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USING PLANT CANOPY TEMPERATURE TO IMPROVE IRRIGATED CROP MANAGEMENT

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ABSTRACT

Remotely sensed plant canopy temperature has long been recognized as having potential as a tool for irrigation management. However, a number of barriers have prevented its routine use in practice, such as the spatial and temporal resolution of remote sensing platforms, limitations in computing capacity and algorithm accuracy, and the cost and ruggedness of sensors and related components that can transmit and receive data wirelessly. Recent advances in all of these areas have made remote sensing more feasible in providing real-time feedback of field conditions. This can potentially reduce management time, maintain crop yield and crop water productivity, and detect unusual conditions such as equipment malfunctions or biotic stress sooner. Center pivots equipped with wireless infrared thermometers (IRTs) have been found to be suitable as a remote sensing platform. Canopy temperature-based algorithms have successfully automated drip and center pivot irrigation schedules where crop yield, water use efficiency, seasonal water use, and irrigation amounts applied were comparable to irrigations scheduled manually with a field-calibrated neutron probe. Even without automation, these algorithms can provide timely and valuable information on plant and soil water status, which can improve the management of irrigated crops.

INTRODUCTION

Plant canopy temperature is useful as an irrigation management tool because it is related to the water status of the plant and soil, and it can be measured noninvasively by remote sensing. As plants transpire, the evaporation of water from liquid to vapor state consumes heat energy, which lowers the leaf temperature; this and the movement of water vapor away from the canopy removes heat and results in a cooling effect. When the plant evapotranspiration (ET) rate is reduced, such as by soil water depletion, the rate of heat removal is reduced and the canopy temperature increases. This process links canopy temperature with crop water stress and ET. Detection of crop water stress and ET enable rational irrigation timing and application amounts, which can increase crop water productivity, reduce leaching of water and nutrients below the root zone, and reduce the time required for irrigation management. Measurement of canopy temperature is possible using radiometers that are filtered to the thermal infrared (8 to 14 μm) wavelengths, making them non-contact infrared thermometers (IRTs). Because all surfaces emit thermal radiation, temperature can measure an area from a few cm^2 to several km^2. These characteristics can carry advantages over sensors that require physical contact with the plant or soil, which often sample an area or volume of insufficient size to be representative of the soil – plant – atmosphere energy and water balance.

The concept of using remote sensing for farm management, including irrigation management, dates to the 1960s. Monteith and Szeicz (1962) and Tanner (1963) were the first to report plant canopy measurements using portable radiometers, from which evolved the basic design of modern hand-held and miniature IRTs. Wiegand et al. (1968) and Bartholic et al. (1972) were among the first to use airborne thermal scanners to differentiate crop and soil water status. The launch of the Landsat series of satellites beginning in 1972 led to agricultural monitoring applications such as commodity market forecasting, but mainly on a seasonal basis and at regional scales, because the spatial resolution and repeat frequency of satellites were inadequate for real-time and farm field-scale management (Moran, 1994). Phene et al. (1985) described one of the earliest applications of IRTs aboard a moving irrigation system. These developments prompted further research in agricultural remote sensing, which have been reviewed by Jackson (1982; 1984), Moran et al. (1997), and Gowda et al. (2008). Several technical barriers have impeded the widespread adoption of remote sensing for real-time irrigation management. These are related to remote sensing platform requirements, the need for wireless data transmission, sensor cost and ruggedness, computing capacity, and crop water stress and ET models, among other factors. However, many of these barriers have been mitigated in recent years, which may finally make remote sensing a feasible and cost-effective option for producers.

This paper provides a brief review of the use of remotely sensed plant canopy temperature for irrigation management. The review includes an overview of canopy temperature algorithms, remote sensing platforms, and some recent experimental results in irrigation automation at the USDA Agricultural Research Service Conservation and Production Research Laboratory at Bushland, Texas.

OVERVIEW OF CANOPY TEMPERATURE-BASED ALGORITHMS

Canopy temperature is a component of the soil-plant-atmosphere energy and water balance; it is the result of complex interactions with the soil and plant water status, crop phenology, and the crop micrometeorological climate. Because of this, a single measurement of canopy temperature by itself usually does not reveal much about plant water status. Hence algorithms have been developed that in various ways integrate canopy temperature with the physical environment. Three general types of algorithms shown to be useful in irrigation management are (i) water stress indices, (ii) the time – temperature threshold, and (iii) the ET-based soil water balance. Each can provide guidance on the timing of irrigation, and the ET-based soil water balance can also provide guidance on the appropriate amount of irrigation.

Water Stress Indices

The word stress, in the context of plants, is a broad term used to describe some type of adversity that, if prolonged, can result in economic yield loss (Jackson, 1982). Water stress then describes a condition where the supply of water in plant leaves inhibits photosynthesis and respiration. The shortage of water could be caused by abiotic stresses (i.e., resulting from soil water depletion) or biotic stresses (i.e., resulting from pests or disease that inhibit water flow to leaves). Under water stress conditions, transpiration is reduced, resulting in a greater amount of available energy at the canopy surface being converted to sensible heat compared with what would have occurred for non-water-stressed conditions. The result is that the temperature of the plant canopy (i.e., the ensemble of plant leaves) increases over the temperature that would have resulted for no shortages in water.

Crop water stress index

The Crop Water Stress Index (CWSI; Jackson et al., 1981; Idso et al., 1981) has received the most attention of any water stress index. It is derived from the energy balance where, for a given set of meteorological conditions, a range of canopy - air temperature differences exist that are bound by a lower limit (no water stress) and an upper limit (complete water stress where no ET is occurring). The measured canopy - air temperature difference should fall within these lower and upper limits, and is normalized as an index where a value of zero indicates no water stress and a value of unity indicates complete water stress:

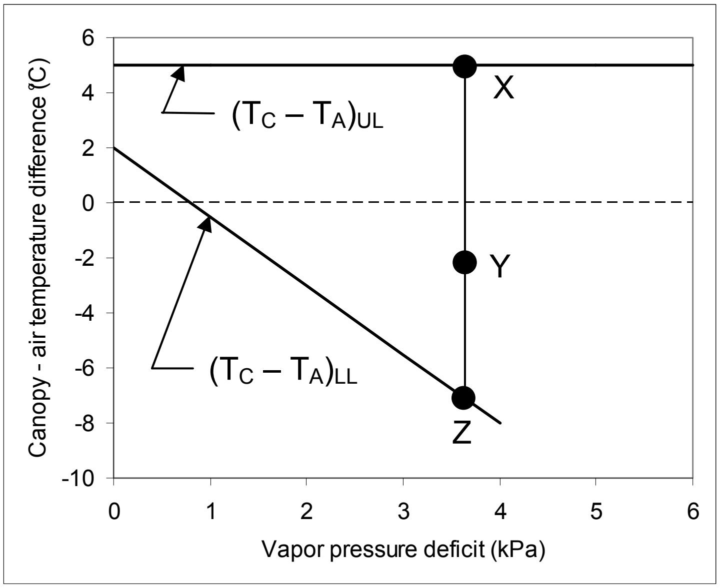
$$CWSI = \frac{(T_C - T_A)_M - (T_C - T_A)_{LL}}{(T_C - T_A)_{UL} - (T_C - T_A)_{LL}} = \frac{YZ}{XZ} \quad (1)$$

where T_C and T_A are the canopy and air temperatures, respectively (°C), the subscripts M, LL, and UL denote measured, lower limit (no stress), and upper limit (complete stress), respectively, and YZ / XZ is the graphical calculation in Figure 1, where measured canopy temperature (T_C) is at point Y. The $(T_C - T_A)_{LL}$ and $(T_C - T_A)_{UL}$ can be calculated using equations based on the surface energy balance (Jackson et al., 1981), which require concurrent measurement of micrometeorological variables (solar irradiance, air temperature, relative humidity, and wind speed) and some information on the crop (height, width, row spacing, row orientation). It is also possible to measure $(T_C - T_A)_{LL}$ and $(T_C - T_A)_{UL}$ directly over well-watered and dry crop surfaces, respectively. Although direct measurement can reduce potential biases compared with calculations (calculation biases can be caused by faulty meteorological data, assumptions within the model, or both), maintaining well-watered and dry surfaces is not really practical in day-to-day farm operations. Several simplifying approaches have been used to calculate $(T_C - T_A)_{LL}$ and $(T_C - T_A)_{UL}$ with some success, such as substituting T_C in the lower limit with the wet bulb temperature, which is close to $T_{C,UL}$, and taking $T_{C,UL}$ as the maximum daily air temperature plus 5°C (O'Shaughnessy et al., 2011a).

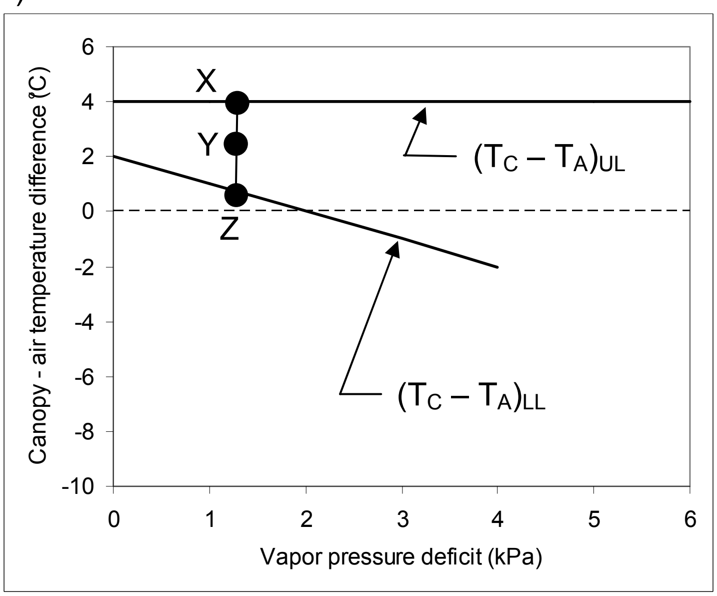
The $(T_C - T_A)_{LL}$ has been shown to have a strong inverse linear correlation with vapor pressure deficit (VPD) (Figure 1). Here, VPD is related to relative humidity, where increases in VPD correspond to decreases in relative humidity. As VPD increases (i.e., air becomes drier), T_C of well-watered plants decreases relative to T_A because drier air induces a greater evaporation rate of water. Since a completely stressed canopy has no water available, VPD has no influence on $(T_C - T_A)_{UL}$, resulting in the upper limit line being flat in Figure 1. Both $(T_C - T_A)_{LL}$ and $(T_C - T_A)_{UL}$ also depend on crop species, solar irradiance, and wind speed, any of which will impact the location of the lines and points in Figure 1. A non-water stressed canopy may be cooler or warmer than air depending on meteorological variables (mainly VPD); however, a completely water stressed canopy is generally warmer than the air during the daytime.

The accuracy of the CWSI is impaired when VPD is small. As VPD decreases, the range between the $(T_C - T_A)$ upper and lower temperature limits becomes smaller, and the distances between points X, Y, and Z in Figure 1 decrease. The result is that small errors in $(T_C - T_A)_M$, $(T_C - T_A)_{LL}$, and $(T_C - T_A)_{UL}$ will lead to increasingly larger errors in CWSI, increasing the probability of out-of-bounds CWSI values; i.e., less than zero and greater than one (Jones, 2004). Somewhat related is the influence of solar irradiance, where overcast skies also reduce the range of temperature limits. Both conditions are more prevalent in humid climates, but in arid and semiarid climates, low VPD is common in the morning (especially over irrigated fields) and, in the U.S. Great Plains, greater cloud cover occurs frequently in the afternoon during summer months. Consequently, the

CWSI is less responsive to plant and soil water conditions in humid locations, and has been found to be most responsive during clear skies and within a few hours of solar noon.



a)



b)

Figure 1. Crop Water Stress Index (CWSI), defined as CWSI = YZ / XZ, where lower and upper temperature limits are $(T_C - T_A)_{LL}$ and $(T_C - T_A)_{UL}$, respectively, for a) arid and b) humid conditions (Jackson, 1982).

Incomplete canopy cover, which exists during some (and perhaps all) of the irrigation season, can also a serious limitation of the CWSI and other canopy temperature based algorithms. The temperature of dry, sunlit soil can be 30 °C greater than green, transpiring vegetation (Kustas and Norman, 1999).

Therefore, T_C measurements can be greatly overestimated, resulting in overestimates of CWSI if soil appears in the radiometer view. The temperature of shaded soil is also usually different from vegetation, which may also introduce errors in CWSI calculations. The view of vegetation can be maximized and soil minimized by aiming a radiometer at an angle below the horizon and perpendicular to crop rows (e.g., Colaizzi et al., 2003a), and the radiometer can be designed to have a more narrow field of view (e.g., O'Shaughnessy et al., 2011b). However, the radiometer view still may not be completely free of soil, especially early in the season.

<u>Water deficit index</u>

The Water Deficit Index (WDI, Moran et al., 1994) is an extension of the CWSI that accounts for varying canopy cover and the influence of soil temperature, but is defined in a similar way. The WDI is represented graphically as a trapezoid, and WDI = YZ / XZ, analogous to the CWSI (Figure 2). The four corners represent (1) non water stressed canopy; (2) completely water stressed canopy; (3) wet bare soil; and (4) dry bare soil. Hence the top and bottom horizontal lines of the trapezoid represent full vegetation cover and bare soil, respectively. Similar to the CWSI, the surface – air difference ($T_S – T_A$) for each trapezoid corner can be calculated using surface energy balance equations, or can be measured directly if suitable surfaces are available. Note that ($T_C – T_A$) has been replaced with ($T_S – T_A$), which refers to a composite surface that may include both canopy and soil temperatures. The fraction of canopy cover that appears in the radiometer view (f_{CR}) can be estimated by empirically relating f_{CR} to a reflectance-based vegetation index. Concurrent to the temperature measurements, a vegetation index, such as the normalized difference vegetation index (NDVI), is calculated from measurements of reflectance, usually the red and near-infrared bands. The $(T_S – T_A)_{LL}$ and $(T_S – T_A)_{UL}$ (i.e., points Z and X in Figure 2, respectively) are then calculated by linear interpolation as

$$\left(T_S - T_A\right)_{LL} = f_{CR}\left(T_S - T_A\right)_1 + \left(1 - f_{CR}\right)\left(T_S - T_A\right)_3 \tag{2a}$$

$$\left(T_S - T_A\right)_{UL} = f_{CR}\left(T_S - T_A\right)_2 + \left(1 - f_{CR}\right)\left(T_S - T_A\right)_4 \tag{2b}$$

where all terms as as defined previously. WDI is calculated using equation (1) where ($T_C – T_A$) is replaced with ($T_S – T_A$) in each term. Colaizzi et al. (2003b) showed that the WDI was well-correlated to soil water depletion for a wide range of canopy cover and soil water profiles for cotton in Arizona. However, the WDI has not received as much attention as the CWSI, perhaps because it also requires reflectance measurements (or other suitable method) to estimate f_{CR}, and may also share the limitations of the CWSI under humid or overcast conditions.

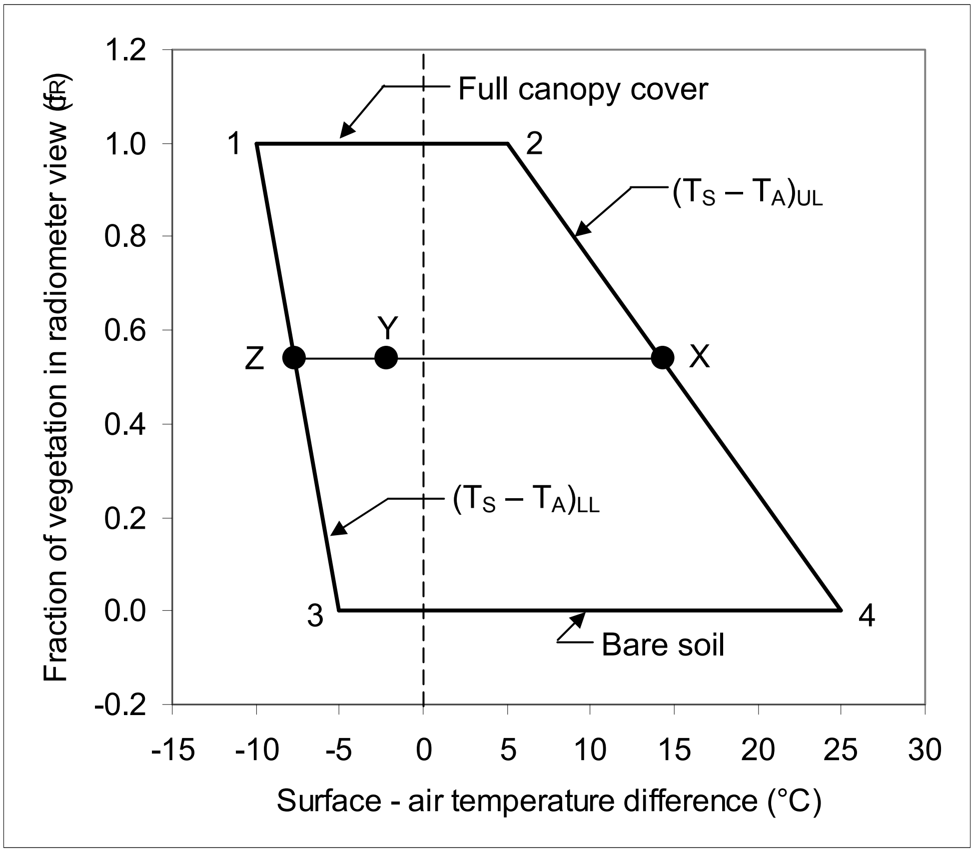


Figure 2. Water Deficit Index (WDI), defined as WDI = YZ / XZ. Point 1 is non water stressed full canopy, 2 is completely water stressed canopy, 3 is wet bare soil, and 4 is dry bare soil, and the lower and upper temperature limits are $(T_S – T_A)_{LL}$ and $(T_S – T_A)_{UL}$, respectively (Moran et al., 1994).

Time – Temperature Threshold

The time – temperature threshold (TTT) method was developed from the observation that plant enzymes are most productive under a relatively narrow range of temperatures, termed the thermal kinetic window (Burke, 1993; Burke and Oliver, 1993). Although the plant canopy temperature varies with meteorological conditions, and may not always be within its thermal kinetic window, the concept of a threshold canopy temperature has proven to be useful in irrigation management (Wanjura et al., 1992; 1993; 1995). A system using this approach, termed the Biologically – Identified Optimal Temperature Interactive Console (BIOTIC), was issued US Patent No. 5,539,637 (Upchurch et al., 1996).

In the TTT method, the accumulated time that the canopy temperature exceeds a threshold temperature is used as the criterion for an irrigation event (Figure 3). Here, the threshold temperature for corn was 28 °C, the threshold time is 240 min, and the canopy temperature was measured over corn. On day of year 234, the canopy temperature exceeded the threshold temperature for longer than 240 min. Therefore, an irrigation occurred that evening. The following day, the canopy temperature also exceeded the threshold temperature, but for a duration of less than 240 min. Therefore, no irrigation occurred on day of year 235. The TTT method is advantageous over the CWSI and the WDI for its simplicity, in that it does not require calculation or measurement of lower and upper temperature limits. Furthermore, it is a time-integrating approach and appears to be more responsive to a wider range of meteorological conditions, such as low VPD and overcast skies, compared with one-time-of day water stress indices (O'Shaughnessy and Evett, 2010a).

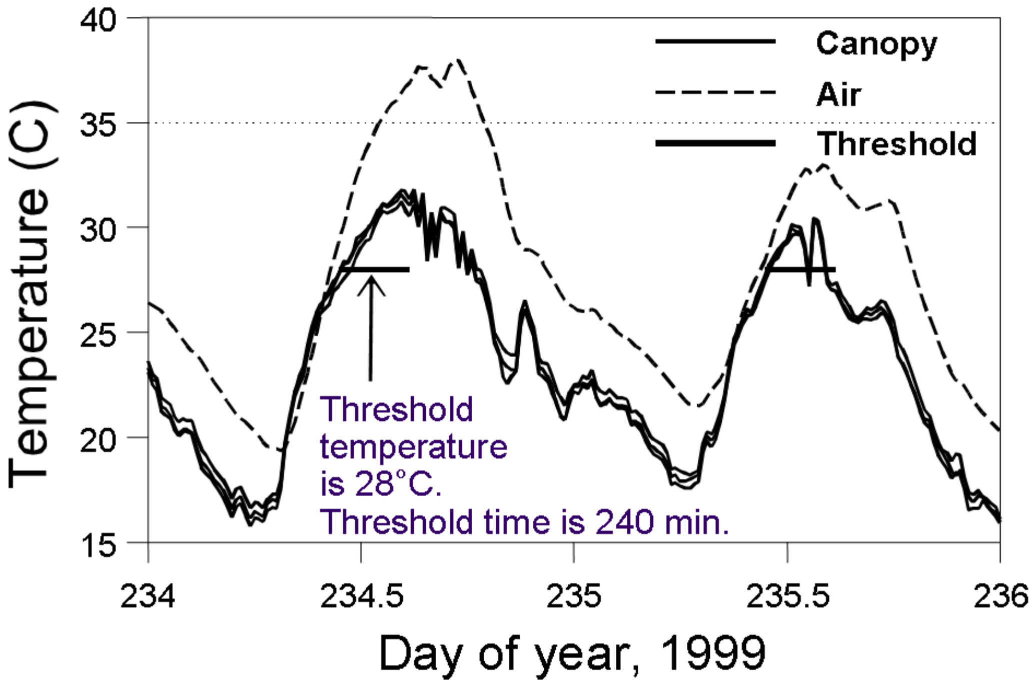


Figure 3. Canopy, air, and threshold temperature for corn at Bushland, TX. The canopy temperature exceeded the threshold temperature (28° C) for a duration greater than the threshold time (240 min) on day 234 but not on day 235. Therefore, irrigation was applied automatically on the evening of day 234 but not on day 235 (Evett et al., 2000; Peters and Evett, 2008).

The TTT method requires canopy temperature data throughout the daytime. In its initial development and application, continuous canopy temperature measurements were provided by stationary IRTs that viewed drip irrigated plots (Wanjura et al., 1995; Evett et al., 2000; Mahan et al., 2010). Thus at first it would appear that the TTT method would not be amenable to an array of moving IRTs, such as those aboard a moving center pivot. In this case, only a single canopy temperature measurement every few days would be possible at a remote location. However, Peters and Evett (2004) showed that the diurnal canopy temperature for remote locations can be calculated using a scaling procedure based on a one-time-of-day measurement ($T_{RMT,t}$) taken at a field (remote) location and a diurnal reference temperature (T_{REF}) taken at a stationary location:

$$T_{RMT} = T_E + \frac{(T_{RMT,t} - T_E)(T_{REF} - T_E)}{(T_{REF,t} - T_E)} \quad (3)$$

where T_{RMT} is the calculated remote canopy temperature at any time of day, T_E is the predawn canopy temperature (assumed to be the same throughout the entire field), $T_{RMT,t}$ is the measured remote canopy temperature at the single time of day t (i.e., when the center pivot carries the IRT over the remote location), T_{REF} is the measured reference temperature at any time of day, and $T_{REF,t}$ is the reference temperature at the single time (t) of day. A stationary IRT at some location in the field provides the reference temperatures T_{REF} (throughout the day), $T_{REF,t}$ (at the time of day t when $T_{RMT,t}$ is measured), and T_E. During the day, T_{RMT} and T_{REF} will probably differ due spatial variability in the field, but follow a similar overall trend (Figure 4).

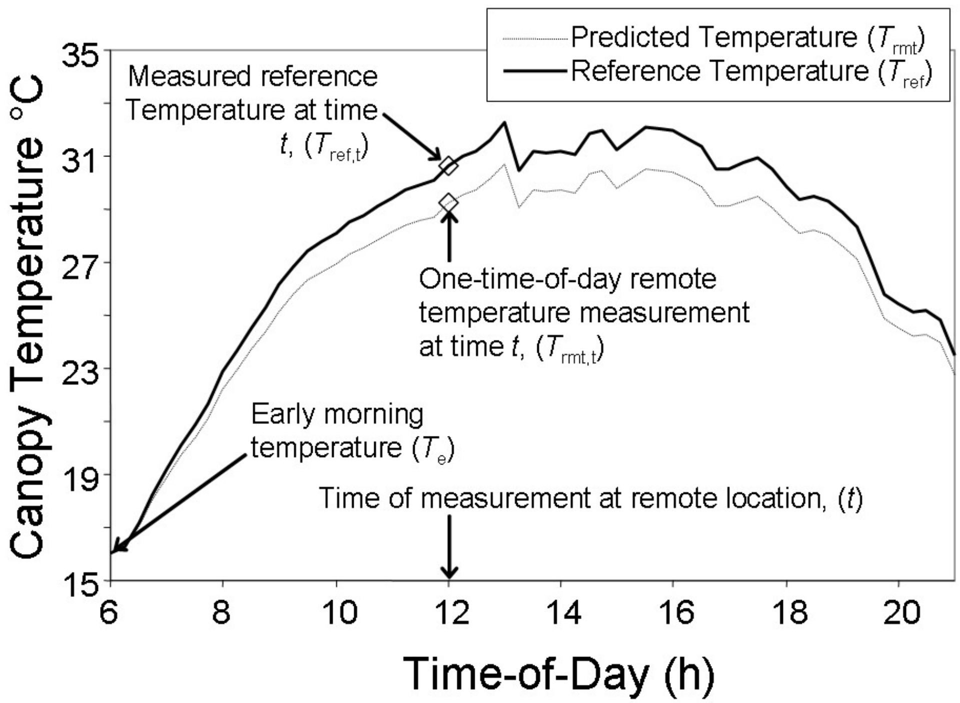


Figure 4. Scaling diurnal canopy temperature from one-time-of-day canopy temperature measurement (Peters and Evett, 2004).

The scaling method permits use of one-time-of-day canopy temperature measurements over a wide duration of the day. Peters and Evett (2004) reported that the mean absolute error between calculated (using equation 3) and measured T_{RMT} was less than 0.5 °C if $T_{RMT,t}$ was measured within the period approximately 2 h after sunrise and 2 h before sunset, but increased to over 6° C within 2 h of sunrise or sunset. For example, if the day length is 14 h, up to a 10 h window would be available to obtain remote measurements. As discussed later, the scaling method has expanded application of the TTT method to the automation of center pivots. The scaling method can also be applied to calculate water stress indices over a longer portion of the day. This was recently developed and shown to be effective in automatically scheduling center pivot irrigations for grain sorghum using a time-integrated water stress index (O'Shaughnessy et al., 2012).

ET-Based Soil Water Balance

Water stress indices such as the TTT method can improve irrigation management by providing guidance, including automation, on the *timing* of irrigations. With the TTT method, the amount of irrigation is preset, usually at some multiple of the crop's peak daily water use. The premise is that if the crop is water stressed, then the root zone soil will be depleted enough to accept that much water. Being a feedback system, the TTT algorithm will repeat such irrigations each day that a water stress is sensed. However, the exact *amount* of irrigation that the soil will accept depends partly on soil water depletion in the root zone (infiltration is also limiting). Soil water depletion is determined most directly by in-situ measurement of the soil water profile. Gravimetric/volumetric sampling and the neutron probe are the most accurate measurement methods, but these are cost and labor intensive, which imposes limitations in the number of locations and the repeat frequency of measurements. Furthermore, the neutron probe is a radioactive device that is subject to regulation, and cannot be operated unattended. Recently, wireless electromagnetic profile probes (capacitance type) have become available that can be operated remotely and continuously, but the depth of sampling is usually less than the depth of the fully developed root zone for most crops, and capacitance type electromagnetic devices can be impacted by soil temperature, soil salinity, and small-scale variations in soil water content and bulk electrical conductivity that affect the volume of soil being measured, among other factors. All of these have been shown to limit their accuracy, and the unit cost of a device may still preclude obtaining an adequate number of measurement locations in fields (Evett et al., 2012).

With measurement frequency being one fundamental constraint (at least until recently), soil water depletion has usually been calculated between measurement times using a soil water balance, where ET is the primary sink. ET is most readily calculated by the reference ET – crop coefficient method, which does not require canopy temperature and hence avoids many of the barriers that have previously been associated with remote sensing. The reference ET – crop coefficient method has been used for irrigation management for several decades, and can be effective even when minimal soil water profile measurements are available (Howell et al., 1998; Colaizzi et al., 2009). Nonetheless, real-time feedback on a spatial basis of plant and soil water status, including ET, is desirable in order to prioritize irrigation schedules, detect unexpected field conditions (e.g., biotic stress, malfunctioning or broken sprinkler heads, misapplication of fertilizer or chemicals, salinity, hail or wind damage) or conditions otherwise not readily captured by modeling alone (e.g., soil texture variability) (Peters and Evett, 2007; O'Shaughnessy et al., 2011a).

ET can also be calculated by using canopy temperature directly in an energy balance model. In this approach, canopy temperature measurements provide the real-time feedback aspect. Since water stress indices are also derived from energy balance considerations, they are related to ET in the following general form:

$$ET = ET_P(1 - WSI) \tag{4}$$

where WSI is a water stress index (e.g., CWSI or WDI), and ET_P is the potential ET where water is non-limiting (i.e., when WSI = 0). This shows that if the required ancillary information is available to calculate a WSI (i.e., incoming solar irradiance, air temperature, humidity, wind speed, canopy temperature, and crop phenology), then ET can also be calculated and applied to a soil water balance model (Colaizzi et al., 2003a). Recent refinements to a two-source energy balance model (where the energy balance of the soil and canopy sources are calculated separately) improved the accuracy of the calculated soil evaporation (E) and plant transpiration (T_P) components, as well as total ET, for row crops with partial cover (Colaizzi et al., 2012a; 2012b). From this development, the two-source energy balance model will be tested in scheduling irrigations for a center pivot equipped with wireless IRTs, as a continuation of the work described in O'Shaughnessy et al. (2012). In addition, separate calculation of E and T_P can be a powerful tool in assessing management strategies aimed at reducing E losses and increasing water use efficiency (Evett and Tolk, 2009).

REMOTE SENSING PLATFORMS

Measurement of canopy temperature or other remotely sensed variable requires some type of platform. Remote sensing platforms generally consist of three types, including ground-based, aircraft, or satellite. Ground-based platforms may be either stationary or moving; in the case of the latter, the remote sensors may be hand-held or otherwise portable, or aboard moving machinery such as a center pivot or spray rig. Spatial scales range from a few cm^2 using ground-based or aircraft platforms, to several km using satellite platforms. In general, moving platforms enable the greater spatial coverage using fewer sensors compared with stationary ones. However, there is usually a trade-off between coverage and measurement frequency, where moving platforms typically obtain measurements at a single time-of-day but at many locations in a field, whereas a stationary device can obtain measurements continuously but at only one field location. As noted previously and explained below, combining these can routinely provide continuous coverage over at least some part of a field.

In order for plant canopy temperature to be useful as an irrigation management tool, measurements must meet several criteria in terms of spatial scale, repeat frequency, and data processing time. Jackson (1984) reviewed measurement requirements for day-to-day farm management in the context of remote sensing platforms, and described these as having ~5 m or less spatial scale, a repeat frequency of no more than 7 days, with continuous (minute to hourly) monitoring ideal, and data processing time (i.e., the time from measurement to meaningful information product) of a few minutes. In addition, measurements should contain adequate coverage of the area to be managed, which is usually met by aircraft and satellite platforms, but may not be met by ground-based platforms.

Historically, each type of platform has in some way fallen short of these requirements. Some commercially-available satellites (e.g., QuickBird) now nearly meet these requirements, but measure only in the visible and near-infrared wavelengths. Most algorithms that have been shown to be useful for irrigation management require measurements in the longer thermal infrared wavelengths. A satellite platform equipped with a thermal sensor system that also meets all measurement criteria for real-time irrigation management is technically feasible, but such a platform is not expected to become commercially available in the foreseeable future. As an alternative, Norman et al. (2003) and Anderson et al. (2004) described a thermal sharpening procedure where frequent, coarse resolution thermal satellite data (i.e., daily and 1-km pixels) were combined with less frequent, fine resolution reflectance satellite data. However, Agam et al. (2007) found that this procedure had limited accuracy for wet soil with less than full canopy cover in the Texas High Plains. Some crop consulting services offer aircraft imagery with sufficient spatial resolution and coverage, but these also usually lack the thermal band, and flights more frequent than 7 days can be cost prohibitive. Both satellite and aircraft platforms also carry substantial image processing requirements (e.g., atmospheric and geometric correction), which increases their cost and usually prevents the timeliness requirement of a few minutes from being met (Moran, 1994).

Ground-based sensors (e.g., IRTs) largely circumvent the disadvantages of satellite and aircraft platforms, but measure a relatively small area of a few m^2 or less. Therefore, adequate field coverage would require a relatively large number of sensors. The appropriate number of sensors to be deployed depends on many factors that are beyond the scope of this paper, but a few examples include field slope and soil variability, the profit margin of the crop, and the sensor cost. The number of sensors could be reduced if a platform that passes over the field at sufficient intervals was available, such as a center pivot irrigation system, which is the dominant irrigation method in the US Great Plains (USDA, 2008; Colaizzi et al., 2009). Therefore, recent efforts have focused on designing ground-based remote sensing systems specifically for center pivots, including algorithms (Peters and Evett, 2004; Colaizzi et al., 2010); wireless sensor networks (O'Shaughnessy and Evett, 2010b), and low-cost wireless IRTs (O'Shaughnessy et al., 2011b). Nonetheless, subsurface drip irrigation continues to grow substantially in the Texas High Plains (Bordovsky et al., 2012), which can be managed using stationary IRT networks (Wanjura et al., 1995; Evett et al., 2000).

The Smartcrop© Automated Crop Stress Monitoring System (Smartfield, Inc., Lubbock, Texas) is a wireless IRT system that is now commercially available, and has been used as a stationary system to manage drip irrigation schedules (Mahan et al., 2010), but could also be used to manage gravity or sprinkler systems.

IRRIGATION AUTOMATION AT BUSHLAND, TX

Canopy temperature – based algorithms have been used successfully to automate irrigation scheduling and provide field maps of crop water status, where the latter can reduce irrigation management time even if automation is not employed. Several canopy temperature – based automation schemes have been investigated and compared with manual scheduling, where the latter entails measurement of the soil water profile with a field-calibrated neutron probe. To be viable, automatic scheduling should achieve similar or better crop yield and crop water productivity compared with manual scheduling. The following briefly reviews some automatic vs. manual results at the USDA Conservation and Production Research Laboratory, Bushland, Texas.

The TTT method has been used to automate both drip and center pivot systems for various crops, including corn, cotton, and soybean. Evett et al. (2000) used wired, stationary IRTs that measured canopy temperatures in a drip irrigated, four year corn and soybean rotation. For each crop, four TTT combinations were used, and these were compared to manually – irrigated plots where three irrigation rates (33%, 67% and 100% of meeting full crop ET) were used. Corn threshold temperatures were 28 °C and 30 °C, and threshold times were 240 and 160 min. Soybean threshold temperatures were 27 °C and 29 °C, and threshold times were 256 and 171 min. The automatic irrigation decision interval was 1 d, and each automatic irrigation event was 10 mm (i.e., equivalent to expected peak daily crop ET). Manual treatments were irrigated at weekly intervals. The automatic treatments generally resulted in similar or greater yield, similar seasonal irrigation amounts applied, and similar seasonal ET compared with the 100% manual irrigation treatment.

Peters and Evett (2008) used the TTT method to schedule irrigations for two seasons (2004 and 2005) of soybeans irrigated with a center pivot equipped with low energy precision applicator (LEPA) drag socks. The IRTs used to schedule irrigations were wired and aboard the center pivot, and viewed the canopy ahead of the direction of travel to avoid viewing the area being irrigated. Diurnal canopy temperature data required for the TTT method were calculated with the scaling method (equation 3; Peters and Evett, 2004), where IRTs aboard the center pivot provided one-time-of-day measurements ($T_{RMT,t}$ in equation 3), and stationary IRTs provided the other required variables (T_{REF}, $T_{REF,t}$, and T_E in equation 3). The threshold temperatures were 30 °C and 27 °C in 2004 and 2005, respectively, and the threshold time was 256 min in both years. Automatic and manual treatments included 33%, 67%, and 100% of the full irrigation rate. The automatic and manual irrigation decision intervals were 2 d, and each 100% automatic irrigation event was 20 mm, and deficit irrigation events were 33% and 67% of 20 mm. In 2004, yield, irrigations applied, seasonal ET, and water use efficiency (WUE = Yield/ET) were mostly greater for the manual compared with the automatic treatments, because a defect in the IRTs resulted in too large of a threshold temperature (30 °C instead of the desired 27 °C), resulting in the automatic plots being under-irrigated. In 2005, the desired 27 °C threshold temperature was achieved, and yield, seasonal ET, and WUE were greater (sometimes significantly so) in the automatic compared with the manual treatments.

In that same experiment, Peters and Evett (2007) showed that soybean yield, above ground biomass, and seasonal ET were well-correlated to canopy temperatures. They also used a novel approach where the statistical process control method was applied to canopy temperatures to detect significant spatial and temporal variability (Figure 5). Statistical process control is commonly used in manufacturing to detect product defects. The variability shown was caused by an intentional over-application of herbicide and was not apparent by visual observation.

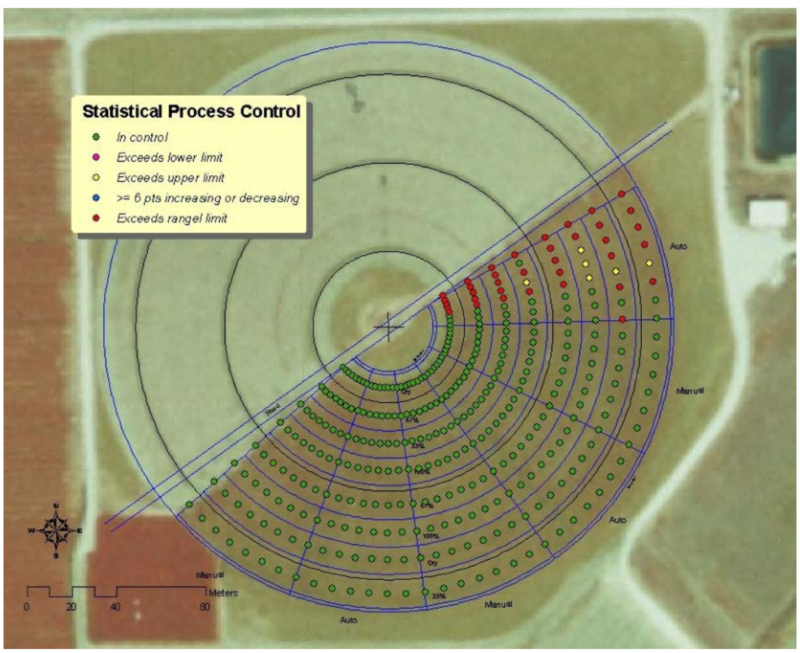


Figure 5. Canopy temperature measurement locations in soybean irrigated by center pivot, day of year 258, 2005, Bushland, TX. Canopy temperature measurements were evaluated by statistical process control to detect unusual spatial and temporal variability. Green indicates “in control” locations, and yellow and red locations indicate “out of control” locations where the field was sprayed by herbicide in order to test the sensitivity of the statistical process control algorithm. The algorithm detected the damage even though it was not apparent by visual observation (Peters and Evett, 2007).

O'Shaughnessy and Evett (2010a) used the TTT method to automatically schedule center pivot irrigations (equipped with LEPA drag socks) for the 2007 and 2008 cotton seasons. The experiment was similar to that of Peters and Evett (2008), where automatic and manual irrigation treatments were 33%, 67%, and 100% of full irrigation. IRTs were wired in 2007 and wireless in 2008. For cotton, the temperature and time thresholds were 28 °C and 452 min, the irrigation frequency was not more than 2 d, but the irrigation decision interval was 1 d, where canopy temperature measurements from the previous 1 d (not 2 d) determined whether an irrigation event was to occur. Each 100% automatic irrigation event was 20 mm, and the deficit irrigation events were 33% and 67% of 20 mm. In both years, total irrigation applied and seasonal ET were less for automatic compared with manual scheduling within an irrigation rate treatment. In 2007, lint yield and WUE were generally not significantly different for automatic vs. manual treatments among irrigation rates, but in 2008, lint yield and WUE were greater (often significantly so) for the automatic compared with the manual control methods among all irrigation rate treatments.

Data from the O'Shaughnessy and Evett (2010a) experiment and the soybean data from Evett and Peters (2007; 2008) were used in calculating a slightly different version of the CWSI (O'Shaughnessy et al., 2011a). They set the upper temperature limit ($T_{C,UL}$) as the maximum daily air temperature plus 5 °C, and used for the lower temperature limit ($T_{C,LL}$) the wet bulb temperature calculated at $T_{C,UL}$. They used canopy temperatures (T_C) found by the scaling method for a 2-hour window near solar noon. They found that the CWSI calculated in this way and averaged over the season had generally good correlation with midday leaf water potential, seasonal ET, and grain and lint yields. A few exceptions where correlation was poor were related to unfavorable growing conditions in 2008. This demonstrates the application of multiple canopy temperature algorithms, where the TTT was used to automate irrigations, and the CWSI was used to estimate midday leaf water potential, and final yield and ET. It should be noted that although leaf water potential was measured around midday, this was not necessarily the case for canopy temperature, as the temperature scaling method permitted measurements over a much wider span of the day to be used to estimate T_C near solar noon. Their study also demonstrated the utility of a CWSI map, where differences in irrigation rates were clearly visible as the season progressed, and could be used to prioritize manual irrigation scheduling (Figure 6).

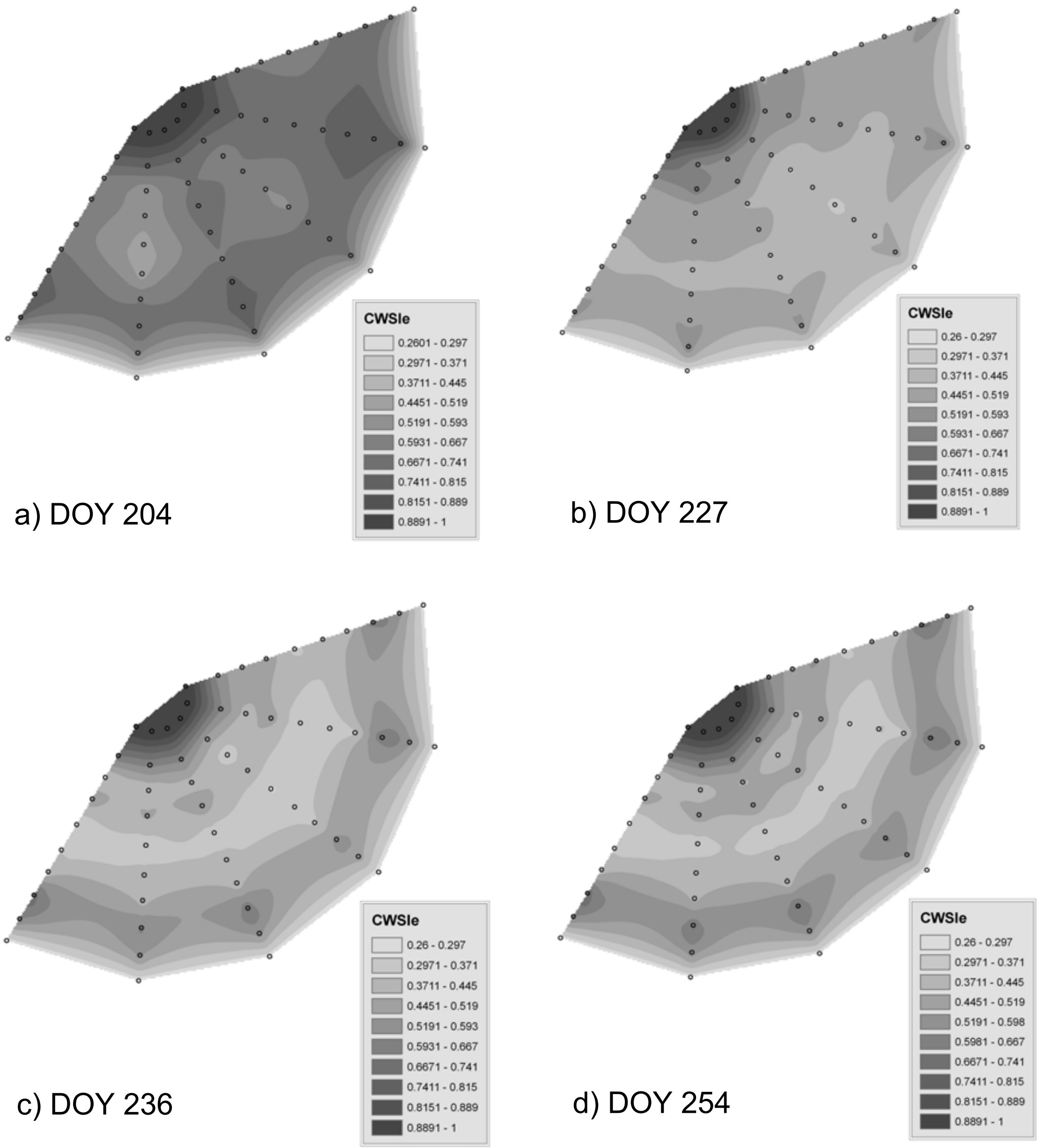


Figure 6. Maps of CWSI for cotton at Bushland, TX, average CWSI from DOY 198 to (a) DOY 204; (b) DOY 227; (c) DOY 236; (d) DOY 254 (O'Shaughnessy and Evett, 2011a). Darker shading means less water stress.

Algorithms based on time integration, such as the TTT method, attempt to account for conditions over most of the day. This likely has certain advantages over algorithms that relate only to instantaneous conditions, such as the conventional CWSI. Time integration can average short-term fluctuations in meteorological conditions, which would reduce the algorithm's sensitivity to the time of day that measurements are obtained. O'Shaughnessy et al. (2012) hypothesized that a time-threshold form of the CWSI (termed CWSI-TT) could automate irrigation scheduling and exploit the time-integrating and energy balance strengths of the TTT and CWSI methods, respectively. They tested this approach over two seasons (2009 and 2010) for grain sorghum that was irrigated by a center pivot equipped with LEPA drag socks and wireless IRTs. As with previous experiments, automatic and manual treatments were compared, but irrigation rates were 30%, 55%, and 80% of full crop ET. The CWSI was calculated at 5-minute intervals during the daytime, and the lower and upper temperature limits were calculated following Jackson et al. (1981). The threshold CWSI value was taken as 0.45, and the threshold time was 420 min. For each 5-min interval, if CWSI > 0.45, then 5-min was added to the accumulated time. If accumulated time exceeded 420 min by midnight over the previous 24 h, then irrigation was initiated the following morning. The threshold time was determined by analyzing well-watered sorghum canopy temperature data acquired in previous years on the large weighing lysimeters at Bushland. In both years, grain yield and WUE were not significantly different between automatic and manually scheduled plots for most irrigation rates. Two exceptions were in 2009 in the 30% and 55% irrigation rates, where grain yields were significantly less in the automatic compared with the manual treatment. This was related to greater variability in soil water at the beginning of the season, which somewhat favored the manually irrigated treatment plots. Total irrigation amounts applied to the automatic compared with the manual treatments were less in 2009 but nearly the same in 2010.

The ARS irrigation research team at Bushland is currently involved in a Cooperative Research and Development Agreement with a center pivot irrigation system manufacturer to transfer the technology in the successful ARS irrigation automation system to commercial production.

SUMMARY AND CONCLUSIONS

This paper reviewed the use of remotely sensed plant canopy temperature for irrigation management. This included an overview of canopy temperature – based algorithms, remote sensing platforms, some recent results in irrigation automation research at the USDA Agricultural Research Service Conservation and Production Laboratory at Bushland, Texas.

Canopy temperature algorithms were categorized as water stress indices, the time temperature threshold method, and the ET – based soil water balance. Each type of algorithm can provide guidance on the timing of irrigation, and ET – based approaches also indicate the varying needed irrigation application amounts as demand varies over time.

In order to be useful for day-to-day, site-specific irrigation management, canopy temperature data generally must have a spatial resolution of a few meters, a repeat frequency of no more than 7 d, and a turnaround time (i.e., the time from measurement to useful information product) of a few minutes. In addition, field coverage must be adequate in terms of the number and spatial distribution of samples. Historically, neither, ground-based, aircraft, or satellite platforms have been able to meet these requirements. However, recent advances in wireless technology, computing capacity, canopy temperature data processing algorithms, and reductions in infrared thermometer (IRT) and related component costs, appear to have made feasible a ground-based system where a center pivot is used as the platform to transport IRTs over the field.

A center pivot platform equipped with IRTs was used by the USDA at Bushland, TX, to automate irrigation schedules, and automatic treatments were compared with manual treatments where a field-calibrated neutron probe was used to schedule irrigations. The time temperature threshold method was evaluated for soybean and cotton, and a crop water stress index threshold time method was evaluated for grain sorghum. Previous research also evaluated the time temperature threshold method using stationary IRTs on drip irrigated corn and soybean. In most cases, the automatic treatments compared favorably with manual treatments in terms of crop yield, seasonal water use, water use efficiency, and irrigation amounts applied. This indicates that canopy temperature-based algorithms are a viable tool in automating irrigation scheduling, which can reduce management time required but achieve the same crop water productivity that is possible with manual scheduling.

Even if automation is not chosen, canopy temperature-based algorithms were shown to be strongly correlated to crop yield, water use efficiency, seasonal ET, midday leaf water potential, irrigation rates, and herbicide damage not visible by eye. This can provide timely information not previously available that can also reduce management time, prioritize irrigation schedules, and improve crop water productivity. Additional research will investigate how well ET-based algorithms can prescribe appropriate irrigation application amounts, where ET is calculated using a canopy temperature driven energy balance model.

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