Evaluation of thermal remote sensing indices to estimate crop evapotranspiration coefficients

Emily G. Kullberg^{a,b}, Kendall C. DeJonge^{c,*}, José L. Chávez^a,

^a Dept. of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO 80523 USA

^b Aqua Engineering Inc., Fort Collins CO 80525

^c USDA-ARS, Water Management Systems Research Unit, Fort Collins, CO 80526 USA

* corresponding author.

Address: 2150 Centre Ave, Bldg. D Ste. 320, Fort Collins CO 80526

Tel.: +01 970 492-7417; fax: +01 970 492-7408.

E-mail address: Kendall.DeJonge@ars.usda.gov

ABSTRACT. Remotely sensed data such as spectral reflectance and infrared canopy temperature can be used to quantify crop canopy cover and/or crop water stress, often through the use of vegetation indices calculated from the near-infrared and red bands, and stress indices calculated from the thermal wavelengths,. Standardized dual crop coefficient methods calculate both a non-stressed transpiration coefficient (K_{cb}) that is related to canopy cover, and a stress or transpiration reduction coefficient (K_s) that can be related to soil water deficit or other stress factors (e.g. disease). This study compares several remote sensing methods to determine K_{cb} and

K_s and resulting evapotranspiration (ET) in a deficit irrigation experiment of corn (*Zea mays L.*) near Greeley, Colorado. Three methods were used to calculate K_{cb} (tabular, normalized difference vegetation index - NDVI, and canopy cover). Four canopy temperature based methods were used to calculate K_s : Crop Water Stress Index – CWSI, Canopy Temperature Ratio - Tcratio, Degrees Above Non-Stressed – DANS, Degrees Above Canopy Threshold – DACT. Crop ET predicted by these methods was compared to observation and water balance based ET measurements. Thermal indices DANS and DACT were calibrated to convert to K_s . Results showed that stress coefficient methods with less data requirements such as DANS and DACT are responsive to crop water stress as demonstrated by low RMSE of ET calculations, comparable to more data intensive methods such as CWSI. Results indicate which remote sensing methods are appropriate to use given certain data availability and irrigation level, in addition to providing an estimation of the associated error in ET.

Keywords:

Canopy temperature

Crop coefficient

Crop water stress index

DANS index

DACT index

LIST OF SYMBOLS AND ABBREVIATIONS

DACT	degrees above canopy threshold (°C)
DANS	degrees above non-stressed canopy (°C)
D_r	root zone depletion, or soil water deficit (mm)
DP	deep percolation (mm)
ET	evapotranspiration (mm/day)
ET_c	crop evapotranspiration (mm/day)
ET_r	alfalfa-based reference evapotranspiration (mm/day)
f_c	fractional vegetation cover
GW	ground water input (mm)
I	total net irrigation amount applied (mm)
IRT	infrared thermometer (°C)
K_c	crop coefficient
K_{cb}	basal crop coefficient
K_s	stress crop coefficient
LIRF	Limited Irrigation Research Farm
MAD	maximum allowable depletion (mm)
NDVI	normalized difference vegetation index
P	effective precipitation (mm)
RAW	readily available water (mm)
RH	relative humidity (%)
R_{nir}	reflectance in the near infrared band

R_{red}	reflectance in the red band
SWD	soil water deficit (mm)
TAW	total available water (mm)
TDR	time domain reflectometer
T_c	crop canopy temperature (°C)
T_{cNS}	non-stressed canopy temperature (°C)
$T_{critical}$	critical canopy temperature threshold (°C)
VI	vegetation index
VWC	volumetric water content (m ³)

1. Introduction

As climate change and population growth both place unprecedented demand on the world's finite fresh water supply, competition among various water users (e.g. irrigation, recreation, industry, and municipal) is likely to increase. As the largest consumptive water user, irrigated agriculture experiences pressure to reduce water use while maintaining high yields (Allen et al., 2007). An additional challenge is presented by climate change which may alter historical precipitation patterns and increase droughts (Walthall et al., 2012). In order to continue to sustain a rapidly growing population with vulnerable and limited water resources, producers must be adequately prepared to adapt irrigated agriculture practices.

One strategy under current research is regulated deficit irrigation where irrigation applications are less than the full crop water requirement. Through regulated deficit irrigation, high water productivity is achieved by careful monitoring of crop water status and timing of irrigation applications. Deficit irrigation ideally results in no water losses due to deep percolation because it never fully replenishes the crop root zone. In addition, evaporation losses may be reduced by less frequent irrigation applications. Additionally, crops often have varying water stress sensitivity at different growth stages, which can inform the producer as to when placing more stress on the plant will have a smaller impact on yield (Feres and Soriano, 2007).

Many farms have been historically over-irrigated, often sacrificing irrigation efficiency for yield stability, although there may still be harmful effects of over-irrigating such as waterlogging and salinity (Montoro et al., 2011). When irrigation water becomes expensive or limited the producers will move from a stress prevention approach to a stress management approach, and deficit irrigation during critical growth periods may be an effective way to maintain production while decreasing water use. A review on deficit irrigation by Feres and

Soriano (2007) affirms the idea that applying less than full irrigation can increase water productivity and even farmers' profits. They noted that successful deficit irrigation strategies are typically found within situations that permit the application of at least 60% of crop water requirement and are designed based on crop drought sensitivity during each development stage. Many other recent studies have explored the outcomes of deficit irrigation with similar results (Conaty, 2010; DeJonge et al., 2011; Fereres and Soriano, 2007; Kang et al., 2000; Taghvaeian et al., 2012).

Managed deficit irrigation relies on quantification of crop water use, or evapotranspiration (ET). Standardized methods of measuring and estimating ET assume fully irrigated conditions and therefore do not accurately estimate water use if soil water deficit conditions limit ET. Thus, methods that are sensitive to crop development and stress are necessary during droughts or under deficit irrigation. Reference evapotranspiration is the ET from a reference crop (12 cm high clipped grass or 50 cm tall full-cover alfalfa) and therefore incorporates the effects of weather into the ET estimate (ASCE, 2005). To use the reference ET calculation method to estimate crop ET, the ratio of a cropped and reference surface is combined into a crop coefficient according to ASCE (2005) as:

$$ET_c = ET_r \cdot K_c \quad (1)$$

where K_c is the crop coefficient, ET_c is crop ET (mm), ET_r is alfalfa or tall reference surface ET (mm). The effect of microclimate on ET is described by ET_r and the properties of the crop which affect ET are quantified by K_c (Allen et al., 1998). This method can be used to calculate the ET of a crop under "standard" (i.e. non-stressed) conditions, but cannot directly estimate the ET of a water stressed crop. Allen et al. (1998) separated the crop coefficient into evaporation and plant

transpiration components, the latter which included a stress coefficient for soil water limiting conditions (K_s) shown as:

$$ET_c = (K_{cb}K_s + K_e)ET_r \quad (2)$$

where K_{cb} is the basal crop coefficient representing transpiration when the plant is under no stress, and K_e is the evaporation coefficient.

The basal crop coefficient K_{cb} can be obtained from published tabular values such as those listed for a short crop reference in Allen et al. (1998) and typically has a trapezoidal shape that has a strong relationship with canopy cover. A source of error with tabulated values is that corn under different environmental and management conditions does not grow at the same rates. Basing the crop coefficient on growing degree days may be more accurate, but even this method can vary from with regional, management, and climatic variability. Water stress may further alter growth rates based on timing of water deficit or water application, and Mahan et al. (2014) suggest canopy temperature should be considered along with growing degree days to improve the utility of heat units. Alternately, canopy cover or reflectance data can be used to estimate K_{cb} throughout the season.

Reflectance-based basal crop coefficient (K_{cb}) methods developed by Neale et al. (1989) and Bausch (1993) have been used to improve irrigation scheduling of corn. Reflectance-based basal crop coefficient methods rely on remote sensing data to calculate a vegetation index and a linear relationship between the vegetation index and the reflectance-based crop coefficient. One of the most commonly used vegetation indices is the normalized difference vegetation index (NDVI):

$$NDVI = \frac{R_{nir} - R_{red}}{R_{nir} + R_{red}} \quad (3)$$

where R_{nir} is reflectance in the near infrared band and R_{red} is reflectance in the red band. Using NDVI, Neale et al. (1989) developed a relationship for corn in Greeley, Colorado, to determine the basal crop coefficient K_{cb} from remotely sensed data (NDVI). A more recent development in the estimation of actual crop coefficients was the work of Trout et al. (2008) and Johnson and Trout (2012) which showed that K_{cb} can be estimated from fractional vegetation cover (f_c). Johnson and Trout (2012) also demonstrated that if f_c measurements are not available, NDVI can be used to estimate f_c by

$$f_c = 1.26 (\text{NDVI}) - 0.18 \quad (4)$$

Once f_c has been obtained either through Eq. (4) or more directly by image processing, the basal crop coefficient can be estimated as

$$K_{cb} = 1.13 f_c + 0.14 \quad (5)$$

Reflectance-based crop coefficients assess current crop conditions instead of assuming the crop is under “standard” conditions, an advantage over tabular values. Whether measured vegetation indices or fractional vegetation cover is used to calculate K_{cb} , it will determine ET_c better than a tabulated crop coefficient because it reflects not only the actual growth stage of the crop but also reductions in canopy cover due to previous stresses.

The dual crop coefficient approach reduces the stress coefficient K_s when the soil water content is less than the level of maximum allowable depletion (MAD) (Allen et al., 1998). K_s represents the fraction of potential transpiration rate that a crop is experiencing reduced from 1.0 according to the level of water stress. Thus, under soil water limiting conditions, K_s will be less than 1. K_s can be as low as 0 in the case that the plant can no longer extract water from extremely dry soil. K_s , according to the Allen et al. (1998) FAO-56 soil water depletion method, is calculated by:

$$K_s = \frac{TAW - D_r}{TAW - RAW} \quad (6)$$

where TAW is the total available soil water in the root zone (mm), D_r is the root zone depletion (mm), and RAW is readily available water (mm). RAW is the portion of TAW which a crop can extract from the root zone without water stress impacts on ET, growth, and yield.

Daily ET_c must be calculated in order to determine the soil water deficit through the water balance method. The water balance method uses inputs of ET_c (mm), deficit for the day of interest ($D_{r,i}$, mm), effective precipitation (P , mm), net irrigation (I , mm), deep percolation (DP , mm), and ground water flux (GW , mm) to calculate daily soil water deficits (Allen et al., 2007):

$$D_{r,i} = D_{r,i-1} + ET_c - P - I + DP - GW \quad (7)$$

In the absence of a high water table, GW inputs are assumed negligible. $D_{r,i}$ is calculated by taking into account the cumulative effect of the daily inputs and outputs on the previous day's deficit ($D_{r,i-1}$).

One caveat of the water balance method is that reliable spatially and temporally variable soil water content data are expensive and difficult to obtain. Plant-based methods to assess plant stress and ET reductions may have advantages in ease of use and of measuring stress in multiple locations within a field so a more accurate average stress level can be determined. Remotely-collected data such as spectral reflectance, fractional vegetation cover, and canopy temperature can indicate plant water stress (Maes and Steppe, 2012), are non-destructive, and have the capability to be applied on various spatial and temporal scales. Land surface multispectral reflectance and crop canopy temperature information from remote sensing data have been used to quantify crop water stress through the use of different temperature indices calculated from the thermal waveband (Jackson et al., 1981; Idso, 1982; O'Shaughnessy and Evett, 2010; Bausch et

al., 2011; Taghvaeian et al., 2014b; DeJonge et al., 2015) and vegetation indices calculated from the near-infrared band and the red band (Neale et al., 1989; Bausch, 1993; DeJonge et al., 2016).

Remotely sensed crop canopy temperature can be a simple indicator of crop water stress. If there is adequate water in the root zone, available atmospheric energy will be used by the plant for evaporating water (transpiration). Once the water which the crop can easily extract (*RAW*) has been depleted from the soil profile, available energy will instead cause heating of the plant (Maes and Steppe, 2012). Clawson and Blad (1982) were some of the earliest to demonstrate use of infrared thermometry for scheduling irrigation: their canopy temperature-scheduled deficit plot had only a 5% yield reduction compared to full irrigation plot scheduled with neutron probe data. Clawson and Blad concluded that crop canopy temperature data best indicates the plant water stress severity by identifying canopy temperature difference between a stressed plot and a fully-irrigated reference crop. Other recent studies have looked at infrared thermometry in northern Colorado (Bausch et al., 2011; DeJonge et al., 2015; Taghvaeian et al., 2012, 2014a, 2014b).

Jackson et al. (1981) demonstrated the potential of using infrared thermometers for irrigation scheduling by devising the CWSI method, which relies on the linear relationship between the difference between canopy and air temperature and the vapor pressure deficit – thus is a function of canopy temperature, air temperature, relative humidity, and user-defined baseline parameters. CWSI varies from 0 (no stress) to 1 (maximum stress). CWSI, as well as all other canopy temperature methods, are less reliable when full cover has not yet been attained because canopy temperature measurements inevitably incorporate soil temperature (Jackson et al., 1981). Nonetheless, CWSI irrigation scheduling has proven to have the potential to be effective and to reduce water consumption. CWSI method has been widely used in deficit irrigation studies and

is considered a standard for irrigation scheduling under deficit irrigation (Alderfasi and Nielsen, 2001; Irmak et al., 2000; Taghvaeian et al., 2012; Zia et al., 2011). Because Jackson et al. (1981) showed that CWSI is inversely related to the water use of the crop under consideration, an alternative to calculating the stress coefficient K_s from soil water data (Eq. 3) K_s can also be calculated from CWSI as:

$$K_s = (1 - \text{CWSI}) \quad (8)$$

While CWSI has been researched for several decades, the data requirements besides canopy temperature (namely air temperature and VPD) can be restrictive to practical application. An alternative method to evaluate water stress that only requires crop canopy temperature was proposed by Bausch et al. (2011):

$$K_s = T_{\text{cratio}} = \frac{T_{cNS}}{T_c} \quad (9)$$

where T_{cratio} is a stress coefficient proposed to be a surrogate for the water stress coefficient K_s from FAO-56 (Allen et al., 1998), T_c is the measured canopy temperature of a crop under water stress and T_{cNS} is the temperature of a fully irrigated, non-stressed canopy. This temperature ratio was found to be capable of quantitatively monitoring water stress and potentially be used in the place of the water stress coefficient when soil water measurements are not available (Bausch, 2011). However, this method does have drawbacks in that the parameter would typically not approach zero under high stress where $T_c \gg T_{cNS}$, and also that there are scaling issues dependent on the temperature scale used (DeJonge et al., 2015).

Other canopy temperature-based methods have recently been proposed which can indicated crop water stress, but like the T_{cratio} method of Bausch et al. (2011) require less inputs than CWSI. Degrees Above Non-Stressed canopy (DANS, Taghvaeian et al., 2014a) is the difference between canopy temperatures of stressed and non-stressed plants

$$\text{DANS} = \min(0, T_c - T_{cNS}) \quad (10)$$

where T_c is the canopy temperature for the crop condition of interest and T_{cNS} is the canopy temperature at the same time of a nearby fully irrigated crop, which ideally is the same variety and growth stage. As discussed in DeJonge et al. (2015), the T_{cratio} and DANS methods, which rely on a nonstressed reference, require numerically that $T_{cNS} \leq T_c$ to ensure that $T_{cratio} \leq 1$ and $\text{DANS} \geq 0$. To ensure this requirement, T_{cNS} was chosen as the lowest observed T_c at the given timestamp, including *all* treatments. Advantages and risks of this technique are discussed in more detail in DeJonge et al. (2015).

Another similar parameter is Degrees Above Canopy Threshold (DACT, DeJonge et al., 2015), which is similar to DANS except that the canopy temperature threshold ($T_{critical}$) is simply a known constant for a given crop

$$\text{DACT} = \max(0, T_c - T_{critical}) \quad (11)$$

It is assumed that if the crop canopy is less than $T_{critical}$, it is not under stress and DACT will return a value of 0. Temperature threshold ($T_{critical}$) of 28°C for corn represents the crop temperature at which photosynthetic enzyme activity is at its highest (Burke, 1996). This threshold has been used in other studies in conjunction with the time temperature threshold (TTT) method which similarly evaluates the amount of time the canopy temperature is above the threshold (O'Shaughnessy et al., 2010).

DACT has the advantage of only requiring a single canopy temperature measurement, opposed to DANS which also requires canopy temperature of a fully irrigated crop. Both DACT and DANS suggest spot measurements to be taken around solar noon on sunny days, similar to CWSI, and have been found to have a comparable ability to monitor water stress (DeJonge et al.,

2015). However, no study to date has directly converted the DANS or DACT indices into a stress coefficient (K_s) and compared predicted ET with observed datasets.

The overall goal of this study is to compare the performance of several water stress coefficient methods to estimate evapotranspiration of corn in Northeastern Colorado under various levels of deficit irrigation. Specific objectives are:

1. Use two years of data from a corn field experiment near Greeley, Colorado to calibrate conversion of DANS and DACT indices into stress coefficients (K_s).
2. Use two different years of data from the same experiment to estimate daily ET_c , through a combination of three methods to determine the basal crop coefficient K_{cb} (tabular, NDVI, canopy cover) and four methods to determine the stress coefficient K_s (CWSI, T_{ratio} , DANS, DACT).
3. Compare accuracy of each method by computing mean biased error (MBE) and root mean squared error (RMSE) of results as compared to ET_c calculated by soil water balance.
4. Provide suggestions of appropriate methods for evaluating water use and monitoring stress under different levels of irrigation and data availability.

2. Methods

2.1. Site and data description

The field study was conducted from 2010 through 2013 at a Limited Irrigation Research Farm (LIRF) near Greeley, CO (40° 26' N, 104° 38' W, and 1428 m elevation). LIRF is a facility operated and maintained by the United States Department of Agriculture (USDA) Agricultural Research Service Water Management Research Unit (ARS-WMRU). LIRF is

irrigated with a pressurized surface drip system. Treatments received irrigation corresponding to percentage of full (100%) crop ET. In 2010 and 2011 there were 3 irrigation treatments and in 2012 and 2013 there were 7 irrigation treatments used for this study, with 4 replications of each treatment (Table 1). In all years Treatment 1 received 100% of ET_c , fully satisfying water requirements through the entire growing season. In 2010 and 2011, deficit irrigation treatments aimed for ET_c to be proportional to Treatment 1 throughout the season. In 2012 and 2013, deficit irrigation treatments aimed for ET_c to be proportional to Treatment 1 during vegetative and maturity growth stages, but allocated 100% ET_c during sensitive reproductive growth stages. In order to have multiple independent years of data to calibrate and validate DANS and DACT index equations, the 2010 and 2011 growing seasons of corn were chosen for calibration. For evaluation and comparison of methods, 2012 and 2013 data were used. Table 1 displays the irrigation treatment structure of the plots used for this study, with first number being percent ET applied during vegetative stage and second number being percent ET applied during maturation growth stage.

Permanent stationary IRTs (model: SI-121, Apogee Instruments¹, Inc., Logan, Utah, USA) took continuous readings of canopy temperature (measured every 5 seconds and averaged over 30 minute intervals). IRT measurements and subsequent T_c -based indices used in this study were all taken at 1400h (approximate time of peak stress), unless indicated otherwise. To test the overall utility and robustness of all of the methods, data was not sorted for cloud cover. IRTs were attached to telescoping posts and adjusted throughout growing season to maintain a height

¹ Mention of trade names or commercial products in this manuscript is solely for the purpose of providing specific information, and does not imply recommendation or endorsement by the U.S. Department of Agriculture or the Agricultural Research Service of any product or service to the exclusion of others that may be suitable.

of approximately 0.8 meters above the canopy. In order to minimize the background effect of the
 soil, IRTs were installed at an angle 23° below horizon and 45° east from north (rows were in
 north/south orientation). Spectral reflectance measurements were taken weekly near solar noon
 under conditions of minimal cloud cover with Exotech (100BX-T, Exotech Inc., Gaithersburg,
 MD) sensors in 2010-2011 or Skye (SKR1850ND, Skye Instruments, Llandrindod Wells, UK)
 sensors in 2012-2013. Canopy cover, or fractional vegetation cover (f_c), was estimated by
 processing nadir RGB (red/green/blue) images using software that identifies green pixels
 (vegetation) and non-green pixels (soil), and outputs VF for each image. IRT readings when $f_c <$
 80% were omitted from analysis. Soil water content measurements were taken with a neutron
 probe (CPN-503DR Hydroprobe, InstroTec, San Francisco, CA) at depths of 30 cm to 105 cm
 from the surface before and after irrigation events, approximately 2 or 3 times a week. Accuracy
 ranges for neutron probe measurements are typically reported between 0.01 and 0.024 mm/m
 according to Huisman et al. (2003). Evett et al. (2006) found that with field calibration, as was
 done for these measurements, all RMSE values were less than $0.01 \text{ m}^3 \text{ m}^{-3}$. The neutron probe
 relies on the gravimetric method for its volumetric water content calibration, so its accuracy is
 closely related to that of the gravimetric sampling method (Topp and Ferré, 2002). A time
 domain reflectometer (TDR) (miniTrase, 6050X3K1) was used to measure the volumetric water
 content within the top 15 cm of the soil profile. Meteorological data were obtained from the
 LIRF onsite weather station (CoAgMet Weather Station Network, Station GLY04,
 www.coagmet.com), located on a 0.4 ha grass plot adjacent to the LIRF research fields. Average
 daily weather parameters and total rainfall amounts during study periods (July 7 – September 7)
 in 2010 through 2013 are presented in Table 2. Total precipitation values can be compared to the
 long term total precipitation average for this time period of 70.7 mm in order to infer whether a

period was above or below average. ET_r , or reference ET from a tall reference crop, was used in this study because alfalfa has historically been the reference crop for Colorado and better captures the climatic effects such as wind on ET of tall crops.

2.2. Estimation of crop ET

Crop ET was calculated using measured soil water content data and a water balance procedure. Approximately 2 to 3 times per week throughout the growing season, soil water content measurements were subtracted from the field capacity to obtain soil water deficit (mm). On days where soil water deficit was not measured, a water balance method was applied by using a spreadsheet into which the irrigation events and effective precipitation events were input, deep percolation was calculated, and finally soil water deficit was calculated as described in Eq. 7. Estimates of volumetric water content at field capacity for each depth (0 to 150, 150 to 450, and 750 to 1050 mm) of each treatment were measured using pressure plate analysis and later adjusted with SWC observations following irrigation and rainfall events. Root zone depth was modeled throughout the season based on observations of soil water uptake and used in order to find the total soil water deficit of the root zone. If the total deficit of the root zone was calculated to be negative, then the deficit value is assumed to be zero and the excess water is assumed to be lost to deep percolation. ET_r from the onsite weather station and K_{cb} based on canopy cover are utilized to predict ET_c .

2.3. Basal crop coefficient K_{cb}

Three methods to calculate K_{cb} were used in this study. The first method was tabular K_{cb} , which was determined by constructing a curve using crop-specific values for planting and full cover dates with the method specified by the ASABE Monograph for alfalfa reference ET (Allen et al., 2007). The method of obtaining K_{cb} from fractional cover data represents the second K_{cb}

method used in this study, a linear interpolation between tabular values of initial K_{cb} (0.15) and mid-season K_{cb} (0.96) at $f_c \geq 0.8$. The third method chosen was to estimate f_c from NDVI (Eq 4) to represent situations where direct f_c measurements are not available, and K_{cb} was calculated using Eq. 5. Quality of the canopy cover and NDVI data obtained and the accuracy of the Eqs. 4 and 5 will govern which method performs best. By applying all three methods to obtain basal crop coefficient values, the absolute and relative accuracies can be observed within the context of this study.

2.4. DANS and DACT calibration to K_s

Stress detection methods DANS and DACT required transformation in order to be used in the place of a K_s value. For this evaluation of DANS and DACT as stress coefficients, Eq. (12) and (13) were calibrated with data from LIRF 2010 and 2011 corn growing season. This causes them to differ from the other methods in this study by containing an empirically calibrated component while other methods were not calibrated for local conditions; however, as described earlier both CWSI (Eqn. 8) and T_{cratio} (Eqn. 11) are assumed to have simple and previously established transformations to K_s . This is a preliminary study to evaluate the feasibility of applying these simple measures of stress to improve deficit irrigation water management with limited data.

Because temperature indices DANS and DACT both have units of °C and a theoretical scale of zero for no stress and an unbounded positive number for high stress, they need to be normalized for use as stress coefficients. An independent dataset of both temperature data and FAO-56 method water stress coefficients (K_s) were used to calibrate these methods before use in this study, so that the ET_c found by using a K_s from DANS or DACT would closely match ET_c

281 found by the water balance. LIRF 2010 and 2011 corn data were used with the following
282 equation

$$K_s = \max\left(1 - \frac{\text{DANS}}{x}, 0\right) \quad (12)$$

283 where K_s is the DANS-based stress coefficient, and x is a variable optimized to reduce the RMSE
284 between K_s determined from DANS and K_s from water balance soil water deficit (Eqs. 6 and 7)
285 for the data from 2010 and 2011 LIRF corn. The fully irrigated corn was assumed to be non-
286 stressed. Similarly, the stress coefficient from DACT (K_s) is calibrated by:

$$K_s = \max\left(1 - \frac{\text{DACT}}{y}, 0\right) \quad (13)$$

287 where y is a variable optimized to reduce RMSE between K_s determined from DANS and K_s
288 from water balance soil water deficit, also using 2010 and 2011 corn data. These equations were
289 designed to reach practical limits for K_s ; that is, when DANS and DACT are zero, there is no
290 stress and K_s is thus equal to 1 similar to Eq. 7. However, $\text{DANS} = x$ or $\text{DACT} = y$, would
291 indicate maximum stress therefore $K_s = 0$. This study will focus on the performance of each
292 index under different irrigation treatments.

293 **2.5. Stress coefficient K_s**

294 New values of K_s obtained by stress detection methods CWSI, DANS, DACT, and T_c ratio
295 were all used in the place of the soil water deficit based K_s , in order to evaluate the potential for
296 replacing soil water data with alternative inputs of canopy temperature and reflectance data.
297 DANS and DACT methods were applied according to Eq. (10) and Eq. (11) respectively, for
298 each treatment replication using temperature data collected at 1400h and then those K_s values
299 were averaged in order to find a daily value of K_s for each method.

T_{ratio} method was similarly applied using Eq. (9) with temperatures collected at 1400h. T_{ratio} does not fully conform to the definition of an index [0,1] since the method cannot produce a value of 0 even in the case of a non-transpiring crop. Despite this range issue, they are both presented as potential surrogates of the FAO-56 water stress K_s and were therefore be directly evaluated as such (Bausch et al., 2011; DeJonge et al., 2016).

2.6. Method comparison

Stress detection methods used to estimate stress coefficients (K_s) are summarized in the following list. For the sake of this comparison each was converted into an index before it was used to calculate ET. In order to isolate and analyze the effect a particular K_{cb} method may have on the accuracy of each K_s method, each stress coefficients were applied with each of tabular, canopy cover, and NDVI based K_{cb} values. ET_a using all combinations of the four K_s methods and three K_{cb} methods were compared to ET_a from the data-assimilated water balance, as described earlier. All four K_s methods were obtained from stationary IRTs, with daily values coming from 1400h, approximate time of peak stress:

- 1) CWSI as calculated with the empirical baseline (Eqn. 8, Idso et al.,1981)
- 2) Ratio of non-stress T_c (T_{cNS}) to stress T_c (Eqn. 11, Bausch et al., 2011)
- 3) DANS method (Eqn. 12, Taghvaeian et al., 2014a), normalized to yield values from 0 to 1
- 4) DACT method (Eqn. 13, DeJonge et al., 2015), normalized to yield values from 0 to 1

Once all stress coefficients had been calculated for the study period in 2012 and 2013, each was evaluated compared to the observed neutron probe and soil water balance ET measurements. The main statistics to evaluate the performance of each method are the root mean square error (RMSE) mean biased error (MBE), shown respectively as:

$$\text{RMSE} = \left[N^{-1} \sum_{i=1}^N (P_i - O_i)^2 \right]^{0.5} \quad (14)$$

$$\text{MBE} = N^{-1} \sum_{i=1}^N (P_i - O_i) \quad (15)$$

where N is the number of observations, P is the model-prediction, and O is an observation.

RMSE summarizes model error in terms of magnitude and MBE describes model bias.

3. Results and Discussion

3.1. Example dataset

Because this study uses a combination of nine unique treatments over a course of four years (Table 1), it is infeasible to have comprehensive datasets of daily soil water content or deficit, canopy temperature, and other seasonal measurements such as yield or ET. However, to help the readers of this manuscript gain an understanding of the soil water deficits and canopy temperatures observed, a subset of Treatments 1, 8, and 12 from the year 2013 are used as an illustrative example. These three treatments have increasing levels of water stress, receiving a goal of 100%, 65%, and 40% of full ET, respectively, during vegetative and maturity growth stages (Table 1). Soil water deficit (D_r , Eq. 7) and readily available water in the root zone are shown in Figure 1A, daily canopy temperature (T_c) at 1400h is shown in Figure 1B, and crop yield at 15.5% moisture and cumulative seasonal ET_c are shown in Figures 1C and 1D, respectively.

In Figure 1A, the red line (RAW) represents the readily available water in the root zone, which grows throughout the season due to root growth. Simply put, if D_r is above the RAW line, the crop will experience water stress (Eq. 7). In the time series figures for D_r and T_c , the sensitive reproductive growth stage where the crop is taken out of water stress is shown in grey. At this

time, soil water deficit for all treatments is reduced to near 0 following irrigation events (Figure 1A), and consequently canopy temperature T_c is also reduced (Figure 1B). In this example, vegetative stress was achieved in Trts 12 and 8, however late season rainfall (which caused significant flooding in northern Colorado) made it difficult to achieve desired levels of stress in Trt 8 in the reproductive growth stages.

As with soil water deficit, canopy temperature T_c had increasing values throughout the season between Trts 1, 8, and 12 respectively. Early season temperatures were higher than mid-season, likely because at this time the crops had not achieved full canopy cover and the sensors were viewing soil background (crops not under full cover were screened from later analysis). Throughout most of the season, Trt 1 typically remained at or below 28 °C, the threshold at which DANS indicates stress. Even under full irrigation, under high evaporative demand and ambient temperature crops will sometimes spike to higher canopy temperatures, which may be due to heat stress rather than water stress. Further research is needed to categorize the often confused distinction between water stress and heat stress, and to quantify to what extent heat stress alone can reduce ET_c .

Treatments 1, 8 and 12 yielded 15699, 13903, and 8567 kg ha⁻¹; and had seasonal ET_c of 627, 542, and 450 mm, respectively (Fig 1C and 1D). These numbers are typical of the treatment differences found in our experiment. It is likely that Trt 8 did not see as much of a drop in yield in 2013 due to the large rainfall events during the maturity growth stages (following reproductive), which took it largely out of stress (e.g. canopy temperatures in late season were very close to Trt 1).

3.1. DANS and DACT calibration

DANS and DACT are both in units of °C, so in order to use them as unitless stress coefficients a method to normalize them was required. In order to calibrate parameters x and y in Eq. (12) and (13), FAO-56 soil water-based K_s values were calculated from a neutron probe calibrated soil water balance from corn at LIRF in 2010 and 2011. These K_s numbers were then used to identify the values for x and y which minimized the RMSE of DANS and DACT K_s values for 2010 and 2011. Considering all treatments and both years, optimized values for x and y used in this study were 29.1 and 27.7 °C, respectively. The optimized values for both DANS and DACT were similar because the non-stress crop was often near 28°C. Average 1400h temperature of the non-stress canopy was 27.6 for 2010 and 27.9 in 2011, and for the stressed crops (all but Treatment 1) at same time of day, average canopy temperature was 29.3 for 2010 and 31.0 for 2011. Measured temperatures of near 28°C for the non-stress crop supports the use of 28°C as the threshold for stress in DACT index to represent the temperature that a well-watered crop will maintain under conditions when the canopy of a water-stressed crop will be higher. Calibrations from 2010 and 2011 data yielded very similar RMSE and MBE values for both DANS and DACT stress coefficients, comparing similar treatments (Figures 2 and 3). Low RMSE and MBE values indicate that DANS and DACT are closely related to a water stress index and have the potential to be used to calculate stress coefficients.

Figures 2 and 3 illustrate how the error in K_s calculated from DANS and DACT change for different experimental years and treatment combinations, with varying values of calibration coefficients x and y . These graphs show that for parameter values above 15, the overall error is nearly constant with asymptotic behavior around a minimum RMSE of approximately 0.15 when considering all treatments. This indicates the indices may not be overly sensitive to these coefficients but stress level can still help predict what best value of x or y will be. A non-stress

crop will have lowest error with an infinitely large value for x or y in order to force all K_s values to 1, while a severely-stressed crop such as Treatment 5 in this study appears to have highest accuracy when using a variable of x or y within a range of roughly 16 to 19. A moderately stressed crop, represented by Treatment 4, may be best described by a parameter between 20 and 30 for either DANS (or DACT) indices. Eliminating non-stress plots from this analysis resulted in optimized x values of 23.2 in 2010 and 20.1 in 2011, and y values of 26.6 in 2010 and 24.4 in 2011, which may indicate that the range of 20 to 30 is an optimal range for either index if the exact stress level is unknown, as optimized values fall within this range for all deficit treatments in this study. On the other hand, if calibrating specifically for application with very stressed crops, lower values of x and y (i.e. 15 to 20) may be ideal. Further research is necessary to fine tune the relationship between optimal empirical values and stress level in order to establish confidence in choosing these parameters without data from previous years and determine the sensitivity and transferability under different climactic conditions, crops, and/or hybrids. The sensitivity to stress level may also indicate that the normalization equations or methodology may need to be adjusted, either by applying more severe stress functions, and/or focusing solely on stressed treatments for calibration.

3.2. Evaluation of ET_c estimates

All K_s methods were evaluated within a soil water balance spreadsheet which uses FAO-56 dual crop coefficient method to estimate actual evapotranspiration. Daily ET_c estimations for all combinations of K_s and K_{cb} were compared to daily ET_c values from observed soil water content and calculated soil water balance. ET_c RMSE (mm/day) estimates from each combination of K_s and K_{cb} method over the study period in 2012 and 2013 are shown in Table 3. For all K_s methods in 2013, the effect of using canopy cover measurements instead of tabular

values resulted in only slightly reduced error (an average of 0.04 mm/day) and using NDVI to calculate canopy cover also only slightly improved accuracy over using tabulated values (an average of 0.05 mm/day, Table 3). The five K_s methods performed at similar levels of accuracy, and the low RMSE of DANS and DACT as compared with CWSI indicates that these indices have potential to be used as stress coefficients. Tabulated K_{cb} values resulted in more error over canopy cover K_{cb} values in 2012, increasing RMSE an average of 0.17 mm/day compared to the 0.04 mm/day seen in 2013. In 2012 CWSI performed slightly worse than the other methods with an average RMSE of 0.96 mm/day compared to the average RMSE of all other methods which was 0.84 mm/day.

Each method's predicted ET_c was compared with FAO-56 derived ET_c , as shown by scatterplots (Figure 4) which include bias measurement via best fit line (assuming intercept of 0) and coefficient of determination R^2 for each method. CWSI ET_c showed the least bias with slope of 0.989, while DACT and T_{cratio} ET_c had slope of 0.953 and DANS with 0.949. CWSI ET_c and DANS ET_c had the highest R^2 values of the methods with 0.86 and 0.85, respectively. Both CWSI and DANS had high scatter for lower ET_c values, with DANS more consistently overestimating on days with less ET_c . DANS, while having an overall slightly lower R^2 than CWSI has less scatter among the mid-range ET_c values which demonstrates that DANS performs very well for days with average ET_c , while CWSI had quite a bit of scatter throughout the whole range of ET_c values. High error among all methods on days with lower ET_c can also be attributed to these days being those with lower reference ET_c and therefore having lower stress, which is what these methods are designed to detect. DACT and T_{cratio} both had R^2 values of 0.83, respectively.

Figure 5 displays the RMSE (mm/day) of daily ET_c estimates for each stress coefficient method separated by treatment in order to see the effect of irrigation level on the performance of each method. This figure shows that the performance of each stress coefficient was similar for all treatment levels, with higher stress treatments incurring higher errors from all methods. Figure 6 displays the MBE of daily ET_c estimates over the study period and this chart shows that all of the K_s methods slightly over-estimated ET_c with canopy cover-based K_{cb} values and slightly underestimate ET_c when applied with NDVI and tabular K_{cb} values. In addition this figure indicates that a composite K_{cb} model, averaging the three methods, could be the least biased estimate for K_{cb} , although both NDVI and f_c can always be biased by methodology and sensors used

In order to evaluate the performance of each K_s method by cumulative water use estimations, average values from the three K_{cb} methods (tabular, f_c , NDVI) were used eliminate its effect on the outcome. Cumulative seasonal error in estimations of total ET_c (mm) over 2013 for each K_s method is shown graphically in Figure 7. All K_s methods consistently underestimated ET_c for less stressed treatments 1 – 3, and often overestimated ET_c for the more stressed treatments. DANS had less error than CWSI for the deficit treatments, which shows that the DANS method has promise under water stress conditions. However, one must consider that the CWSI method was applied in this study with relative humidity and air temperature data obtained from the nearest weather station. This is, not with in-situ data as the method prescribes. If in-situ relative humidity and air temperature were available, most probably more accurate values of CWSI could have been obtained, which would lead to more appropriate irrigation scheduling (Taghvaeian et al., 2014b). Similarly, the average seasonal performance of DACT with only - 0.5% error in total ET_c estimation compared to 1.0% error of CWSI shows that if there is no

onsite air temperature and relative humidity data, DACT has the potential to perform as well as CWSI for prediction of stress and estimation of ET_c with only the single input of a canopy temperature measurement.

3.3. Practical considerations

This study has practical ramifications for consultants, producers, and researchers choosing between different water stress and irrigation water management techniques. Data availability governs the available options discussed in this paper. Table 4 summarizes the data requirements for each method and presents the RMSE of daily ET_c for each in order to analyze if increased data requirement corresponds to increased accuracy. In Table 4, “target” refers to the crop in question for which a K_s value is being assigned.

DANS and DACT have fewer data requirements, yet only a decrease in accuracy of 0.03 mm/day (0.6%) in ET_c estimation compared to CWSI. This comparability of DACT to CWSI is particularly noteworthy because the DACT method only requires a single canopy temperature measurement. DACT also may be applicable in more situations than DANS or T_{ratio} because, in times of drought, a comparable non-stress canopy may not exist, or there could be stresses other than water stress contributing to higher canopy temperatures (i.e. disease, high air temperatures, etc.). However, it is worth noting that the DACT and DANS methods have been locally calibrated (trained) and therefore a good performance was expected while the other methods have been applied as they have been published in the literature (i.e., without local calibration and in the case of the CWSI index without *in situ* weather data). The analyses in previous figures and tables provide guidelines for a variety of different irrigation levels and data availability.

Although canopy temperature data was acquired on a continuous basis, only data from 1400h was used in the creation of the indices and subsequent analysis. This time was chosen

based on numerous other studies which choose evaluation times near solar noon, or when peak stress often occurs. If farmers were to use these techniques for irrigation scheduling, they may be more likely to obtain a “snapshot” within a specific timeframe of the day (either from an integrating sensor, or possibly a spatial thermal infrared image) than to have continuous stationary sensors (DeJonge et al., 2015). Further work is suggested to specifically define and categorize the optimal timeframe for canopy temperature evaluation, which may lend itself to even better accuracy.

For methods like DANS and T_{cratio} , the use of a non-stressed crop to determine T_{cNS} can be somewhat problematic, as it has the additional requirement of maintaining a fully irrigated, non-stressed crop. This additional step may have practical limitations in regard to additional requirements for producers. It is conceivable that this information, through manipulation of the Penman-Monteith reference ET equation, could be indirectly found by nearby reference ET weather stations such as those provided by CoAgMet. DANS and T_{cratio} also have numerical limitations, requiring either choosing the lowest observed T_c as T_{cNS} , or by setting a numerical limit for the value (e.g. $\text{DANS} \geq 0$, $T_{\text{cratio}} \leq 1$). Limitations of these methods are discussed in more detail in DeJonge et al. (2015).

4. Conclusion

This study compared and evaluated the accuracy of several water stress coefficient methods for estimating crop ET_c under different levels of deficit irrigation. Results can inform users which stress coefficient will most likely perform best given the available data and irrigation level in addition to providing an estimation of the expected error in ET_c estimations. Using the most appropriate water stress coefficient method has the potential to improve irrigation

scheduling to more precisely manage stress and therefore allow crops to reach the maximum possible yield given a limited irrigation water supply. Results also give researchers indications of which methods have the most potential to be further investigated and refined. Methods using only canopy temperature measurements (DANS, DACT, and T_{cratio}) performed with comparable error to more data intensive methods such as CWSI and demonstrated the potential for simple methods to be used for irrigation scheduling.

Future studies should evaluate how stress coefficient methods perform in various climates, for different crops, and under different irrigation methods. This study focused on drip irrigated corn in Northern Colorado over 2 years. Future work is needed to investigate the transferability of DANS and DACT as stress coefficients and the sensitivity of the empirical component. A wider range of environmental conditions would be required to test the performance of these methods for various climatological conditions. Use of a large monolithic weighing lysimeters to validate daily ET_c values increase confidence in the results. This study was conducted with research grade IRTs, but future work should test the sensitivity of each temperature-based K_s method to errors in crop canopy temperature in order to study feasibility of using less expensive IRTs to monitor crop water stress. Another study could apply each method using remotely sensed reflectance and temperature from aerial platforms and compare the performance of various stress coefficient methods when applied on different levels. Results from comparing various platforms of remote sensing to calculate stress coefficients could provide irrigation districts with recommendations how to inexpensively use remote sensing on a larger scale to estimate crop water use and improve water management under deficit irrigation.

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6. REFERENCES

- Alderfasi, A.A., Nielsen, D.C., 2001. Use of crop water stress index for monitoring water status and scheduling irrigation in wheat. *Agric. Water Manage.* 47(1), 69-75.
- Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome, 300, 6541.
- Allen, R.G., Wright, J.L., Pruitt, W.O., Pereira, L.S., Jensen, M.E., 2007. Water requirements, in Hoffman, G.J., Evans, R.G., Jensen, M.E., Martin, D.L., Elliott, R.L. (Eds.), *Design and Operation of Farm Irrigation Systems*. 2nd ed. American Society of Agricultural and Biological Engineers.
- ASCE, 2005. The ASCE Standardized Reference Evapotranspiration Equation. ASCE-EWRI, Reston, VA.
- Burke, J.J., 1996. Personal communication to S.R. Evett from the USDA-ARS Crop Stress Research Laboratory, Lubbock, Texas.

Bausch, W.C., 1993. Soil background effects on reflectance-based crop coefficients for corn. *Remote Sens. Environ.* 46(2), 213-222.

Bausch, W., Trout, T., Buchleiter, G., 2011. Evapotranspiration adjustments for deficit-irrigated corn using canopy temperature: A concept. *Irrig. Drain.* 60(5), 682-693.

Clawson, K.L., Blad, B.L., 1982. Infrared thermometry for scheduling irrigation of corn. *Agron. J.* 74(2), 311-316.

Conaty, W., 2010. Temperature time thresholds for irrigation scheduling in precision application and deficit furrow irrigated cotton. Doctoral dissertation, Faculty of Agriculture Food and Natural Resources, The University of Sydney, NSW, Australia.

DeJonge, K.C., Andales, A.A., Ascough II, J.C., Hansen, N.C., 2011. Modeling of full and limited irrigation scenarios for corn in a semiarid environment. *Trans. ASABE* 54(2): 481-492.

DeJonge, K.C., Taghvaeian, S., Trout, T.J., Comas, L.H., 2015. Comparison of canopy temperature-based water stress indices for maize. *Agric. Water Manage.* 156, 51-62.

DeJonge, K.C., Mefford, B.S, Chávez, J.L. 2016. Assessing corn water stress using spectral reflectance. *Int. J. Remote Sens.* 37(10): 2294-2312.

Evett, S.R., Tolk, J.A., Howell, T.A., 2006. Soil profile water content determination: sensor accuracy, axial response, calibration, temperature dependence, and precision. *Vadose Zone J.* 5(3), 894-907.

Fereres, E., Soriano, M.A., 2007. Deficit irrigation for reducing agricultural water use. *J. Exp. Bot.* 58(2), 147-159.

Huisman, J.A., Hubbard, S.S., Redman, J.D., Annan, A.P., 2003. Measuring soil water content with ground penetrating radar. *Vadose Zone J.* 2(4), 476-491.

567 Idso, S.B., Jackson, R.D., Pinter Jr., P.J., Reginato, R.J., Hatfield, J.L., 1981.
 568 Normalizing the stress-degree-day parameter for environmental variability. *Agric. Meteorol.*
 569 24(1), 45-55.

570 Idso, S.B., 1982. Non-water-stressed baselines: a key to measuring and interpreting plant
 571 water stress. *Agric. Meteorol.* 27, 59-70.

572 Jackson, R.D., Idso, S.B., Reginato, R.J., Pinter, P.J., 1981. Canopy temperature as a crop
 573 water stress indicator. *Water Resour. Res.* 17(4), 1133-1138.

574 Johnson, L.F., Trout, T.J., 2012. Satellite NDVI assisted monitoring of vegetable crop
 575 evapotranspiration in California's San Joaquin Valley. *Remote Sens.* 4(2), 439-455.

576 Kang, S., Shi, W., Zhang, J., 2000. An improved water-use efficiency of maize grown
 577 under regulated deficit irrigation. *Field Crops Res.* 67: 207-214.

578 Maes, W.H., Steppe, K., 2012. Estimating evapotranspiration and drought stress with
 579 ground-based thermal remote sensing in agriculture: a review. *J. Exp. Bot.* 63(13), 4671-4712.

580 Mahan, J.R., Young, A., Payton, P. Bange, M. Stout, J. 2014. Effect of differential
 581 irrigation on accumulation of canopy temperature-based heat units in cotton. *J. Cotton Sci.* 18:
 582 129-136.

583 Montoro, A., López-Fuster, P., Fereres, E., 2011. Improving on-farm water management
 584 through an irrigation scheduling service. *Irrig. Sci.* 29(4), 311-319.

585 Neale, C.M.U., Bausch, W.C., and Heerman, D.F., 1989. Development of reflectance-
 586 based crop coefficients for corn. *Trans. ASAE* 32(6): 1891-1899.

587 O'Shaughnessy, S.A., Evett, S.R., 2010. Canopy temperature based system effectively
 588 schedules and controls center pivot irrigation of cotton. *Agric. Water Manage.* 97(9), 1310-1316.

589 Taghvaeian, S., Chávez, J.L., Hansen, N.C., 2012. Infrared thermometry to estimate crop
590 water stress index and water use of irrigated maize in Northeastern Colorado. *Remote*
591 *Sens.* 4(11), 3619-3637.

592 Taghvaeian, S., Comas, L., DeJonge, K.C., Trout, T. J., 2014a. Conventional and
593 simplified canopy temperature indices predict water stress in sunflower. *Agric. Water*
594 *Manage.* 144, 69-80.

595 Taghvaeian, S., Chávez, J.L., Bausch, W.C., DeJonge, K.C., Trout, T.J., 2014b.
596 Minimizing instrumentation requirement for estimating crop water stress index and transpiration
597 of maize. *Irrig. Sci.* 32(1), 53-65.

598 Topp, G.C., Ferré, P.A., 2002. Water content, in Dane, J.H., Topp, G.C. (Eds.), *Methods*
599 *of Soil Analysis: Part 4, Physical Methods.* Soil Sci. Soc. Am. Book Ser., v5, 417-446. Soil Sci.
600 Soc. Of Am., Madison, Wis.

601 Trout, T.J., Johnson, L.F., 2007. Estimating crop water use from remotely sensed NDVI,
602 crop models, and reference ET, in Clemmens, A.J., Anderson, S.S. (Eds.), *The Role of Irrigation*
603 *and Drainage in a Sustainable Future: Proceedings of the USCID Fourth International*
604 *Conference on Irrigation and Drainage, Sacramento, CA, 3-6 October 2007,* pp: 275-285.

605 Trout, T.J., Johnson, L.F., Gartung, J., 2008. Remote sensing of canopy cover in
606 horticultural crops. *HortScience* 43(2), 333-337.

607 Trout, T.J., 2016. USDA-ARS Colorado maize water productivity dataset 2008-2011. *Ag*
608 *Data Commons.*

609 United Nations, 2012. *The 2012 Revision of the World Population Prospects.* United
610 Nations, New York.

611 Walthall, C.L., Hatfield, J., Backlund, P., Lengnick, L., Marshall, E., Walsh, M., Adkins,
 612 S., Aillery, M., Ainsworth, E.A., Ammann, C., Anderson, C.J., Bartomeus, I., Baumgard, L.H.,
 613 Booker, F., Bradley, B., Blumenthal, D.M., Bunce, J., Burkey, K., Dabney, S.M., Delgado, J.A.,
 614 Dukes, J., Funk, A., Garrett, K., Glenn, M., Grantz, D.A., Goodrich, D., Hu, S., Izaurrealde, R.C.,
 615 Jones, R.A.C., Kim, S-H., Leaky, A.D.B., Lewers, K., Mader, T.L., McClung, A., Morgan, J.,
 616 Muth, D.J., Nearing, M., Oosterhuis, D.M., Ort, D., Parmesan, C., Pettigrew, W.T., Polley, W.,
 617 Rader, R., Rice, C., Rivington, M., Rosskopf, E., Salas, W.A., Sollenberger, L.E., Srygley, R.,
 618 Stöckle, C., Takle, E.S., Timlin, D., White, J.W., Winfree, R., Wright-Morton, L., Ziska, L.H.,
 619 2012. Climate Change and Agriculture in the United States: Effects and Adaptation. USDA
 620 Technical Bulletin 1935. Washington, DC.

621 Zia, S., Sophrer, K., Wenyong, D., Spreer, W., Romano, G., Xiongkui, H., Müller, J.,
 622 2011. Monitoring physiological responses to water stress in two maize varieties by infrared
 623 thermography. *Int. J. Agric. Biol. Eng.* 4(3), 7-15.
 624

628 Fig x. Soil water deficit (A), 1400h canopy temperature (B), yield (C), and cumulative
629 ET_c (D) for Treatments 1, 8, and 12 in 2013. RAW in (A) designates readily available water
630 (mm). Reproductive growth stage in grey indicates when crops were taken out of stress.
631

Figure 2. Optimization of transfer from DANS to crop stress coefficient K_s . DANS calibration RMSE with varying x values for each treatment and year combination. $\text{DANS } K_s = \max(1 - \text{DANS}/x, 0)$; values were compared with K_s found from soil water deficit. Optimized at $x = 27.7$ (RMSE = 0.15, MBE = 0.033).

Figure 3. Optimization of transfer from DACT to crop stress coefficient K_s . DACT calibration RMSE with varying y values for each treatment and year combination. $DACT K_s = \max(1 - DACT K_s / y, 0)$; values were compared with K_s found from soil water deficit. Optimized at $y = 29.1$ (RMSE = 0.14, MBE = -0.031).

Figure 4. Scatterplots of ET_c obtained using various stress coefficient methods vs. ET_c obtained by neutron probe soil water balance. Methods include CWSI, DANS, DACT, and T_{ratio} .

Figure 5. Daily ET_c estimate RMSE (mm/day) of each K_s method for each treatment, as compared to ET_c from neutron probe soil water balance.

Figure 6. Daily ET_c estimate MBE (mm/day) of each combination of K_s and K_{cb} methods, as compared to ET_c from neutron probe soil water balance. K_{cb} methods used are canopy cover (CC), normalized difference vegetation index (NDVI), and tabular values (TAB).

Figure 7. Cumulative ET_c (mm) error of each K_s method for each treatment over the 2013 season.

670 Table 1. Irrigation treatments used in study. All treatments had four replicates unless indicated
671 otherwise.

Years	Treatment #	Vegetative % ET	Reproductive % ET	Maturity % ET
2010, 2011	1	100	100	100
	4	70	70	70
	5	55	55	55
2012, 2013	1	100	100	100
	2	100	100	50
	3	80	100	80
	6	80	100	40
	8 ^a	65	100	65
	10 ^b	65	100	40
	12	40	100	40

^a Three replicates in 2012

^b No T_c observations in 2012

674 Table 2. Average daily weather parameters during study period (7 July – 7 Sept.) for 2010 –
675 2013

Parameter	2010	2011	2012	2013
Mean air temp. (°C)	21.2	22.3	22.1	21.6
Max air temp. (°C)	30.7	32.0	32.0	31.0
Min air temp. (°C)	12.5	13.8	13.1	13.5
Mean Vapor pressure (kPa)	1.4	1.5	1.3	1.5
Max. relative humidity (%)	91.9	92.1	87.7	93.8
Min. relative humidity (%)	22.8	21.3	18.8	26.2
Wind run (km d ⁻¹)	125.7	136.7	136.4	142.3
Solar irradiance (MJ m ⁻² d ⁻¹)	22.6	22.3	22.9	21.2
Precipitation (mm)	67.3	56.4	37.8	60.2

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679 Table 3. Daily ET_c estimate RMSE (mm day^{-1}) of each K_s and K_{cb} combination in 2012 and
680 2013.

Year	K_s estimation method	K_{cb} estimation method		
		Canopy Cover	NDVI	Tab
2012	CWSI	0.93	*	0.99
	DANS	0.71	*	0.92
	DACT	0.77	*	0.97
	T _{cratio}	0.72	*	0.94
2013	CWSI	0.77	0.76	0.78
	DANS	0.77	0.80	0.84
	DACT	0.77	0.80	0.84
	T _{cratio}	0.80	0.83	0.85

681 *NDVI data was not taken in 2012

682

683 Table 4. Comparison of basic data required for each K_s method tested and associated ET_c
684 estimation RMSE.

Category	Requirement	K_s method			
		CWSI	DANS	DACT	T_{ratio}
Canopy Temperature	Target	X	X	X	X
	Non-Stressed Reference		X		X
Environmental	Relative Humidity	X			
	Air Temperature	X			
	Clear Sky	X	X	X	X
Pre-Calculation	Baselines (locally calibrated)	X			
	Threshold Temperature			X	
	Scaling Coefficient (locally calibrated)		X	X	
	Daily ET_c RMSE (mm/day)	0.77	0.80	0.80	0.83
	Daily ET_c RMSE (%)	14.6	15.2	15.2	15.6