THESIS

EVALUATION OF STRESS COEFFICIENT METHODS TO ESTIMATE CROP EVAPOTRANSPIRATION

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ABSTRACT

EVALUATION OF STRESS COEFFICIENT METHODS TO ESTIMATE CROP EVAPOTRANSPIRATION

Increased competition for water resources is placing pressure on the agricultural sector to remain profitable while reducing water use. Remote sensing techniques have been developed to monitor crop water stress and produce information for evapotranspiration (ET) based irrigation scheduling decisions. Use of stress detection methods allows producers to avoid exceeding set crop water stress levels and keep operations sustainable under limited irrigation despite some yield reduction. Remote sensing data such as spectral reflectance and infrared canopy temperature can be used to quantify crop water stress, often through the use of vegetation indices calculated from the near-infrared and red bands and temperature indices calculated from the thermal wavelength, respectively. Reference ET methods estimate water use based on crop characteristics and climactic parameters assuming optimum soil water conditions. In order to adjust crop ET for water limited conditions such as drought or water allocation restrictions, ET scaling techniques that are sensitive to crop development and stress are necessary. The performance of five remote sensing techniques to estimate corn ET under drought conditions in Northern Colorado were evaluated: one method based on air temperature, canopy temperature and relative humidity (Crop Water Stress Index (CWSI)), three methods based strictly on canopy temperature including Degrees Above Non-Stress (DANS), Degrees above Canopy Threshold (DACT), and Temperature Ratio, and one method based on multispectral vegetation indices (NDVI Ratio). Data were collected during 2010 through 2013 growing seasons at the USDA-

ARS Limited Irrigation Research Farm near Greeley, CO. Varying water deficit levels were imposed on corn (*Zea mays L.*) under pressurized drip irrigation. ET estimates from the five remote sensing techniques were compared to soil water balance (via neutron probe) and ET calculations. 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 (CWSI = 0.77 mm/day, DANS = 0.80 mm/day, DACT = 0.80 mm/day, T_c Ratio = 0.83 mm/day, NDVI Ratio = 0.85 mm/day). Detailed tables 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. Using the most appropriate stress coefficient method has the potential to improve irrigation scheduling and therefore allow crops to reach the maximum possible yield given the level of deficit irrigation. Methods with fewer data requirements, such as DACT with only a single canopy temperature measurement requirement, may be more appropriate to improve on-farm water management in certain situations. Results justify use of simplified measures of stresss to improve deficit irrigation water management with limited data.

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LIST OF SYMBOLS

DACT	degrees above canopy threshold (°C)
DANS	degrees above non-stressed canopy (°C)
D_i	daily soil water deficit for current day (mm)
D_{i-1}	daily soil water deficit of previous day (mm)
D_r	root zone depletion (mm)
DP	deep percolation (mm)
ET	evapotranspiration (mm/day)
ET_a	actual crop evapotranspiration (mm/day)
ET_c	crop evapotranspiration (mm/day)
ET_{ref}	reference evapotranspiration (mm/day)
f_c	fractional vegetation cover
GW	ground water input (mm)
H	sensible heat flux (W/m^2)
I	total net irrigation amount applied (mm)
IRT	infrared thermometer (°C)
K_c	crop coefficient
K_{cb}	basal crop coefficient
K_s	stress reduction coefficient
L	adjustment factor for soil type and growth stage
LE	latent heat flux (W/m^2)
LIRF	Limited Irrigation Research Farm
MAD	maximum allowable depletion (mm)
NDVI	normalized difference vegetation index
P	precipitation which infiltrates the soil (mm)
RAW	readily available water (mm)
RH	relative humidity (%)
R_{nir}	reflectance in the near infrared band
R_{red}	reflectance in the red band
R_z	root zone (mm)
SAVI	soil adjusted vegetation index
SWB	soil water balance
SWD	soil water deficit (mm)
TAW	total available water (mm)
TDR	time domain reflectometer
T_{act}	crop transpiration under actual conditions (mm/day)
T_{ref}	reference crop transpiration under non-water-stress conditions (mm/day)
T_c	crop canopy temperature (°C)
T_{cNS}	crop canopy temperature of a non-stress plant(°C)
$T_{critical}$	canopy temperature threshold (°C)
VI	vegetation index
VWC	volumetric water content (m^3)

CHAPTER 1: INTRODUCTION

Competition for limited water resources to supply the needs of a rapidly increasing global population places increasing pressure on agriculture to increase production while decreasing water use. The roles of population growth and climate variability in the future of water scarcity are explained in the following sections, followed by the pressure on producers to adapt to continuing to produce crops while applying less than full irrigation. Successful limited irrigation demonstrations are discussed, along with an explanation of how to closely monitor crop water use in order to accurately schedule irrigation applications under water scarce conditions. Next, a variety of methods used to monitor crop stress levels under limited irrigation are explored. Finally, the specific objectives of this evaluation are presented.

1.1 Water Supply Challenges

As climate change and population growth both place unprecedented demand on the world's finite fresh water supply, heightened competition between various water users is likely to emerge. Irrigation, recreation, industry, and municipal users all rely on this limited resource. As the largest consumptive water user, irrigated agriculture experiences pressure to reduce water use while maintaining high yields (Hoffman and Evans, 2007). An additional challenge is presented by climate change which may alter historical precipitation patterns and limit farmers from applying full irrigation due to unprecedented droughts (Walthall et al., 2012). Priority for water supply to meet municipal demand will cause pressure for farms to lease or sell water rights to cities and discontinue production. In order to continue to sustain a rapidly growing population with vulnerable and limited water resources, producers must be adequately prepared to adapt historical irrigated agriculture practices.

1.1.1 Population

Global population is rapidly increasing, with population projected to be above 10.9 billion by 2100 and an expected 88.2 percent of global population living in less developed regions (United Nations, 2012). In order to produce more food with the same water resources, there will be pressure on producers to increase agricultural water productivity. Especially in areas with limited irrigation management data, adaptation will not be trivial. Increased population will result in higher crop demand for human consumption, livestock feed, and biofuels. In order for crop production to meet these quickly escalating needs, agricultural water productivity will need to improve significantly through use of innovative technology and methods to improve water management (Walthall et al., 2012).

1.1.2 Climate

Changes in precipitation and temperature patterns are causing uncertainty for producers globally. Farmers in semi arid places will need to adapt to this change in order to keep farming operations sustainable. Climate change is largely driven by the increase in emissions of greenhouse gases, but even if these are reduced in the future, it is predicted that effects will last for decades (IPCC, 2007). In the very near future, producers will need to adapt to new technologies and methods for irrigation water management in drought conditions. Changes in temperatures, precipitation patterns, and extreme events could have devastating ramifications on global food production if methods to overcome these new challenges are not developed and successfully applied (Walthall et al., 2012).

1.2 Limited Irrigation

Increased competition for water resources is placing pressure on the agricultural sector to maintain profits while reducing water use. A strategy under much 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 very careful monitoring of crop water status and corresponding irrigation event timing and amount. Deficit irrigation ideally causes no water losses due to deep percolation because it never fully replenishes the crop root zone. If deficit irrigation is growth stage based, there could be losses during growth stages receiving full irrigation but not during deficit irrigation applications. In addition, evaporation losses may be reduced by less frequent irrigation applications, giving the environment a reduced number of chances within a season to evaporate irrigation water from the soil surface before the crop is able to put that water to a beneficial use. Additionally, crops often have varying water stress sensitivity at different growing periods, which can help inform the producer when placing more stress on the plant will have a smaller impact on yield (Fereres and Soriano, 2007). Perceived high risk of reducing irrigation is often the reason producers choose to sell their land rather than apply less water in times of limited water resources (e.g., reduced well capacity, drought, and reduced water rights). Regulated deficit irrigation has the potential to enable producers to keep plant water stress within targeted limits and still produce an adequate yield. One economic incentive of deficit irrigation is that producers potentially have the option to lease water rights to other users such as municipalities, ultimately producing more profit from the lease of water in addition to the reduced yield than applying all available water as irrigation.

1.2.1 Demonstration of Deficit Irrigation Practices

Many farms have been historically over-irrigated, so using a tightly-budgeted deficit irrigation schedule may improve crop yield because it eliminates the harmful effects of over-irrigating such as waterlogging and salinity (Montoro et al., 2011). A study by Li et al. (2005) was conducted in the Western Jilin province in China on a farm with furrow-irrigation and a Chernozem soil.

Results showed that compared to a rainfed control plot of corn, full irrigation increased yield 49% and on average plots with supplemental irrigation increased yields 44% with corresponding irrigation totals of 327 mm and 260 mm respectively. Supplemental irrigation was applied four times in the season, corresponding to the periods when corn is most sensitive to stess including the time of sowing, vegetative stage, silking and heading stages and in the milk stage. These results indicate that deficit irrigation during critical growth periods may be an effective way to maintain production while decreasing water use. A review on deficit irrigation by Fereres 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 applying at least 60% of crop water requirement and are designed based on crop drought sensitivity during each development stage. Clawson and Blad (1982) demonstrated use of infrared thermometry for scheduling irrigation. A canopy temperature-scheduled deficit plot had only a 5% yield reduction compared to full irrigation plot scheduled with neutron probe data. Only 127 mm of irrigation was applied to the stressed plot while the well-watered plot received 283 mm. 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. Many other recent studies have explored the outcomes of deficit irrigation with similar results (Conaty, 2010; Kang et al., 2000; Fereres and Soriano, 2007; Taghvaeian et al., 2013).

1.2.2 Estimation of Evapotranspiration Under Drought Conditions

Standardized methods of estimating crop water use (ET) assume fully irrigated conditions and therefore do not accurately estimate water use if soil moisture conditions are limiting. 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 specific 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-EWRI, 2005). Eq. (1.1) is used to determine reference evapotranspiration according to ASCE-EWRI (2005)

$$ET_{sz} = \frac{0.408\,\Delta\,(R_n - G) + \gamma \frac{C_n}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma\,(1 + C_d \cdot u_2)} \tag{1.1}$$

where ET_{sz} is the standardized reference crop evapotranspiration for reference surfaces (mm d^{-1} for hourly time steps), R_n is the net radiation at the crop surface (MJ m^{-2} d^{-1} for houly time steps), G is the soil heat flux density at the soil surface (MJ m^{-2} d^{-1} for houly time steps), T is the mean hourly air temperature at 1.5 to 2.5-m height (°C), u_2 is the mean hourly wind speed at 2-m height (m s^{-1}), e_s is the saturation vapor pressure at 1.5 to 2.5 m height (kPa), e_a is the mean actual vapor pressure at 1.5 to 2.5-m height (kPa), Δ is the slope of the saturation vapor pressure-temperature curve (kPa °C^{-1}), γ is the psychometric constant (kPa °C^{-1}), C_n is the numerator constant for each reference type and calculation time step (K mm s^3 Mg^{-1} h^{-1}), C_d is the denominator constant for each reference type and calculation time step (K mm s^3 Mg^{-1} h^{-1}), and units for the 0.408 coefficient are m^2 mm MJ^{-1}. 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 Allen et al. (2005) as shown below in Eq. (1.2)

$$ET_c = ET_{ref} \cdot K_c \tag{1.2}$$

where K_c is the crop coefficient, ET_c is crop ET (mm), ET_{ref} is reference surface ET (mm). The effect of climate on ET is described by ET_{ref} and the properties of the crop which affect ET are quantified by K_c (Allen et al., 2005). This method can be used to calculate the potential ET of a crop, but if used without adjustment for crops with severe water deficits it can become highly inaccurate. To account for soil water limiting conditions, Allen et al. (1998) separated the crop coefficient into evaporation and plant transpiration components, the latter which included a stress coefficient (K_s) shown in Eq. (1.3) to quantify the effect of the water stress on crop transpiration

$$ET_a = (K_{cb}K_s + K_e)ET_{ref} \tag{1.3}$$

where ET_a is the crop ET under water-stressed conditions (mm), K_s is the stress coefficient which provides a quantitative index describing the level of water stress (0 – 1), K_{cb} is the basal crop coefficient, and K_e is the evaporation coefficient. This approach reduces the crop coefficient when the soil water content is less than the level of maximum allowable depletion (MAD) (Allen et al., 1998). K_s values describe the percentage of potential transpiration rate that a crop is experiencing reduced from 100 percent according to level of water stress. In 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. If soil water conditions are not limiting, K_s will not be reduced from 1 because the crop will transpire at the full potential ET rate. K_s according to the Allen et al. (1995) FAO-56 soil moisture method is calculated with Eq. (1.4)

$$K_s = \frac{TAW - D_r}{TAW - RAW} \tag{1.4}$$

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 suffering water stress. Reliable soil moisture data are difficult to obtain. While this soil-moisture based stress coefficient method has been shown to address the plant water status based on soil water availability, it has practical limitations for both commercial use and research. Adequate information about local soils is lacking and gathering frequent soil moisture data for the entire root zone can be prohibitively expensive and difficult. Additionally, spatial variability of soils, both horizontally and vertically, makes it extremely difficult to extrapolate a "point source" measurement of soil moisture to an entire field.

The basal crop coefficient can be obtained from published tabulated values in FAO-56. If needed, K_{cb} values for mid-season can be adjusted for climate, as in the case of FAO-56 published K_{cb} values that are for humid climates and therefore need to be adjusted to be used in arid and semi-arid regions with Eq. (1.5)

$$K_{cb} = K_{cb(tab)} + [0.04(u_2 - 2) - 0.004(RH_{min} - 45)]\left(\frac{h}{3}\right)^3 \quad (1.5)$$

where $K_{cb(tab)}$ can be found in Table 17 of FAO-56, u_2 (m/s) is the mean daily wind speed at 2 m height above grass during mid-season growth stage, RH_{min} (%) is the mean value for minimum relative humidity during mid-season growth stage, and h (m) is the mean value for plant height during mid-season. The shallow soil water evaporation coefficient, K_e, is then calculated using Eq. (1.6)

$$K_e = K_r(K_{c\,max} - K_{cb}) \leq f_{ew} \cdot K_{c\,max} \quad (1.6)$$

where K_e ranges from 0 in the case of a dry soil surface to a maximum value limited by the available energy of the exposed soil for wet surface conditions and depends on the maximum value of K_c following rain or irrigation ($K_{c\,max}$), the dimensionless evaporation reduction coefficient (K_r) and the fraction of the soil that receives sunlight and water from wetting events (f_{ew}) in addition to the previously defined K_{cb}. $K_{c\,max}$ is calculated with Eq. (1.7)

$$K_{c\,max} = \max\left(\left\{1.2 + [0.04(u_2 - 2) - 0.004(RH_{min} - 45)]\left(\frac{h}{3}\right)^3\right\}, \{K_{cb} + 0.05\}\right) \quad (1.7)$$

where all variables have been previously defined. Calculation of K_r assumes a two-stage drying process. In the case of the first drying stage, Eq. (1.8) is used, and in the second drying stage Eq. (1.9) is used.

$$K_r = 1.0 \text{ for } D_{e,j-1} \leq REW \tag{1.8}$$

$$K_r = \frac{TEW - D_{e,j-1}}{TEW - REW} \text{ for } D_{e,j-1} > REW \tag{1.9}$$

where cumulative depletion from soil surface layer at the end of the previous day, ($D_{e\ j-1}$, mm), determines the stage. In the second stage the difference between cumulative depletion and total evaporable water (TEW, mm) governs the magnitude of K_r. Stages depend on whether the soil surface water content is greater or less than the readily evaporable water (REW, mm). Fraction of soil exposed to sunlight and is wetted (f_{ew}) can be calculated with Eq. (1.10)

$$f_{ew} = f_w \left(1 - \frac{2}{3} f_c\right) \tag{1.10}$$

Fraction of the surface that is wetted by irrigation and rain (f_w) depends on irrigation type and is typically assumed to be 0.35 for drip irrigation. Fractional cover (f_c) describes the percentage of bare soil covered by vegetation cover from a nadir view. Once K_c is calculated, Eq. (1.2) can be used to find actual crop ET.

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_i, mm), effective precipitation (P, mm), net irrigation (Irr, mm), deep percolation (DP, mm), and ground water flux (GW, mm) in Eq. (1.11) to calculate daily soil water deficits (Hoffman et al., 2007).

$$D_i = D_{i-1} + ET_c - P - Irr + DP - GW \tag{1.11}$$

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

1.3 Remote Sensing Methods to Detect Water Stress

Remote sensing is one way to monitor crop water stress and make irrigation scheduling decisions that avoid yield-reducing stress levels. Remote sensing techniques are particularly beneficial because they are non-destructive and have the capability to be applied on various spatial and temporal scales. The unique data from remote sensing has been applied through simple methods to track crop health and improve water management decisions. Land surface multispectral reflectance and temperature information from remote sensing data can be used to quantify crop water stress through the use of different temperature indices calculated from the thermal waveband (Bausch, 2011; DeJonge et al., 2015) and vegetation indices calculated from the near-infrared band and the red band (Neale et al., 1989; Bausch, 1993; Mefford, 2014). Additional methods have been developed that estimate fractional vegetation cover measurements from spectral vegetation indices (Trout et al., 2008; Johnson and Trout, 2012).

Reference crop evapotranspiration can be adjusted for limited soil moisture conditions using a wide variety of approaches for estimating stress level and subsequent reduction in crop water use. Alternate methods to measuring soil moisture have significant advantages in ease of use and have the advantage of measuring stress in multiple locations within a field so a more accurate average stress level can be determined and better inform irrigation decisions. Such methods rely on remotely collected data such as spectral reflectance, fractional vegetation cover, and canopy temperature (Maes and Steppe, 2012).

1.3.1 Spectral Reflectance and Fractional Vegetation Cover Methods

Reflectance-based basal crop coefficient (K_{cb_refl}) methods developed by Neale et al. (1989) and Bausch (1993) have been used to improve irrigation scheduling of corn. Eq. (1.12) describes the relationship between actual crop transpiration (T_a), K_{cb}, and reference crop transpiration (T_{ref})

$$T_{act} = K_{cb} \cdot T_{ref} \tag{1.12}$$

where T_{act} is crop transpiration under actual conditions and T_{ref} is reference crop transpiration under non-water-stress conditions. Reflectance-based basal crop coefficient methods rely on remote sensing data to calculate a vegetation index (VI) and the linear relationship between VI and the reflectance-based crop coefficient. Neale et al. (1989) produced the relationship in Eq. (1.13) for corn in Greeley, Colorado

$$K_{cb\_refl} = 1.181(\text{NDVI}) - 0.026 \tag{1.13}$$

where NDVI is the normalized difference vegetation index. NDVI is described by Eq. (1.14)

$$\text{NDVI} = \frac{R_{nir} - R_{red}}{R_{nir} + R_{red}} \tag{1.14}$$

where R_{nir} is reflectance in the near infrared band and R_{red} is reflectance in the red band. Bausch (1993) improved upon this equation by using the soil adjusted vegetation index (SAVI) in instead of NDVI. SAVI minimizes soil background effects by taking into account the soil type and crop growth stage. Bausch (1993) developed the Eq. (1.15) for corn in Fort Collins, Colorado

$$K_{cb\_refl} = 1.416(\text{SAVI})+0.017 \tag{1.15}$$

where all variables have been previously defined. SAVI is calculated as shown in Eq. (1.16)

$$\mathrm{SAVI} = \frac{(R_{nir} - R_{red})(1 + L)}{(R_{nir} + R_{red} + L)} \tag{1.16}$$

where L is an adjustment factor that varies from 0 to 1 for soil type and growth stage. At high densities L is typically less than 0.5, and at low densities L can increase to 1 (Huete, 1998). Reflectance-based crop coefficients improved calculation of actual crop ET compared to the time-based crop coefficient method by tracking actual crop development which may vary due to weather patterns , water status, and agronomic conditions (Neale et al., 1989).

Another 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 as shown in Eq. (1.17) developed by Johnson and Trout (2012) with a combination of 18 row crops, grains, orchards, and vineyards

$$f_c = 1.22(\mathrm{NDVI}) - 0.21 \tag{1.17}$$

where all variables have been previously defined. Once f_c has been obtained either through Eq. (1.17) or by processing a picture taken from a nadir view (above the crop looking straight down) as described by Mefford (2014) to determine which fraction of pixels are vegetation, Eq. (1.18) will give the reflectance crop coefficient

$$K_{cb\_refl} = 1.13 \cdot f_c + 0.14 \tag{1.18}$$

where all variables have been previously defined. Reflectance-based crop coefficients assess current crop conditions instead of assuming the crop is under ideal conditions. Whether measured vegetation indices or fractional vegetation cover is used to calculate K_{cb}, it will describe T_a better than a tabulated crop coefficient because it reflects not only the actual growth stage of the crop but also the water stress condition.

Another way to use multispectral land surface reflectance data to obtain actual crop ET was proposed by Mefford (2014). This method relies on the ratio of NDVI of a deficit plot to the NDVI of a fully irrigated plot, as shown in Eq. (1.19) which was developed in a study on corn in Greeley, Colorado

$$K_{s\ NDVIratio} = \frac{NDVI_s}{NDVI_{ns}} \quad (1.19)$$

where $K_{s\ NDVIratio}$ is the stress coefficient calculated using the NDVI Ratio method, $NDVI_s$ is the NDVI of a stressed plot and $NDVI_{ns}$ is the NDVI of a non-stressed plot. This ratio acts as stress coefficient similar to the water stress K_s in FAO-56 (Allen et al., 1998). An advantage of this method is that it is conceptually simple and requires only reflectance data from the red and near-infrared bands.

1.3.2 Canopy Temperature Methods

Crop canopy temperature can be an indicator of crop water stress, as demonstrated by the energy balance of vegetation described by Eq. (1.20)

$$R_n = LE + H + G \quad (1.20)$$

where LE is the latent heat flux (Wm^{-2}), H is the sensible heat flux (Wm^{-2}), and G is the soil heat flux (Wm^{-2}). Available energy (R_n – G) will be result in either sensible heat flux (crop canopy temperature) or latent heat flux (evapotranspiration). If there is adequate water in the root zone, available energy will be used by the plant for evaporating water (transpiration). Once all 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). Measurements of crop canopy temperature can provide valuable information about soil moisture content by partitioning the fate of available energy into ET and heating categories representative of crop water status. Using various canopy measurement techniques to obtain stress coefficients has the considerable advantage over soil moisture methods of minimal instrumentation and data collection needs in order to be used to estimate actual evapotranspiration. Canopy temperature methods chosen include the Crop Water Stress Index (CWSI) method, temperature ratio, Degrees Above Non-Stress (DANS), and Degrees Above Canopy Threshold (DACT).

Jackson et al. (1981) demonstrated the potential of using infrared thermometers for irrigation scheduling by devising the CWSI method. CWSI relies on the linear relationship between the difference between canopy and air temperature and the vapor pressure deficit. A non-transpiring baseline and a non-water-stressed baseline serve as the extreme bounds of crop water status. Non-transpiring baseline correlates with the difference between the canopy and air temperature for a crop which has completely stopped transpiring due to severe water stress, while the non-water-stressed baseline represents the difference between the canopy and air temperature for a plant which is transpiring at the highest potential for given climatic conditions and is not under any stress. These baselines are displayed graphically in Figure 1 by a solid line for lower limit baseline (dT_LL) and a dashed line for upper limit baseline (dT_UL). CWSI varies from 0 to 1, being 0 if the difference between the canopy and air temperature is the same as the non-water-stressed baseline for a given VPD (no stress), and 1 if the difference is as large as that of the non-transpiring baseline (maximum stress). In the example, shown in Figure 1, the measured value results in a CWSI value of 0.64 which represents a plant that is severely stressed and therefore has an ET rate approximately equal to 36% of a non-water stressed crop.

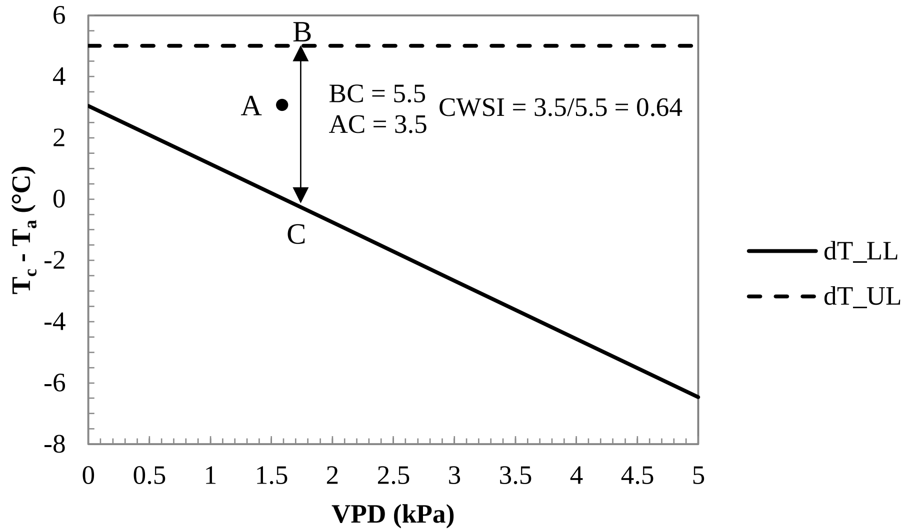

Figure 1. CWSI example with baselines for Greeley, CO

CWSI relies only on inputs of crop canopy termperature, relative humidity (RH), and air temperature if local baselines have already been established (Idso, 1982). 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 (Irmak et al., 2000; Nielson and Alderfasi, 2010; Taghvaeian et al., 2012; Zia et al., 2011)

In this study, the empirical baseline approach was applied using baselines determined for Northeastern Colorado by Taghvaeian (2014). Baselines provide a way to determine where a crop is in relation to minimum or maximum stress conditions as shown in Eq. (1.21)

$$CWSI = \frac{dT_m - dT_{LL}}{dT_{UL} - dT_{LL}} \tag{1.21}$$

where dT_m is the measured or actual difference between air and canopy temperature, dT_{LL} represents the lower limit or non-water-stressed condition, and dT_{UL} is the difference in the upper limit or critically-stressed condition. Assuming a linear relationship between the vapor pressure deficit (VPD) and the lower limit, the empirical baseline approach is valid for a given climate. Taghvaeian (2014) developed the following baseline in Eq. (1.22)

$$dT_{LL} = -1.99(VPD) + 3.04 \tag{1.22}$$

where all variables have been previously defined. Upper baseline was determined to be 5°C from observation. The chosen lower limit baseline described by Eq. (2.4) and the upper limit of 5°C are used in the example displayed in Figure 1. Although CWSI was originally suggested by Idso et al. (1981) to be applied at 2:00 pm (MST), CWSI was applied at 11:00am (MST) for this study according to the suggestion of Taghvaeian et al. (2014) in order to provide a good representation of the average daily stress experienced by the crop. Canopy data were also originally suggested by Idso et al. (1981) to be taken by a handheld IRT directly into the rows of crop, but for this study it was chosen to use IRTs installed at an angle 23° below horizon and 45° east from north (rows were in north/south orientation) in order to minimize the background effect of the soil,

A method to evaluate water stress that only requires crop canopy temperature was proposed by Bausch et al. (2011), according to Eq. (1.23)

$$K_{s\ TcRatio} = \frac{T_{cNS}}{T_c} \tag{1.23}$$

where $K_{s\ TcRatio}$ 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 moisture measurements are not available (Bausch, 2011).

Alternate temperature methods have been proposed by Taghvaeian et al. (2014) and DeJonge et al. (2015) which are comparable to the CWSI, but like the T_c Ratio method of Bausch et al. (2011) require less inputs. The first method proposed by Taghvaeian et al. (2014) is Degrees Above Non-Stressed Canopy (DANS) which is the difference between canopy temperatures of stressed and non-stressed plants as described by Eq. (1.24)

$$DANS = T_c - T_{cNS} \tag{1.24}$$

where T_c is the canopy temperature for the crop of interest and T_{cNS} is the cooler canopy temperature of a nearby crop at the same time which ideally is the same variety and growth stage but fully irrigated. Another similar approach is Degrees Above Canopy Threshold (DACT), which is similar to DANS except that the canopy temperature threshold ($T_{critical}$) is simply a known constant for a given crop. DACT is calculated with Eq. (1.25)

$$DACT = \max(0, T_c - T_{critical}) \tag{1.25}$$

where it is assumed that if the crop canopy is any temperature under $T_{critical}$, it is not under any stress and DACT will return a value of 0. $T_{critical}$ is the threshold temperature for the crop (e.g. 28° C for corn); 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). Temperature threshold of 28°C represents the crop temperature at which photosynthetic enzyme activity is at its highest (Burke, 1996). DACT has the advantage of only requiring a single canopy temperature measurement, opposed to DANS which also requires canpy 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 (De Jonge et al., 2015).

1.4 Objectives

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 2010 and 2011 data from the Limited Irrigation Research Farm (LIRF) to calibrate an equation to convert DANS and DACT indices into stress coefficients (K_s).
2. Use five crop stress detection methods (CWSI, T_c Ratio, NDVI Ratio, DANS, DACT) with 2012 and 2013 corn data from LIRF to estimate daily evapotranspiration. Compare accuracy of each method by computing mean biased error (MBE) and root mean squared error (RMSE) of results compared to ET calculated by a neutron probe calibrated soil water balance.
3. Provide suggestions of appropriate methods for evaluating water use and monitoring stress under different levels of irrigation and data availability.

CHAPTER 2: METHODS

Overview of study details and experimental design can be found in the following section. The first section describes the study area, instrumentation, and data collection. The second part discusses the plan to calibrate DANS and DACT indices. The third section contains the rationale and methodology to compare all methods as stress coefficients in addition to the statistics used to evaluate and compare performance.

2.1 Data Description

Data collection was conducted in 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 at 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 crop ET. In 2010 and 2011 there were 3 different irrigation treatments used for this study, with 4 replications of each treatment. Plot layout maps for 2010 and 2011 can be found in Figures 21 and 22 in the appendix. Irrigation treatments are described in Table 1. In 2010 and 2011, Treatment 1 received 100% of ET_c, fully satisfying water requirements. Treatments 4 and 5 received water seasonally proportional to Treatment 1 in response to critical growth periods. 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. Figure 2 displays the plot layout map for 2013. Table 2 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. All treatments received 100 percent of ET during the reproductive growth stages.

Table 1. 2010 and 2011 irrigation treatments

Treatment #	**% ET Vegetative/ % ET Maturity**
1	100/100
4	70/70
5	55/55

Table 2. 2012 and 2013 irrigation treatments

Treatment #	**% ET Vegetative/ % ET Maturity**
1	100/100
2	100/50
3	80/80
6	80/40
8[a]	65/65
10[b]	65/40
12	40/40

[a] Three replicates in 2012
[b] No T_c observations in 2012

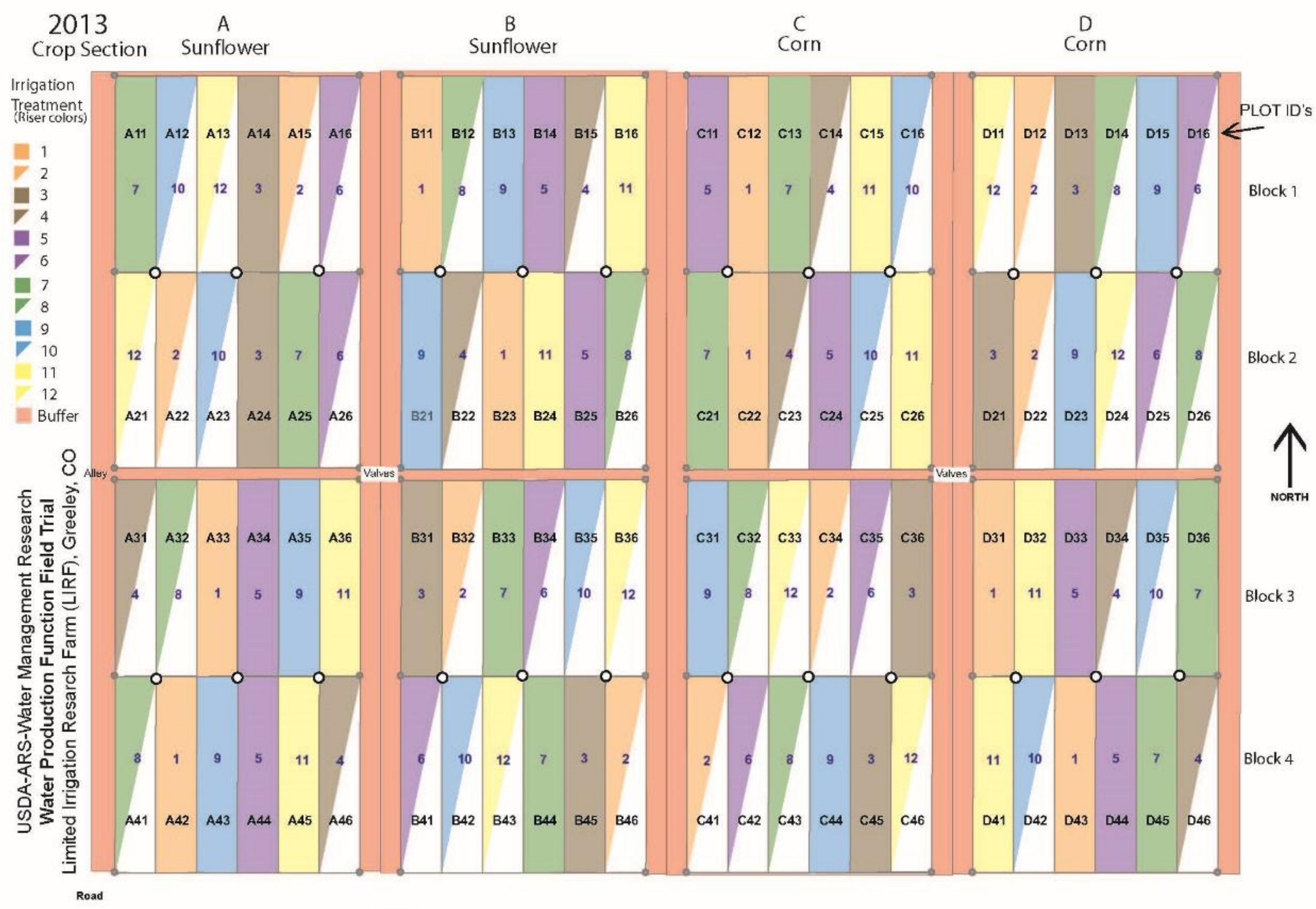

Figure 2. 2013 LIRF Treatment layout

Permanent stationary IRTs (model: SI-121, Apogee Instruments, Inc., Logan, Utah, USA) took continuous readings of canopy temperature (measured every 5 seconds and averaged over 30 minute intervals). IRTs were attached to telescoping posts and adjusted throughout growing season to maintain a height 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 around solar noon under conditions of minimal cloud cover with either Exotech or Skye light sensors. Soil moisture measurements were taken with a neutron probe (CPNInstrotek, 503DR AM-241) at depths of 30 cm to 1050 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. (2003) found that with field calibration all RMSE values were less than 0.01 $m^3 m^{-3}$. The neutron probe relies on the gravimetric method for its volumetric water concent calibration, so its accuracy is closely related to that of the gravimetric sampling method which is reported to be within 0.3% of water content (Topp and Ferré, 2002). A time domain reflectometer (TDR) (miniTrase, 6050X3K1) was utilized for soil moisture measurements on days the neutron probe was used to obtain 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), just west of 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 3. Total precipitation values can be compared to the long term total precipitation averagefor this time period of 70.7 mm in order to infer whether a period was above or below average. Types and method of data collection are detailed in Table 4.

Table 3. Average daily weather parameters during study period for 2010 – 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

Table 4. 2010 - 2013 experimental setup

Experimental Setup	**2010 - 2011**	**2012**	**2013**
Treatments	3	7	6
Replications	4	4	4
IRT equipment	SI-121 Apogee	SI-121 Apogee	SI-121 Apogee
IRT frequency	5 min, 30 min averages	5 min, 30 min averages	5 min, 30 min averages
Multispectral equipment	Exotech sensors	N/A	Skye light sensors
Multispectral frequency	Twice a week	N/A	Twice a week

2.2 Model Calibration

Temperature methods DANS and DACT both have units of °C and a theoretical scale of zero for no stress and a much larger number for high stress. These indices need to be normalized in order to use them as stress coefficients. An independent dataset of both temperature data and FAO-56 method water stress coefficients ($K_{s\ FAO\text{-}56}$) were necessary in order to calibrate these methods before use in this study. LIRF 2010 and 2011 corn data were used for this purpose using Eq. (2.1)

$$K_{s\ DANS} = \max\left(1 - \frac{DANS}{x}, 0\right) \tag{2.1}$$

where $K_{s\ DANS}$ is the DANS-based stress coefficient, and x is a variable optimized to reduce the RMSE between $K_{s\ DANS}$ and $K_{s\ FAO\text{-}56}$ for the data from 2010 and 2011 LIRF corn.. Similarly, the stress coefficient from DACT ($K_{s\ DACT}$) is calibrated with Eq. (2.2),

$$K_{s\ DACT} = \max\left(1 - \frac{DACT}{y}, 0\right) \tag{2.2}$$

where "y" is a variable optimized to reduce RMSE between $K_{s\ DANS}$ and $K_{s\ FAO\text{-}56}$ for the data from 2010 and 2011 LIRF corn.. These equations were designed to reach practical limits for K_s; that is, when DANS and DACT are zero, there is no stress and K_s is thus equal to 1 similar to Eq. (1.4). However, when DANS = x or DACT = y, that would indicate maximum stress therefore K_s = 0. This study will focus on the performance of each index under different irrigation schemes.

2.3 Basal Crop Coefficient, K_{cb}

Three methods to calculate K_{cb} were used in this study. ET_r, or reference ET from a tall reference crop, was chosen in this study because alfalfa has historically been the reference crop for Colorado and better captures the climatic effects such as wind on ET. The first method was tabular K_{cb}, which was determined by constructing a curve using crop-specific values with the method specified by the ASABE Monograph for alfalfa reference ET (Hoffman et al., 2007). In the monograph the tabular values are based on time between planting and effective cover and then later on number of days after full cover. Coefficients were derived in Idaho for a tall reference crop under standardized conditions and adapted for use with the ASCE standardized reference ET equation. A source of error with tabulated values is that corn under different environmental conditions will likely not grow at the same rates. Use of growing degree days may be more accurate, and this could even be different year to year in the same location with local seasonal variability. Additionally, severe water stress may further alter growth rates based on timing of severe water deficit or water application. Tabulated K_{cb} values represent the potential or maximum water transpiration fraction in relation to the reference crop for a certain growth stage and environmental conditions. However, if environmental or agronomic conditions depart from ideal conditions then adjustment of K_{cb} values is needed. If tabulated K_{cb} values are used instead of measured K_{cb_refl} which reflect actual crop conditions, it causes error in the resulting crop ET estimates. In order to more accurately track actual growth progression of deficit irrigation plots, canopy cover or reflectance data can be used to estimate K_{cb} throughout the season.

Trout and Johnson (2007) developed a method to calculate K_{cb} with canopy cover data using Eq. (1.18). This equation was developed with a weighing lysimeter and a combination of 18 row crops, grains, orchards, and vineyards. In order to calibrate K_{cb} values for corn, the coefficients were calibrated with K_{cb_refl} values calculated from actual ET measurements from a Bowen Ratio Energy Balance system at LIRF, therefore producing Eq. (2.3)

$$K_{cb\_refl} = 1.01 \cdot f_c + 0.15 \tag{2.3}$$

where all variables have been previously defined. This method of obtaining K_{cb} from fractional cover data represents the second K_{cb} method used in this study. The third method chosen was to estimate f_c from NDVI to represent situations where f_c data are not available. Reflectance data can be used to estimate fractional cover by entering reflectance data into Eq. (1.14) to estimate NDVI, and then using NDVI within Eq. (1.17) in order to obtain a value for fractional cover. Quality of the canopy cover and NDVI data obtained and the accuracy of the processing methods 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 Stress Coefficient, K_s

Stress detection methods CWSI, DANS, DACT, T_c Ratio, and NDVI ratio were all used in the place of the soil moisture based K_s in order to evaluate the potential for replacing soil moisture data with alternative inputs of canopy temperature and reflectance data. CWSI can be used in Eq. (2.4) to determine water use of the crop according to Jackson et al. (1981)

$$T_a = (1 - CWSI) \cdot T_c \tag{2.4}$$

where T_a is crop transpiration under actual conditions and T_c is crop transpiration under non-water-stressed conditions. It can be seen that in this way, the quantity (1 – CWSI) is equivalent to a stress coefficient, as it represents the percent of crop water consumption compared to non-water-stressed conditions. The CWSI-based stress coefficient ($K_{s\ CWSI}$) is calculated with Eq. (2.5)

$$K_{s\ CWSI} = (1 - CWSI) \tag{2.5}$$

where all variables have been previously defined. DANS and DACT methods were applied according to Eq. (1.24) and Eq. (1.25), respectively, for each treatment replication using temperature data collected at 1400h and then those values were averaged in order to find a daily value of K_s for each method.

T_c Ratio method was similarly applied using Eq. (1.23) with temperatures collected at 1400h. NDVI Ratio method was used with reflectance data as described in Eq. (1.19) in order to obtain a K_s value for each treatment. Neither T_c Ratio or NDVI ratio fully conform to the definition of an index [0,1] since both methods 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 (Mefford, 2014; Bausch et al., 2011).

2.5 Estimation of Crop ET

Actual crop ET was independently calculated from measured soil moisture data using the soil water balance method over the growing season. In order to get daily values of water deficit from soil moisture data, a water balance method was applied by using a spreadsheet into which the irrigation events (I), effective precipitation events (P, mm), deep percolation (DP, mm) were input and soil moisture deficit (D_i) was calculated according to Eq. (2.6) described in Hoffman et al. (2007)

$$D_i = D_{i-1} + ET_a - P - I + DP - GW \tag{2.6}$$

where GW is the ground water input (mm), which is neglected if the water table is not high (i.e. in the root zone), and D_{i-1} is the deficit for the previous day (mm). Soil moisture measurements throughout growing season were used to anchor the soil water deficit calculations to true values. Time domain reflectometer (TDR) readings were used for 0 to 150 mm depth and neutron probe readings were used for 150 to 1050 mm. Neutron probe readings give estimated values for volumetric water content (VWC) of the soil, which can be subtracted from VWC at field capacity (FC) to obtain soil water deficit (SWD). Estimates of VWC at FC for each depth (0 to 150, 150 to 450, and 750 to 1050 mm) of each treatment were procured from Agricultural Research Service – Water Management Unit (ARS-WMU) in Fort Collins, CO using pressure plate analysis and later verified with observations following irrigation and rainfall events. Root zone depth (R_z) was modeled throughout the season based on observation from previous years by ARS-WMU and used in order to find the total SWD of the root zone. If deficit of a section of root zone was calculated to be negative, then the spreadsheet returns a deficit value of zero and the negative value is assumed to be deep percolation. ET_{ref} from the onsite weather station and K_{cb} based on tabular values are utilized to predict ET_a on days with no soil moisture data.

2.6 Method Comparison

Stress detection methods chosen to be converted into stress coefficients (K_s) are identified and briefly described 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 coefficient was applied with each of tabular, canopy cover, and NDVI based K_{cb} values.

1) CWSI as calculated with the empirical baseline (Idso et al.,1981)
2) Ratio of stress NDVI to non-stress NDVI (Mefford, 2014)
3) Ratio of non-stress T_c to stress T_c (Bausch, 2011)
4) DANS method (Taghvaeian et al., 2014), normalized to yield values from 0 to 1
5) DACT method (DeJonge et al., 2014), 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 soil water balance ET estimates. The main statistics to evaluate the performance of each method are the root mean square error (RMSE), mean biased error (MBE) and mean relative error (MRE) as shown in Eq. (2.7), Eq. (2.8), and Eq. (2.9) respectively

$$\mathrm{RMSE} = \left[N^{-1} \sum_{i=1}^{N} (P_i - O_i)^2 \right]^{0.5} \tag{2.7}$$

$$\mathrm{MBE} = \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{P_i}\text{-}\mathrm{O_i}) \tag{2.8}$$

$$\mathrm{MRE} = \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{|\mathrm{P_i} - \mathrm{O_i}|}{\mathrm{O_i}} \tag{2.9}$$

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. MRE measures size of error relative to the size of the observation. Applying RMSE, MBE, and MRE provides information about strengths and weakness of model performance and facilitates comparison between methods.

CHAPTER 3: RESULTS AND ANALYSIS

Transformation of DANS and DACT into indices is detailed and the calibration error statistics are provided in this chapter. Evaluation of all the methods applied daily, weekly, and monthly is presented, in addition to the effects of filtering data for clouds or insufficient canopy cover and taking running averages of stress coefficient values. Finally, recommendations of most appropriate methods considering irrigation level and data availability are provided along with an estimate of associated error.

3.1 DANS and DACT Calibration

Stress detection methods DANS and DACT required transformation in order to be used in the place of a stress index or K_s value. For this preliminary evaluation of DANS and DACT as stress coefficients, Eq. (1.24) and (1.25) 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 CO environmental conditions. 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.

DANS and DACT are both in units of degrees Celsius, 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. (2.1) and (2.2), FAO-56 soil moisture-based K_s values were calculated from a neutron probe calibrated soil water balance (SWB) 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, respectively. For this dataset the optimized values for both DANS and DACT were similar because the non-stress crop was often near 28°C, frequently causing these two indices to converge. Average 14:00 pm (MST) temperature of the non-stress canopy was 27.6 for 2010 and 27.9 in 2011, and for the stressed crop 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 while other treatments were reading much higher temperatures helps confirm 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 much higher.

Training set statistics from 2010 and 2011 data yielded very similar RMSE and MBE values for both DANS and DACT stress coefficients (Table 5). Low RMSE and MBE values indicate that DANS and DACT are closely related to a water stress index and have the potential to serve as stress coefficients.

Table 5. Training set statistics for x and y values which minimize $K_{s\ DANS}$ and $K_{s\ DACT}$ RMSE

Stress Coefficient	**x/y Value**	**K_s RMSE**	**K_s MBE**
$K_{s\ DANS}$	27.7	0.15	0.033
$K_{s\ DACT}$	29.1	0.14	-0.031

In order to analyze how the error in $K_{s\ DANS}$ and $K_{s\ DACT}$ change for each year and treatment combination with different values for “x” and “y” Figure 3 and Figure 4 were constructed. These graphs show that for most logically reasonable scaling values, the error is nearly constant with asymptotic behavior around an error of approximately 0.15 when considering all treatments. A potential advantage of asymptotic behavior is that it indicates the indices may not be overly sensitive to these parameters but irrigation 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 with 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 crops in this study. Further research is necessary to fine tune the relationship between optimal empirical values and irrigation 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.

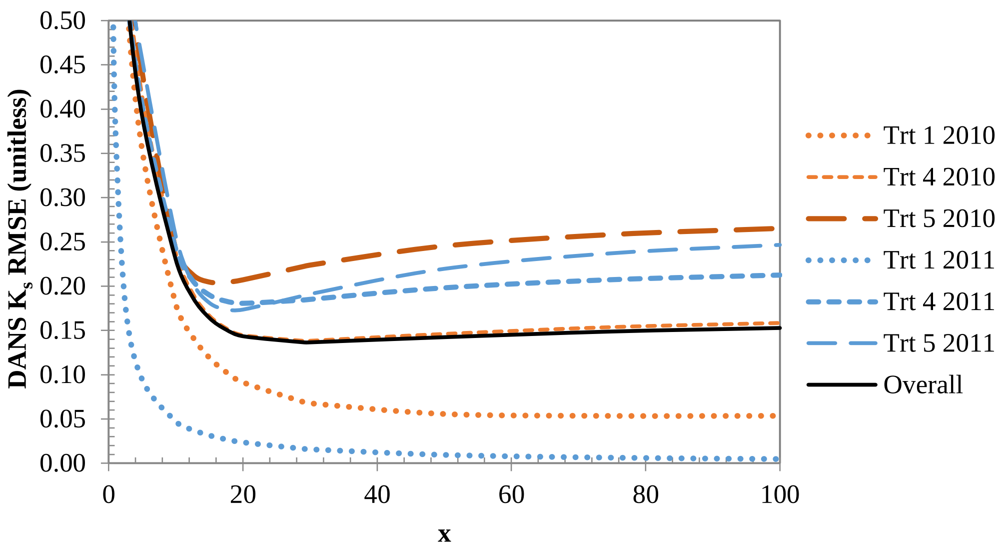

Figure 3. DANS RMSE with varying "x" values for each treatment and year combination

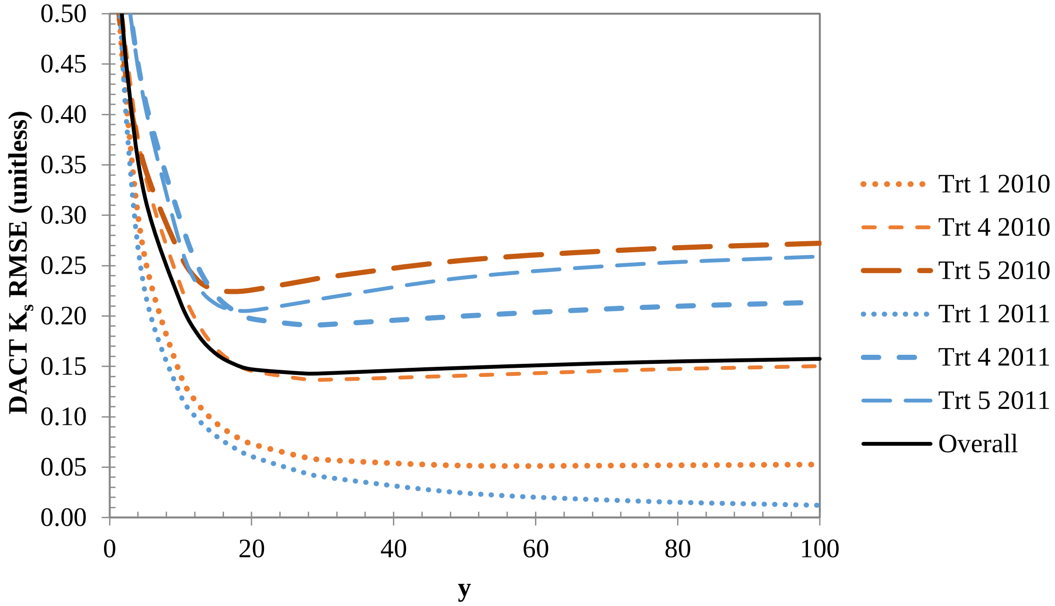

Figure 4. DACT RMSE with varying "y" values for each treatment and year combination

3.2 Evaluation of ET_a Estimates

Once all water stress coefficient equations were determined, 2012 and 2013 corn data from LIRF were used to calculate daily water stress indices for each method. Next, a soil water balance was used in order to obtain values of ET_a using daily K_s values from the five methods and then compare them to the ET_a from the neutron probe calibrated soil water balance. For each water stress coefficient method all three K_{cb} methods (tabular, canopy cover, and NDVI) were applied. Daily, weekly, and seasonal ET_a errors for all K_s methods were evaluated to find the most appropriate time period of ET_a estimation for each method. The effects of filtering data on cloudy days or in cases of insufficient canopy cover were studied in order to identify which indices were more robust throughout the season. Running averages of stress coefficient values were taken to find the effect of smoothing ET_a values to reduce errors. Finally recommendations for the most appropriate method under different irrigation levels and data availability were made.

3.2.1 Daily, Weekly, and Seasonal ET_a Estimation Error

All K_s methods were used within a soil water balance spreadsheet which uses FAO-56 dual crop coefficient method to estimate actual evapotranspiration. Daily ET_a estimations for all combinations of K_s and K_{cb} were compared to daily ET_a values from neutron probe calibrated SWB. ET_a RMSE (mm/day) estimates from each combination of K_s and K_{cb} method over the study period in 2013 are displayed in Figure 5. For 2013, the effect of using tabular values instead of canopy cover measurements resulted in only slightly increased 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). 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. RMSE (mm/day) of ET_a from 2012 for the available data (all except reflectance) is shown in Figure 6 in order to validate the conclusions from Figure 5. 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.

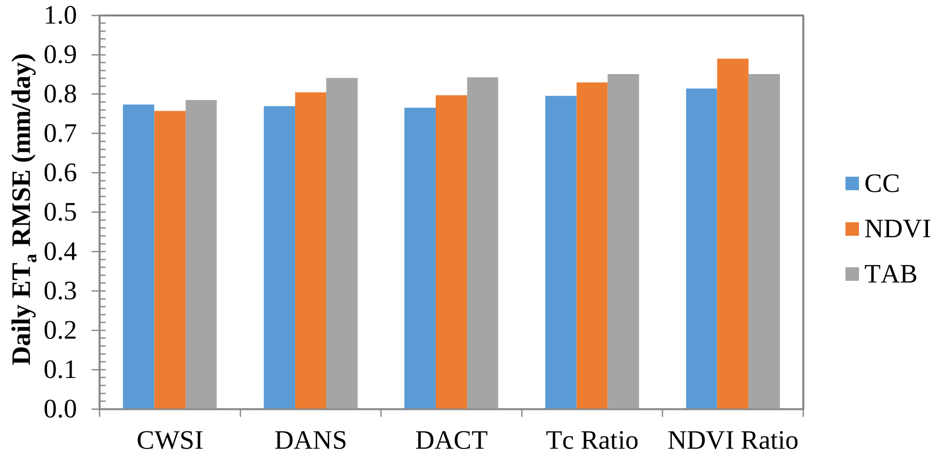

Figure 5. Daily ET_a estimate RMSE (mm/day) of each K_s and K_{cb} combination in 2013

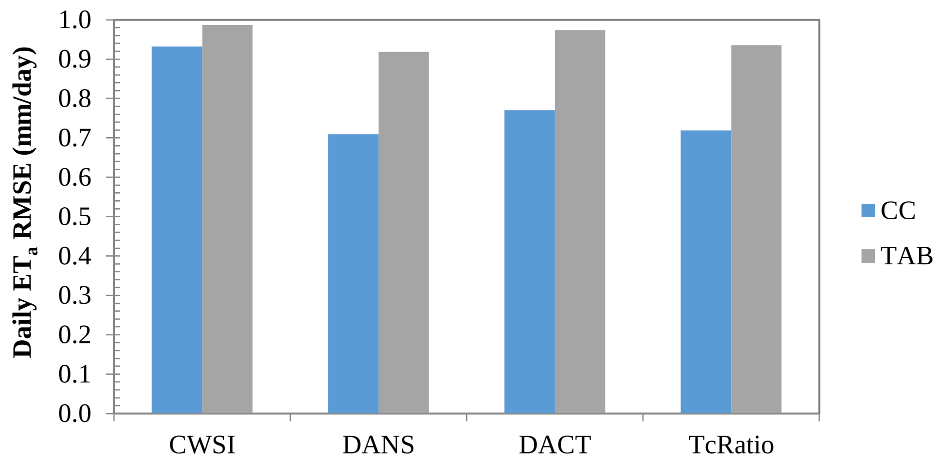

Figure 6. Daily ET_a estimate RMSE (mm/day) of each K_s and K_{cb} combination in 2012

MRE (%) was calculated in order to quantify size of error relative to size of the observation for each method's daily ET_a estimations (Figure 7). This graph shows that CWSI and DACT had lowest MRE error which means they have the smallest percentage errors on a daily basis. All methods performed at similar levels in terms of percentage error, ranging from an average of 10.2% error for CWSI to 11.8% error for NDVI Ratio. Figure 7 shows the effect of using various K_{cb} methods. Canopy cover K_{cb} had an average of 9.5% error among all methods while

NDVI and tabular K_{cb} methods had averages of 10.8% and 13.4% error, respectively, indicating that canopy cover K_{cb} method or NDVI K_{cb} method is preferred in order to lower percentage error in ET_a estimation regardless of K_s method used. Daily ET_a MRE (%) for the 2012 dataset (Figure 8) confirms the conclusions from the 2013 MRE analysis. Similar to 2013, all methods performed on similar levels, ranging from an average of 14.6% error for CWSI to 16.6% error for NDVI Ratio. Canopy cover K_{cb} had an average of 14.0% error among all stress coefficient methods and tabular K_{cb} methods had an average of 18.0 % error, confirming the advantage of using canopy cover K_{cb} values. The main difference between years 2012 and 2013 in terms of MRE is that 2012 MRE is much higher overall, with average error of all K_{cb} and K_s combinations of 16.0% compared to 11.2% in 2013. This can be attributed to the different environmental conditions for those years, as 2012 had less precipitation and higher temperatures on average. Stress coefficient methods are designed to work best in average climate conditions, so when conditions diverge error increases. For example, DACT assumes a non-stress canopy temperature of 28 °C and DANS assumes that there is a non-stress canopy temperature which can be measured, neither of which is true in extremely hot conditions when even crops not under soil moisture limiting conditions will be exhibiting higher stress levels due to divergent environmental conditions.

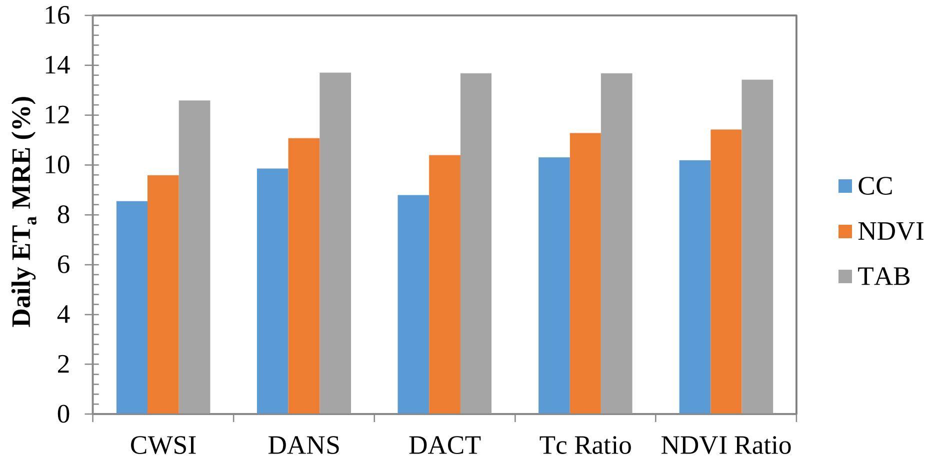

Figure 7. Daily ET_a estimate MRE (%) of each K_s and K_{cb} combination in 2013

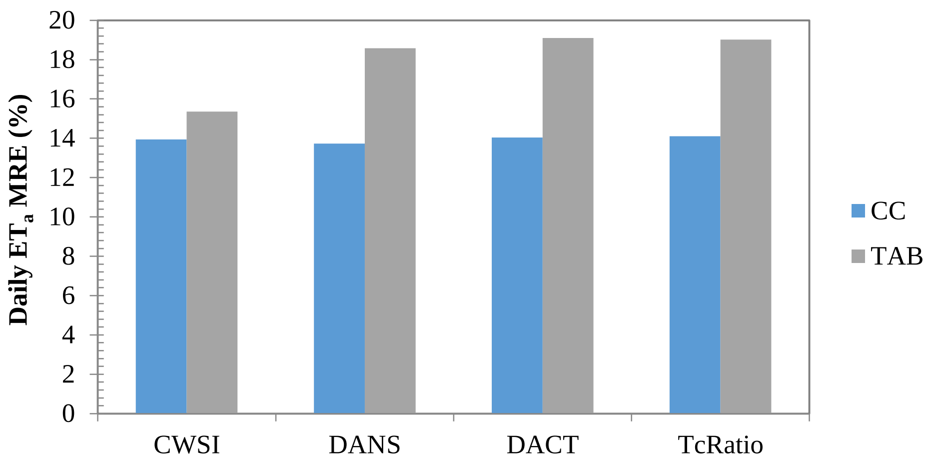

Figure 8. Daily ET_a estimate MRE (%) of each K_s and K_{cb} combination in 2012

In order to quantify how well each tested method predicted ET_a , the coefficient of determination R^2 of each method was calculated and displayed graphically on scatterplots of a given tested method ET_a vs. neutron probe derived ET_a with a 1:1 line shown for reference. CWSI ET_a scatterplot (Figure 9) and DANS ET_a scatterplot (Figure 10) 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_a values, with DANS more consistently overestimating on days with less ET_a. DANS, while having an overall slightly lower R^2 than CWSI has less scatter among the mid-range ET_a values which demonstrates that DANS performs very well for days with average ET_a, while CWSI had quite a bit of scatter throughout the whole range of ET_a values. NDVI Ratio scatterplot (Figure 11) had the lowest R^2 of the stress coefficient methods at $R^2 = 0.76$. NDVI Ratio also displayed most scatter at low ET_a values, possibly demonstrating the range issue dicussed earlier that causes NDVI ratio not to be able to reach low values and therefore may not be able to sufficiently reduce ET_a to represent stressed conditions. High error among all methods on days with lower ET_a can also be attributed to these days being those with lower reference ET_a and therefore having lower heat stress, which is what these methods are designed to detect. DACT and T_c Ratio both had R^2 values of 0.83 and scatterplots are shown in Figure 12 and Figure 13, respectively.

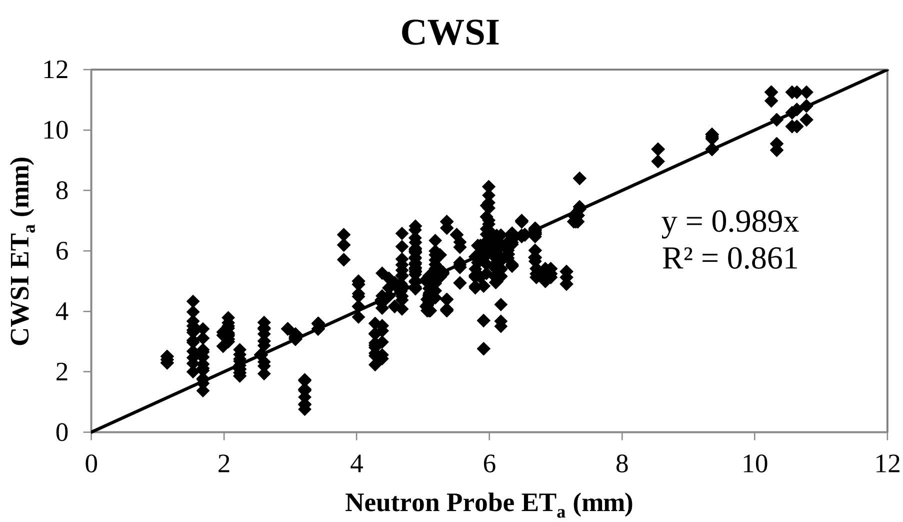

Figure 9. Scatterplot of CWSI ET_a vs. Neutron Probe ET_a (mm), $R^2 = 0.86$

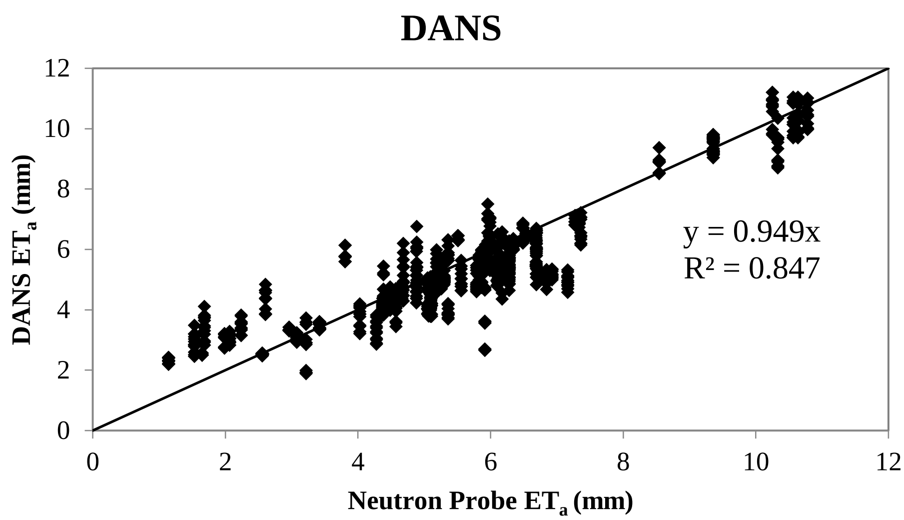

Figure 10. Scatterplot of DANS ET_a vs. Neutron Probe ET_a (mm), R^2 = 0.85

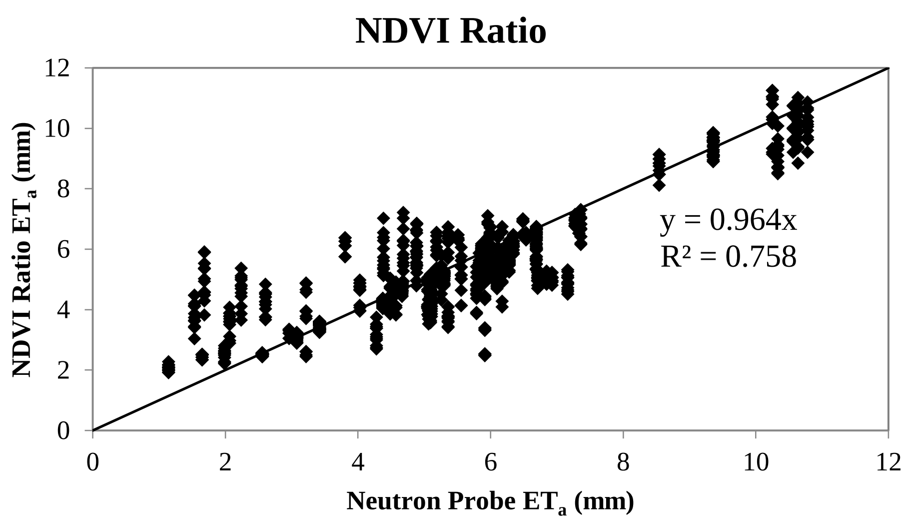

Figure 11. Scatterplot of NDVI Ratio ET_a vs. Neutron Probe ET_a (mm), R^2 = 0.76

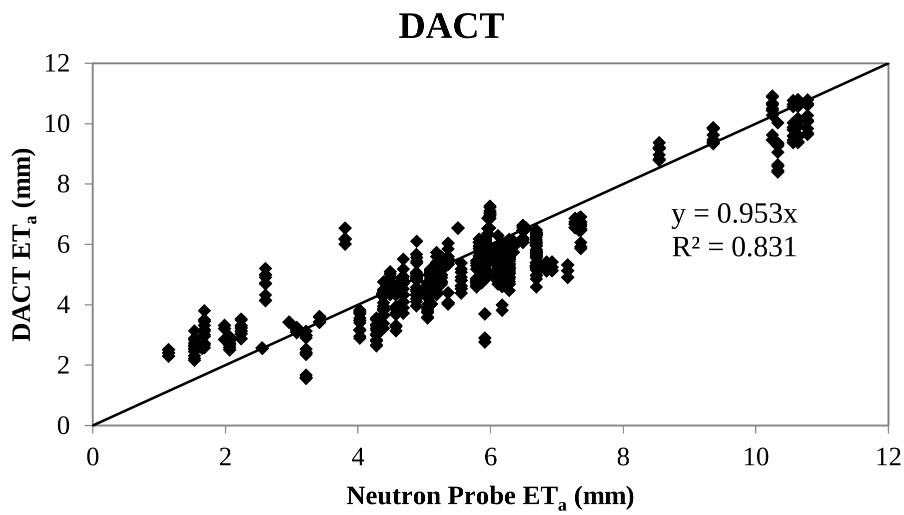

Figure 12. Scatterplot of DACT ET_a vs. Neutron Probe ET_a (mm), R^2 = 0.83

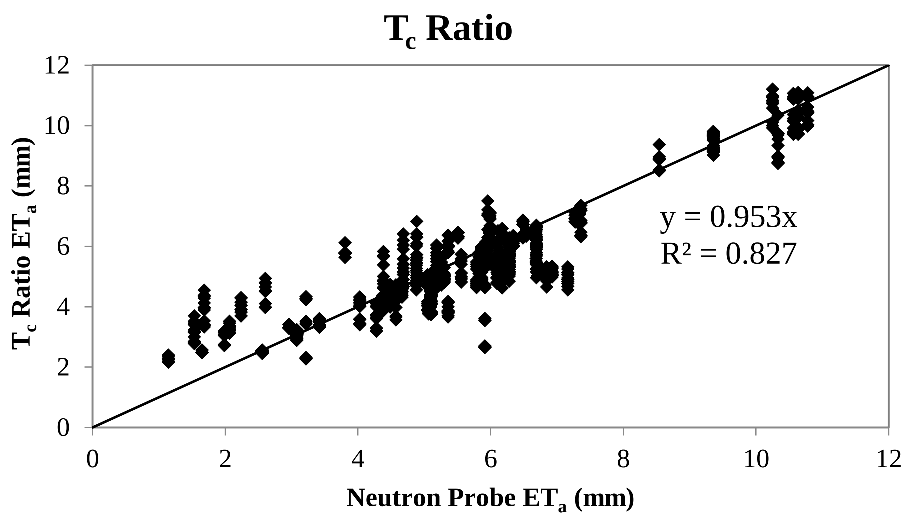

Figure 13. Scatterplot of T_c Ratio ET_a vs. Neutron Probe ET_a (mm), R^2 = 0.83

In the case of the CWSI method, air temperature and relative humidity data were taken from a nearby weather station, as measurements were not available for each plot. With the experimental configuration at LIRF, research plots were too small to meet fetch requirements in addition to having equipment and data logger limitations. It seems that variations in micro-climate among different treatments caused using air temperature and relative humidity from a reference grass weather station to not be optimal for the computation of CWSI. A nearby field under deficit irrigation with *in situ* weather data was used to confirm this hypothesis of micro-climate variation. Three levels of irrigation were applied on the nearby field: high frequency deficit irrigation (HFDI), low frequency deficit irrigation (LFDI), and full irrigation (FI). HFDI experienced moderate water stress, LFDI was placed under severe water stress, and FI was not intentionally water stressed.For further detail on field layout, irrigation, soils, etc. see Taghvaeian et al. (2013). Comparing *in situ* (field) weather data in August for 2012 and 2013 to the off-field or agricultural weather station data at 11:00 am (MST), when CWSI was applied for this study, showed that for all irrigation levels, using nearby weather station introduced error (Table 6). Full irrigation had the highest vapor pressure deficit (VPD) error both years, with RMSE values of 0.31 kPa (14%) and 0.36 kPa (19%) for 2012 and 2013, respectively. Data from 2013 showed that for this year of the study there was consistent underestimation of VPD from weather station data, ranging from -0.07 kPa (-4%) to -0.23 kPa (-11%) for FI and HFDI, respectively. Comparison of weather station to *in situ* VPD supports the idea that in field conditions may diverge from those of a nearby weather station and introduce error into CWSI calculations.

Table 6. MBE and RMSE (in kPa and %) for the VPD datasets from COAGMET at 11am (MST) as compared to *in situ* weather data for all irrigation treatments (FI, LFDI, and HFDI) for August 1-31 in 2012 and 2013

	2012			2013		
Statistic	**FI**	**LFDI**	**HFDI**	**FI**	**LFDI**	**HFDI**
RMSE (kPa)	0.31	0.26	0.25	0.36	0.33	0.36
RMSE (%)	13.7	11.2	10.8	19.4	17.4	18.1
MBE (kPa)	0.06	-0.01	0.02	-0.07	-0.11	-0.23
MBE (%)	2.8	-0.5	0.9	-4.0	-5.7	-11.3

To investigate the effect of VPD error on CWSI calculations from using a nearby weather station instead of in field readings, CWSI was calculated for this nearby field assuming a canopy-air temperature differential of 2.5 ºC and using the same baselines as were used in this study (Table 7). Considering both years, using weather station data incurred an average RMSE in $K_{s\ CWSI}$ values of 0.05 (7.6%) and an average MBE of -0.01 (-1.9%). Errors in $K_{s\ CWSI}$ cause subsequent errors in estimation of ET_a, which reduces the accuracy of CWSI ET_a estimates when *in situ* air temperature and relative humidity data are not used.

Table 7. MBE and RMSE (unitless and %) for $K_{s\ CWSI}$ from COAGMET at 11am (MST) as compared to *in situ* weather data for all irrigation treatments (FI, LFDI, and HFDI) for August 1-31 in 2012 and 2013

	2012			2013		
Statistic	**FI**	**LFDI**	**HFDI**	**FI**	**LFDI**	**HFDI**
RMSE (unitless)	0.04	0.03	0.03	0.06	0.06	0.06
RMSE (%)	6.1	5.4	5.0	9.6	9.3	9.9
MBE (unitless)	0.00	-0.01	0.00	-0.01	-0.02	-0.03
MBE (%)	0.2	-1.0	-0.4	-1.8	-3.4	-5.3

As previously mentioned, CWSI was applied at 11:00 am (MST) for this study, but if it is applied according to Idso et al. (1981) at 2:00 pm (MST), effect of using *in situ* weather data may be different than if CWSI is applied at 11:00 am (MST). To investigate that theory, Table 8 and Table 9 were created identically to Table 6 and Table 7, only changing from 11:00 am (MST) data to 2:00 pm (MST) data in order to directly contrast the two datasets. Average RMSE of VPD for 2:00 pm data was 12.0% as compared to 15.1% for 11:00 am data, displaying that *in situ* weather data in this case varied from the weather station more at 11:00 am than at 2:00 pm. Similarly, average RMSE of $K_{s\ CWSI}$ values for 2:00 pm data was 3.7% and 7.6% for 11:00 am data. Therefore, the choice to apply CWSI at 11:00 am (MST) for this study may better describe the average daily stress experienced by the crop but there may be increased divergent microclimate implications when not applying the method with *in situ* weather data and at the time period prescribed by the method.

Table 8. MBE and RMSE (in kPa and %) for the VPD datasets from COAGMET at 2 pm (MST) as compared to *in situ* weather data for all irrigation treatments (FI, LFDI, and HFDI) for August 1-31 in 2012 and 2013

	2012			2013		
Statistic	**FI**	**LFDI**	**HFDI**	**FI**	**LFDI**	**HFDI**
RMSE (kPa)	0.40	0.35	0.33	0.35	0.28	0.35
RMSE (%)	13.3	11.5	10.9	14.0	10.0	12.2
MBE (kPa)	0.20	0.18	0.22	0.19	-0.05	-0.14
MBE (%)	6.6	5.8	7.2	7.5	-2.0	-4.8

Table 9. MBE and RMSE (unitless and %) for $K_{s\ CWSI}$ from COAGMET at 2 pm (MST) as compared to *in situ* weather data for all irrigation treatments (FI, LFDI, and HFDI) for August 1-31 in 2012 and 2013

	2012			2013		
Statistic	**FI**	**LFDI**	**HFDI**	**FI**	**LFDI**	**HFDI**
RMSE (unitless)	0.03	0.02	0.02	0.03	0.02	0.02
RMSE (%)	4.2	3.6	3.1	4.6	2.9	3.5
MBE (unitless)	0.01	0.01	0.01	0.02	0.00	-0.01
MBE (%)	1.9	1.6	2.1	3.0	-0.3	-0.8

Figure 14 displays the RMSE (mm/day) of daily ET_a 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 water-limited plots incurring higher errors from all methods. Figure 15 displays the MBE of daily ET_a estimates over the study period and this chart shows that all of the chosen K_s methods slightly over-estimated ET_a with CC K_{cb} values and slightly underestimate ET_a when applied with NDVI and Tabular K_{cb} values. In addition, Figure 15 indicates that a composite K_{cb} model, averaging the three methods, may be the least biased estimate for $K_{cb.}$

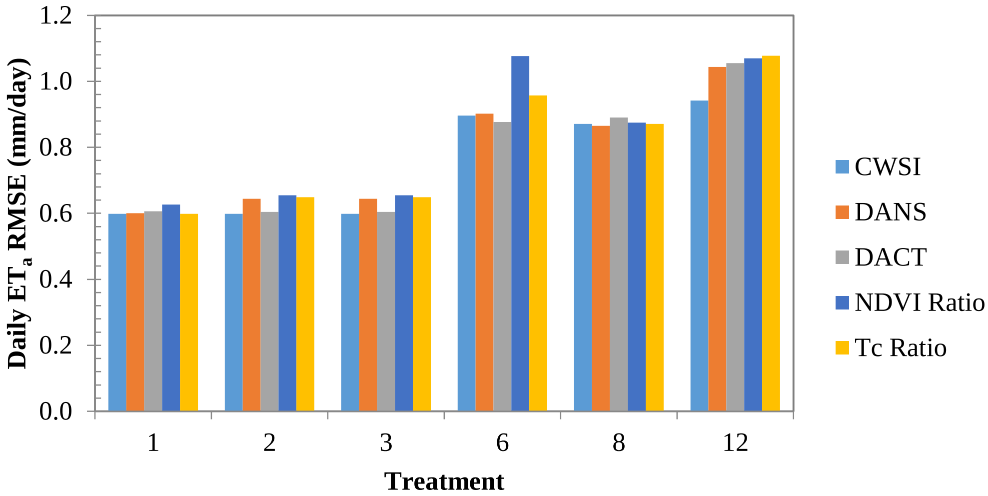

Figure 14. Daily ET_a estimate RMSE (mm/day) of each K_s method for each treatment

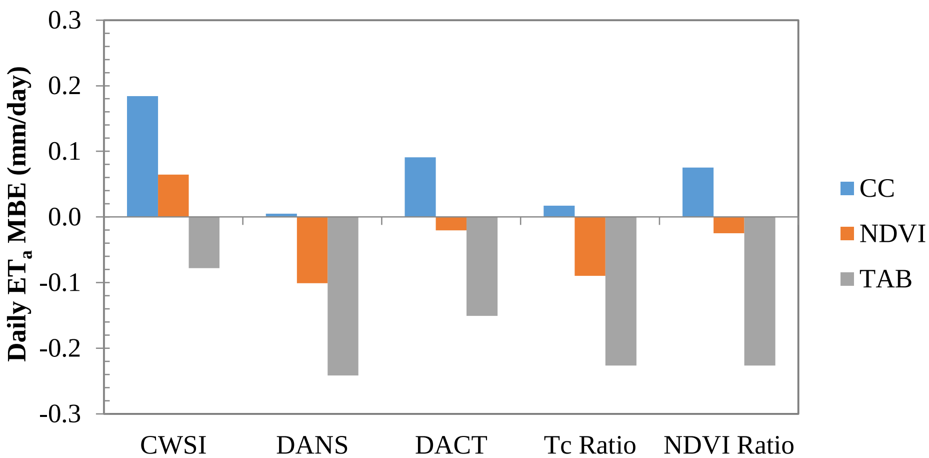

Figure 15. Daily ET_a estimate MBE (mm/day) of each combination of K_s and K_{cb} methods

Evaluating a weekly time step of ET_a estimates may be more relevant for producers since it is a more common interval for irrigation and it also could be preferable to aggregate (or interpret) stress over longer periods of time rather than relying on short term water stress fluctuations. While some estimates may show higher accuracy on a daily time step, this advantage may be lost when considering weekly ET_a estimates. In order to compare daily and weekly ET_a RMSE values, error is displayed for both daily and weekly estimates for ET_a in the same units (mm/day) in Figure 16. In this case, the error in estimated ET_a decreased for all methods when time step was increased from a day to a week. NDVI Ratio improved the least with an error decrease of 0.16 mm/day (19%), and CWSI improved the most with an improvement of 0.25 mm/day (32%). However, the ranking of the performance of the K_s methods remained the same, indicating that in this study the time step did not affect the relative performance of the methods.

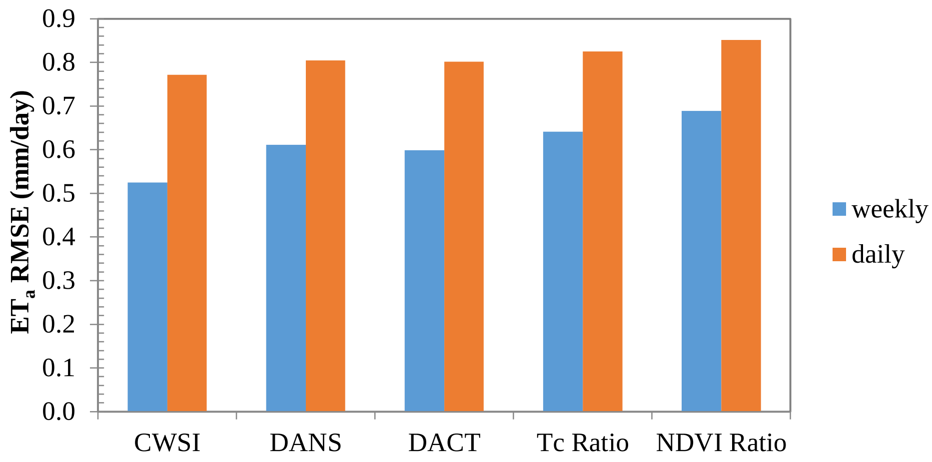

Figure 16. Weekly ET_a estimate RMSE (mm/day) for each combination of K_s and K_{cb}

In order to evaluate the performance of each method by total water use estimations, results from all three K_{cb} were averaged to eliminate its effect on the outcome. Error in estimations of total ET_a (mm) over the study period for each K_s method is shown graphically in Figure 17. To have perspective of error magnitudes, errors of total study period ET_a are displayed again in Figure 18 in terms of percent error . Percent error was chosen instead of MRE for this chart because it is important to know whether certain methods underestimated or overestimated crop water use over the study period. Methods consistently underestimated ET_a for more fully irrigated treatments and often overestimated for the more severe deficit 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 has to have in mind 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 would have been obtained. Similarly, the average seasonal performance of DACT with only -0.5% error in total ET_a 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_A with only the single input of a canopy temperature measurement.

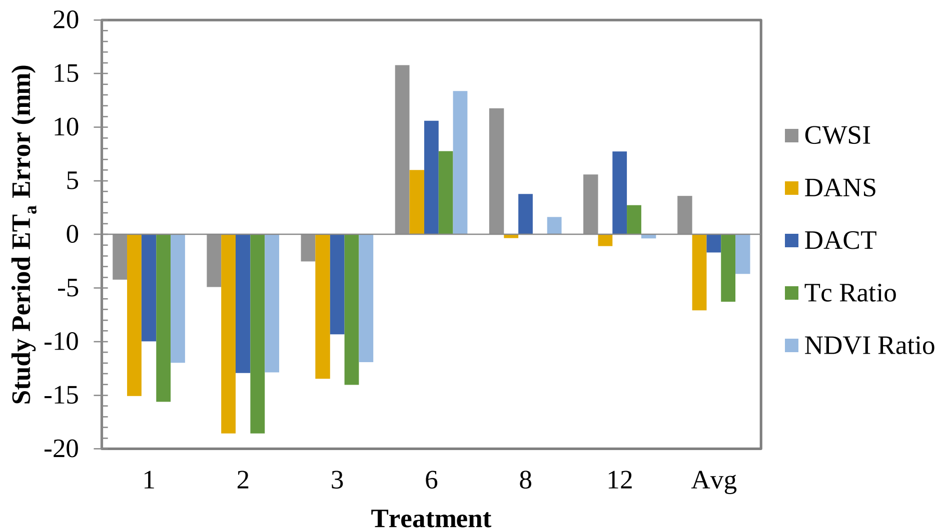

Figure 17. Error in study period ET_a (mm) of each K_s method for each treatment

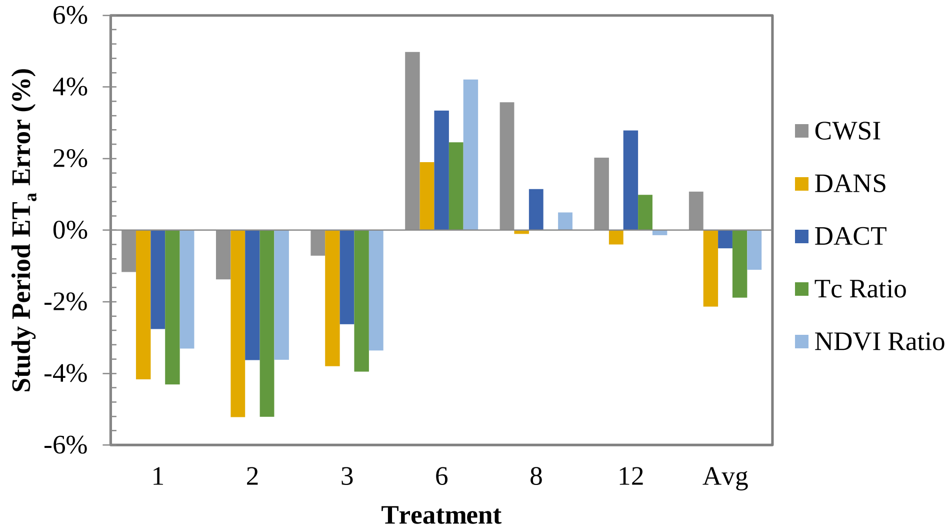

Figure 18. Error in study period ET_a (%) of each K_s method for each treatment

3.2.2 Effect of Filtering and Running Averages

Stress indices which rely on canopy temperature and canopy reflectance often suggest that data are taken during sunny afternoons. Conditions of cloud cover can mask crop water stress by causing temporary cooling of leaves. Canopy temperature indices require the crop to have sufficient canopy cover in order to avoid inaccurate temperature readings which incorporating the warmer temperature of soil into the canopy temperature reading. Filters for canopy cover and cloudy days were applied independently and simultaneously to identify the effect the filters had on ET_a error. Sunny conditions are determined by the ratio of clear-sky solar radiation (R_s) to actual solar radiation (R_{so}). Sufficient canopy cover was considered to be greater than 70% and near clear-sky solar radiation to be (R_s / R_{so}) greater than 80% at the time of data collection. As shown in Figure 19, overall the methods improved slightly with separate cloud filtering and insufficient canopy cover filtering, with an average decrease in ET_a error of 0.03 mm/day (3%) and 0.07 mm/day (10%), respectively. Number of data points (N) with each filter scenario was 1512 for no filtering, 1008 for cloud filtering, 1396 for CC filtering and 908 for both cloud and

CC filtering when considering 2013 data in order to have a full dataset to evaluate and compare stress coefficient methods. Error decreased further when both cloudy days and insufficient canopy cover days were filtered out, an average decrease in ET_a error of 0.13 mm/day (19%). Reduction of ET_a error by filtering for these conditions demonstrates that the accuracy of the methods will improve if early season and cloudy days are avoided for data collection. As displayed in Figure 19, error when evaluating only cloudy days resulted in increased error of 0.03 mm/day (3%) which indicates that while it is suggested to collect data under sunny conditions, the indices may still be useful under cloudy conditions. As defined previously, in this study cloudy conditions are considered to be days where (R_s/R_{so}) is less than 0.8 at the time of data collection, with the lowest R_s/R_{so} ratio in the study period being 0.43.

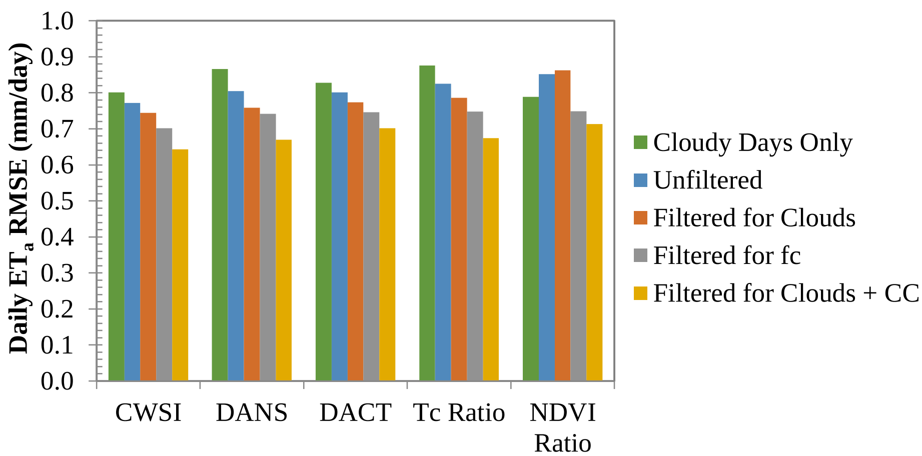

Figure 19. Effects of filtering data for clouds, canopy cover, and for clouds and canopy cover

With dynamic indices such as these temperature based water stress detection methods, there is much variation from day to day which may not be reflecting real plant water stress conditions. The water content may not be fluctuating in the exact way that the temperature methods seem to indicate, due to other environmental conditions that cause the methods to exaggerate or underestimate crop water stress. One way of investigating these sources of variability is to evaluate the effect of running averages of the data in order to see if smoothing K_s values removes noise and increases accuracy of ET_a estimations or reduces the ability of indices to capture daily crop stress.

A running average was performed on the K_s values for each method and then statistics were calculated for the ET_a estimations corresponding to the new K_s values. The original error of the daily indices is plotted next to the daily RMSE of the methods after taking 3, 5, and 7-day running averages on the dataset in Figure 20. From these results it can be seen that running averages did not cause water stress coefficient methods to increase in accuracy. All indices performed best when used on a daily or 3-day time step, and lost accuracy (up to 0.09 mm/day or 10%) when averaged over longer time intervals. This result suggests that accurate monitoring of corn stress status may perform best with frequent (i.e. daily) measurements, and should not be based on less frequent measurements.

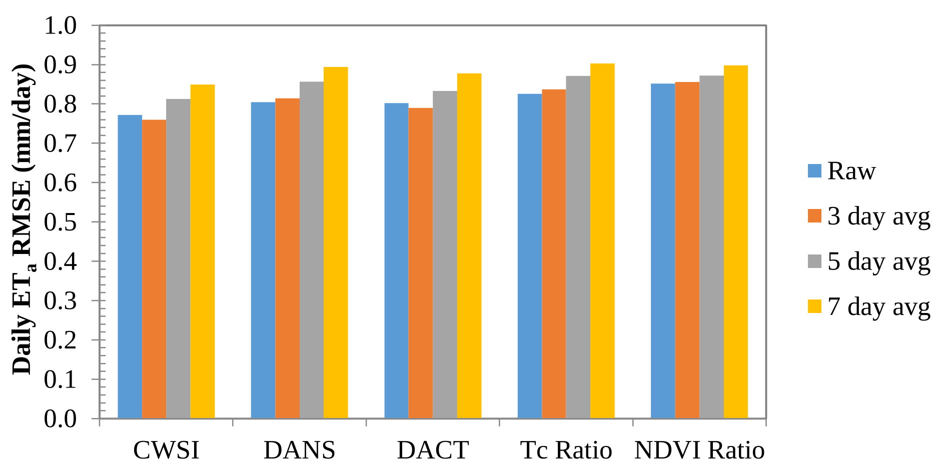

Figure 20. Effect of 3, 5, and 7 day running averages on RMSE of ET_a estimates

3.2.3 Recommendations of Most Appropriate Method

This study has very practical ramifications for consultants, producers, and researchers choosing between different water stress and irrigation water management techniques. Data availability governs the available options and the chosen levels of acceptable water stress further limit which methods will perform well. Table 10 summarizes the data requirements for each method and presents the RMSE of daily ET_a for each in order to analyze if increased data requirement corresponds to increased accuracy. In Table 10, "target" refers to the crop in question for which a K_s value is being assigned.

Table 10. Comparison of basic data required for each K_s method tested and associated ET_a estimation RMSE

		K_s method				
	Requirement	CWSI	DANS	DACT	T_c Ratio	NDVI Ratio
Crop Condition	Full Canopy Cover	X	X	X	X	
Canopy Temp	Target	X	X	X	X	
	Non-Stressed Reference		X		X	
Environmental	Relative Humidity	X				
	Air Temperature	X				
	Clear sky conditions	X	X	X	X	X
Pre-calculation	Baselines (locally calibrated)	X				
	Threshold Temperature			X		
	K_s Scaling Coefficient (locally calibrated)		X	X		
NDVI	Target					X
	Non-Stressed Reference					X
	Daily ET_a RMSE (mm/day)	0.77	0.80	0.80	0.83	0.85
	Daily ET_a RMSE (%)	14.6	15.2	15.2	15.6	16.1

DANS and DACT have fewer data requirements, yet only a decrease in accuracy of 0.03 mm/day (0.6%) in ET_a estimation compared to CWSI. This equivalency 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_c Ratio because in times of drought a non-stress canopy may not exist on site to measure, or there could be stresses other than water stress contributing to higher temperatures (i.e. nutrient deficiency, heat, 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). In the absence of canopy temperature data, the NDVI ratio could be used; however it has the same limitation of needing a non-stress NDVI measurement. In order to provide guidelines for a variety of different irrigation levels and data availability, the analysis was run for all combinations of stress coefficient methods and basal crop coefficient methods to provide the average daily ET_a RMSE in mm of each pair as displayed in Table 11.

Table 11. Average daily ET_a RMSE (mm) by treatment

		Irrigation Treatment (% ET applied in vegetation period/% ET applied in maturation period)					
		1 (100/100)	2 (100/50)	3 (80/80)	6 (80/40)	8 (65/40)	12 (40/40)
CC Keb	CWSI Ks	0.54	0.57	0.64	0.93	0.89	0.95
	DANS Ks	0.52	0.58	0.67	0.87	0.86	1.00
	DACT Ks	0.51	0.53	0.63	0.85	0.87	1.04
	Tc Ratio Ks	0.52	0.59	0.68	0.92	0.87	1.05
	NDVI Ratio Ks	0.56	0.56	0.65	1.07	0.88	1.01
NDVI Keb	CWSI Ks	0.65	0.58	0.59	0.91	0.82	0.93
	DANS Ks	0.64	0.60	0.63	0.94	0.82	1.08
	DACT Ks	0.65	0.57	0.62	0.91	0.84	1.08
	Tc Ratio Ks	0.64	0.61	0.64	1.01	0.82	1.12
	NDVI Ratio Ks	0.68	0.66	0.63	1.21	0.83	1.14
Tabulated Keb	CWSI Ks	0.61	0.65	0.67	0.85	0.90	0.95
	DANS Ks	0.64	0.75	0.72	0.89	0.92	1.06
	DACT Ks	0.65	0.72	0.74	0.87	0.96	1.04
	Tc Ratio Ks	0.64	0.75	0.72	0.95	0.92	1.06
	NDVI Ratio Ks	0.64	0.75	0.72	0.95	0.92	1.06

The user could utilize this table by first identifying the level of irrigation which is most representative of his or her chosen water stress level. Next, the producer could eliminate methods that require more data than he or she has access to or consider all options to identify the additional data required to implement the higher accuracy methods. Finally, the combination of stress coefficient and basal crop coefficient methods with lowest error could be identified. This would provide the producer with not only the best option for water management for his or her field, but also an estimate of expected average daily ET_a RMSE error.

CHAPTER 4: CONCLUSION

This study compared and evaluated the accuracy of various water stress coefficient methods for estimating crop ET_a 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_a estimations. Using the most appropriate water stress coefficient method has the potential to improve irrigation scheduling and therefore allow crops to reach the maximum possible yield given the degree of deficit irrigation. Results also give researchers indications of which methods have the most potential to be further investigated and refined. Methods with only canopy temperature measurements (DANS, DACT, and T_c Ratio) 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. A sensitivity analysis was performed regarding using off-site versus *in situ* air temperature and relative humidity which demonstrated that applying CWSI with off-site weather data incurred a RMSE in $K_{s\ CWSI}$ values of 7.6% when applied at 11:00 am (MST) and a RMSE of 3.7% when applied at 2:00 pm (MST), concluding that using nearby weather station data to calculate CWSI introduces error, and that if weather station data must be used, 2:00 pm (MST) may be a more appropriate time to apply the CWSI method.

Future studies should evaluate how stress coefficient methods perform in various climates and under different irrigation types. A constraint of this study is that it only focused on drip irrigated corn in Northern Colorado over 2 years and therefore is limited in its ability to evaluate a wide variety of applications. 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. Additional limitations include only having a neutron-probe soil water balance in order to estimate crop water use, considering that accuracy of neutron probe soil water content is only within 0.3% of water content. Use of a large monolithic weighing lysimeters could benefit a supplemental analysis in order to provide an additional level of analysis and have increased confidence in the outcomes. This study was conducted with research grade IRTs, but future work could 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 look into applying each method 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.

REFERENCES

Alderfasi, A. A., & Nielsen, D. C. (2001). Use of crop water stress index for monitoring water status and scheduling irrigation in wheat. *Agricultural water management*, *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.

ASCE-EWRI. (2005). The ASCE Standardized Reference Evapotranspiration Equation. Report 07844-0805-X, ASCE Task Committee on Standardization of Reference Evapotranspiration. Reston, Va.: American Society of Civil Engineers.

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 Sensing of Environment*, *46*(2), 213-222.

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

Chávez, J., Neale, C. M., Hipps, L. E., Prueger, J. H., & Kustas, W. P. (2005). Comparing aircraft-based remotely sensed energy balance fluxes with eddy covariance tower data using heat flux source area functions. Journal of Hydrometeorology, 6(6), 923-940.

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

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

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

Evett, S. R., Tolk, J. A., & Howell, T. A. (2006). Soil profile water content determination. *Vadose Zone Journal*, *5*(3), 894-907.

Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany*, *58*(2), 147-159.

Hoffman, G. J., R. G. Evans, M. E. Jensen, D. L. Martin, and R. L. Elliott. (2007b). *Design and Operation of Farm Irrigation Systems*. 2nd ed. American Society of Agricultural and Biological Engineers. (2007): 211-215.

Huete, A. R. (1988). A Soil-Adjusted Vegetation Index (SAVI). *Remote Sensing of Environment* 25: 295-309.

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

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

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

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

Li, Q. S., Willardson, L. S., Deng, W., Li, X. J., & Liu, C. J. (2005). Crop water deficit estimation and irrigation scheduling in western Jilin province, Northeast China. Agricultural water management, 71(1), 47-60.

Maes, W. H., & Steppe, K. (2012). Estimating evapotranspiration and drought stress with ground-based thermal remote sensing in agriculture: a review. *Journal of experimental botany*, *63*(13), 4671-4712.

Mefford, B. (2014). Assessing corn water stress using spectral reflectance (Master's thesis). Retrieved from Colorado State University Libraries Digital Collections.

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

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

O'Shaughnessy, S. A., & Evett, S. R. (2010). Canopy temperature based system effectively schedules and controls center pivot irrigation of cotton.*Agricultural water management*, *97*(9), 1310-1316.

Romano, G., Zia, S., Spreer, W., Sanchez, C., Cairns, J., Araus, J. L., & Müller, J. (2011). Use of thermography for high throughput phenotyping of tropical maize adaptation in water stress. *Computers and Electronics in Agriculture*, *79*(1), 67-74.

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

Taghvaeian, S., Comas, L., DeJonge, K. C., & Trout, T. J. (2014). Conventional and simplified canopy temperature indices predict water stress in sunflower. *Agricultural Water Management*, *144*, 69-80.

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

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

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

United Nations. (2012). The 2012 Revision of the World Population Prospects. United Nations, New York.

Walthall, C.L., J. Hatfield, P. Backlund, L. Lengnick, E. Marshall, M. Walsh, S. Adkins, M. Aillery, E.A. Ainsworth, C. Ammann, C.J. Anderson, I. Bartomeus, L.H. Baumgard, F. Booker, B. Bradley, D.M. Blumenthal, J. Bunce, K. Burkey, S.M. Dabney, J.A. Delgado, J. Dukes, A. Funk, K. Garrett, M. Glenn, D.A. Grantz, D. Goodrich, S. Hu, R.C. Izaurralde, R.A.C. Jones, S-H. Kim, A.D.B. Leaky, K. Lewers, T.L. Mader, A. McClung, J. Morgan, D.J. Muth, M. Nearing, D.M. Oosterhuis, D. Ort, C. Parmesan, W.T. Pettigrew, W. Polley, R. Rader, C. Rice, M. Rivington, E. Rosskopf, W.A. Salas, L.E. Sollenberger, R. Srygley, C. Stöckle, E.S. Takle, D. Timlin, J.W. White, R. Winfree, L. Wright-Morton, L.H. Ziska. (2012). Climate Change and Agriculture in the United States: Effects and Adaptation. USDA Technical Bulletin 1935. Washington, DC. 186 pages.

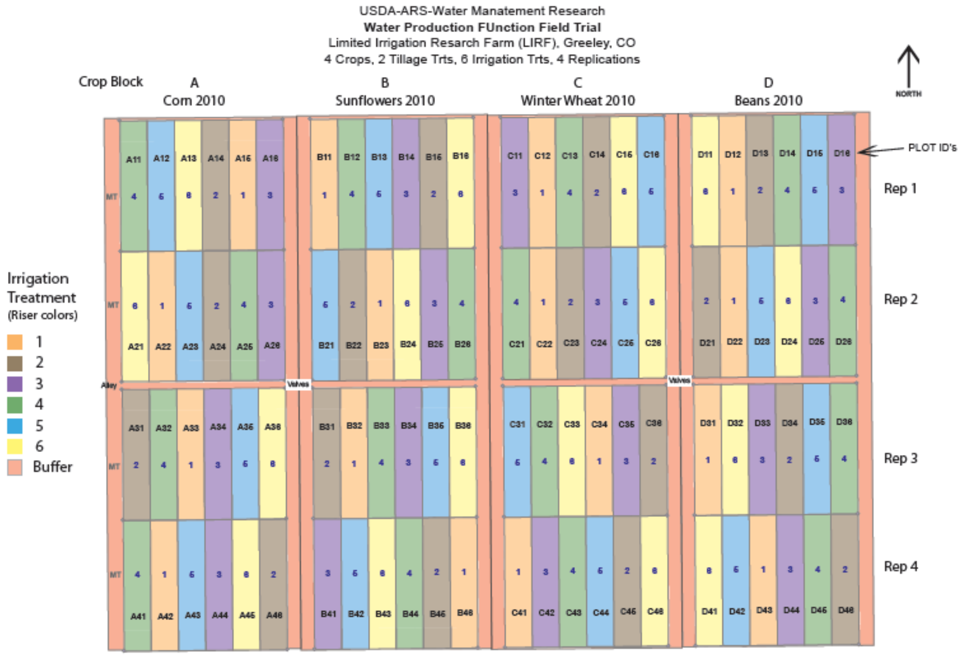

Figure 21. LIRF 2010 Treatment Layout

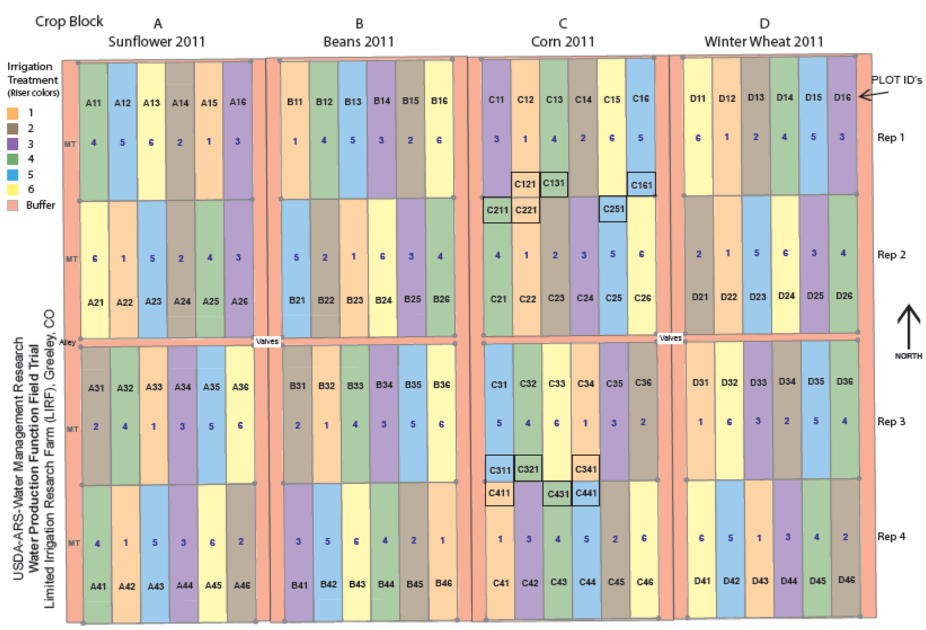

Figure 22. LIRF 2011 Treatment Layout