCI approach for detecting N stress in vegetable crop (Barnes, Clarke, Pinter)
· Contingent on NASA funding to FACE Alfalfa CO_2 by H_2O experiment, crop planted (fall 2001), RS measurements underway. (Pinter, Kimball)</td><td>· Review and analyze spectral crop coefficient and ET_a/ET_o data from 1985-86 WCL Alfalfa Lysimeter Study. (Hunsaker, Pinter)
· Ditto for FACE Cotton with goal of obtaining working spectral K_{cb} algorithms (Hunsaker, Pinter, Kimball, Wall)
· Finalize experimental strategy for field tests of FAO-56 WDI and K_{cb} scheduling in cotton (All)
· Develop and field test backpack radiometer/micromet pkg coupled with GPS for collecting ground-based georeferenced crop coef and WDI data. (Clarke)</td><td>· Journal paper incorporating CWSI index into CERES Wheat model written. (Barnes Pinter)
· Cooperative research with Mississippi underway, preliminary results from 2001 LiMIE Cotton Experiments tabulated. (Barnes)
· Select cotton model amenable to incorporating RS data. (Barnes, Kimball)
· Explore approaches for obtaining aerial imagery in Prec Ag (Fitzgerald, Barnes, Clarke, Adamsen)
· Test spatial interpolation techniques on existing images.</td></tr>
<tr><td>Jan. 2003</td><td>· Complete cotton experiment designed to validate WDI and CCCI. Tabulate, reduce, and analyze data. (All)
· Analyze hyperspectral and CCCI data from FACE Wheat CO_2 by Nitrogen experiment (Pinter, Clarke)
· Plan field plot study to answer specific questions in using spectral or thermal indices to detect water, nutrient, or pest stress</td><td>· Paper(s) summarizing crop coefficient findings for alfalfa & cotton written and submitted to journal (Hunsaker, Pinter)
· 1^{st} cotton irrigation experiment completed (Oct 2002), data tabulated and reduced (All)
· Refine protocol as needed for 2^{nd} cotton irrigation experiment</td><td>· Growth, yield, and water content from cotton field experiment used to validate prec ag approach using cotton model.</td></tr>
</table>

Jan. 2004	· Paper on use of CCCI or comparable index for monitoring N stress in wheat written and submitted to Journal. (Clarke, Pinter)	· 2^{nd} cotton irrigation experiment completed, Oct 2003) data tabulated and reduced. (All) · Finalize experimental strategy for field tests of FAO-56 WDI and K_{cb} scheduling in wheat (All) · 1^{st} wheat irrigation scheduling experiment begun (Nov 2003) (All)	· Growth, yield, and water content from wheat field experiment used to validate prec ag approach using CERES model. · Manuscript on "directed" sampling methods using RS data written. (Barnes et al.)
Jan 2005	· Paper validating CCCI or comparable index for monitoring N stress in cotton written and submitted to Journal. (All) · Data analysis, publication, and presentation of results as significant outcomes arise. (All)	· 1^{st} wheat experiment completed (May 2004), data reduced, tabulated, and analyzed (All) · Refine protocol as needed for 2^{nd} wheat irrigation experiment · 2^{nd} wheat irrigation experiment begun (Nov 2004) (All)	· Paper on techniques for incorporating RS into cotton growth model written and submitted to journal. (Barnes, et al.)
Jan 2006	· Data analysis, publication, and presentation of results as significant outcomes arise. (All)	· 2^{nd} wheat experiment completed (May 2005), data reduced, tabulated, and analyzed (All) · Publication and presentation of results (All)	· Data analysis, publication, and presentation of results as significant outcomes arise.
Sept. 2006	End of Proposed Project Plan		

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