THESIS

MULTISPECTRAL REMOTE SENSING TO ESTIMATE ACTUAL CROP COEFFICIENTS AND EVAPOTRANSPIRATION RATES FOR GRASS PASTURES IN WESTERN COLORADO

Submitted by

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ABSTRACT

MULTISPECTRAL REMOTE SENSING TO ESTIMATE ACTUAL CROP COEFFICIENTS AND EVAPOTRANSPIRATION RATES FOR GRASS PASTURES IN WESTERN COLORADO

Evapotranspiration is the process by which water moves into the atmosphere by evaporation from the soil surface and transpiration from growing plants. Knowledge of crop evapotranspiration (ETc) is important for effective irrigation water management. Among the various methods used to estimate ETc, the standardized FAO56 Penman-Monteith approach, using tabulated generalized Kc values, has been widely adopted to estimate crop evapotranspiration. Remote sensing techniques are growing rapidly as a way to monitor actual crop water use. Remotely sensed data are used in algorithms to measure the spectral reflectance of the crop canopies. The differences in reflectance values, at different bandwidths from typical multispectral signatures, help determine the current or actual canopy properties like fractional crop cover, water stress, nutrient level, etc. The actual crop coefficients (Kca) were calculated using actual crop evapotranspiration (ETa) and alfalfa based reference crop evapotranspiration (ETr) rates. The soil water balance approach was used to calculate ETa for grass hay/pasture during the 2016 and 2017 growing seasons. A handheld multispectral radiometer was used to collect surface/canopy reflectance data. Vegetation indices (VI) were calculated using the surface reflectance data. Vegetation indices are the mathematical combination or transformation of surface reflectance in different spectral bands. Vegetation indices were then related to Kca to develop Kca(VI) models. Among the 11 different Kca(VI) based models evaluated, the Green normalized difference vegetation index (GNDVI) based

Kca(VI) model performed better on a daily timestep. Depending upon the availability of surface reflectance readings, the user can use either of the four Kca(VI) based models: GNDVI, Transformed vegetation index (TVI), Normalized difference vegetation index (NDVI), or Infrared percentage vegetation index (IPVI) to estimate ETa. However, it is recommended to use the GNDVI based Kca(VI) model for increased accuracy. The results from this study can be used to estimate near real-time ETa rates for grass hay/pastures.

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CHAPTER 1: INTRODUCTION

Evapotranspiration (ET) is the process of movement of water into the atmosphere by evaporation from the soil surface and transpiration from growing plants. Evaporation and transpiration have been historically difficult to measure separately, so the two processes are estimated together to quantify agricultural water use in common practice (Taylor and Ashcroft, 1972). Crop consumptive use (CU) is a close analog to ET. The term CU describes the amount or rate of water that is put to beneficial use through evapotranspiration and incorporation into plant tissue (Cabot et al., 2017). As the term implies, CU is water that is consumed and ultimately rendered unrecoverable for immediate reuse. Reliable estimates of water lost to atmosphere via ET is important to conserve water and to avoid over irrigation of the crops. For effective irrigation water management practices, a reasonable degree of confidence is needed in the baseline ET estimates. There are several methods used for this purpose. The modified Blaney-Criddle method (1962) is used to quantify transferable CU in water court in Colorado (Walter, 2004; Montgomery, 2005). The State of Colorado Consumptive Use (StateCU) model, a form of the modified Blaney-Criddle method, is used by the Colorado Division of Water Resources (CDWR) to estimate CU (CDWR, 2011). Another common approach is Denver Water's coefficients for high mountain meadows (Walter et al., 1990). These coefficients were produced from a 5-year lysimeter study conducted in the South Park area of Colorado. However, there are noted inconsistencies and dissimilarities when characterizing CU in regions with higher elevation, such as the upper Gunnison (Smith, 2008; Juday et al., 2011).

1.1 Traditional Approaches for Assessing Actual Consumptive Use

The Blaney-Criddle equation (Blaney and Criddle, 1962) is widely used although it demonstrates variation in estimation of actual ET (Sammis et al., 2011). The use of Blaney-Criddle has gradually declined while updated models such as the Kimberly-Penman (Wright, 1982), Penman-Monteith FAO-56 (Allen et al., 1998), and ASCE Standardized Reference Evapotranspiration (ASCE-EWRI, 2005) have been adopted more widely. These updated crop models are based on a greater number of hydro-meteorological variables, the inclusion of which is expected to provide more accurate estimates of ET for reference crops like alfalfa (*Medicago Sativa)* - a taller, rough agricultural crop, and grass - a short, smooth crop. These estimates, however, are still calibrated to disease-free, well-fertilized, extensive surface (having expanse of at least 100 m of the same or similar vegetation), and unlimited water conditions. As such, they achieve near-full crop production rates under optimum conditions. The State of Colorado's consumptive use model (StateCU) is also based on reference crop models. Reference crop models then use adjustments called crop coefficients (Kc) to estimate Potential Evapotranspiration (PET) for other crops that exhibit canopy, albedo, stomatal, and aerodynamic characteristics different from the reference surface (alfalfa or grass). The accuracy of reference crop models depends upon the crop coefficient to correctly represent crop types and maturity stages. The output from these models is also bound by the extent that local weather station data can be extrapolated to other locations (Cabot et al., 2017). For example, using only temperature data, as the Blaney-Criddle model does, has been demonstrated to give significantly different predictions as compared to lysimeter measurements (Doorenbos et al., 1977). Although further modifications to the reference crop models can be performed using coefficients to adjust for water stress or dual coefficients to distinguish between basal transpiration (Kcb) – the ratio of crop evapotranspiration and reference evapotranspiration, and soil evaporation (Ke), these modifications are still subject to the same effect for extrapolation.

1.2 Reflectance-based coefficient approach

Remote sensing techniques are commonly being used to monitor crop water use to achieve desired yields without over irrigating crops. The reflectance-based coefficient approach is an empirical (based on observations) method using measured surface reflectance data in specific bands to calculate a vegetation index (VI), which distinguishes vegetative biophysical properties (Viña et al., 2011), that are then related to locally calibrated crop coefficients (Kca) for actual field conditions (Seevers et al., 1994; Rafn et al., 2008; Senay et al., 2011). Vegetation indices calculated using the spectral reflectance can help us to understand the various crop properties like crop health, water stress, nutrient status, etc. Vegetation indices were developed to relate canopy reflectance with canopy biophysical characteristics (Gitelson, 2013). Remote sensing technology can also be used as an effective method to estimate locally calibrated crop coefficients, and overcome the issues associated with the traditional use of a single crop coefficient approach (Singh et al. 2009). In a performance evaluation study done by Er-Raki et al. (2007) for winter wheat in Morocco, they found that the accuracy of this approach can be 70-80%, compared to 44% of that for the FAO-56 procedure (Gowda et al., 2008). Remote sensing based crop coefficients can be accurately used for grain, non-grain, and forage crops (Neale et al., 2003).

Vegetation indices are the mathematical combination or transformation of surface reflectance values from different spectral bands. They are derived using reflectance properties of vegetation. Usually, the visible to near-infrared bands are used to calculate vegetation indices. Differences in reflectance values at different bandwidths from typical multispectral signatures help to determine current or actual canopy properties. For example, the spectral signature of a healthy vegetation surface has a low reflectance in the blue band, higher in the green, low in the red, and very high in the near infrared band of the electro-magnetic spectrum (Genc, 2013). These reflectance values are used in a vegetation index equation to understand the effects that various conditions have on plant health, yield, or quality of the crop (Cropscan, 2001).

Vegetation indices derived from remote sensing have been used previously to estimate crop coefficient for crops like corn (*Zea mays*) (Neale et al., 1989; Bausch, 1993), wheat (*Triticum aestivum*) (Hunsaker et al., 2005), potato (*Solanum tuberosum*) (Jayanthi et al., 2007), soybeans (*Glycine max*) and alfalfa (*Medicago sativa*) (Singh et al., 2009) at the field scale. Vashisht (2016) did a similar study to estimate crop coefficients for grass pastures using the Normalized Difference Vegetation Index (NDVI) derived from satellite data (Landsat 7 and 8) for the Gunnison and Uncompahgre areas of Western Colorado. Table 1 below lists some models developed to estimate the average crop coefficient (Kc) or the basal crop coefficient (Kcb) using NDVI, Soil Adjusted Vegetation Index (SAVI), or Fractional vegetation cover (Fc).

Table 1. Some previously developed models relating vegetation index (VI)/vegetation fraction (Fc) and single crop coefficient (Kc)/basal crop coefficient (Kcb)

Study	Study Area	Crop Type	Model
Neale et al. (1989)	Colorado, USA (Fruita) Colorado, USA (Greely)	Corn Corn	Kc = 1.092NDVI – 0.053 Kc = 1.181NDVI – 0.026
Bausch et al. (1993)	Colorado, USA (Fort Collins)	Corn	Kcb = 1.416SAVI + 0.017
Singh & Irmak (2009)	Nebraska, USA	Irrigated corn Irrigated soybean Irrigated sorghum Irrigated alfalfa	Kc = 1.31NDVI + 0.027 Kc = 1.22NDVI + 0.033 Kc = 1.34NDVI – 0.056 Kc = 0.981NDVI + 0.113

Johnson et al. (2012)	California, USA	Garlic Bell pepper Broccoli Lettuce	$Kcb = -0.985Fc^2+1.759Fc+0.272$ $Kcb = -0.078Fc^2+1.124Fc+0.142$ $Kcb = -0.933Fc^2+1.756Fc+0.181$ $Kcb = -0.985Fc^2+1.759Fc+0.209$
Kamble et al. (2013)	Nebraska and South Dakota, USA	Maize Grass Soybean	Kc = 1.457NDVI - 0.1725
Vashisht (2016)	Western Colorado, USA	Grass	Kc = 1.195NDVI – 0.057
Alam et al. (2018)	NSW, Australia	Grass	$Kc = (1.84 \pm 0.41) \times NDVI^2 - (1.03 \pm 0.48) \times NDVI + (0.42 \pm 0.14)$

Where, NDVI = Normalized Difference Vegetation Index, SAVI = Soil Adjusted Vegetation Index, Kc = single crop coefficient (ratio of crop evapotranspiration and reference evapotranspiration), Kcb = basal crop coefficient (ratio of crop evapotranspiration and reference evapotranspiration when soil evaporation is zero), Fc = vegetation fraction.

Appendix 2 provides further information on the data collection instrument, reference crop type, and actual and reference evapotranspiration computation approaches used to develop models listed in Table 1. The crop coefficients listed in column "Model" in Table 1 are further converted to crop evapotranspiration rates by multiplying with reference evapotranspiration rate (ETref). Depending upon the reference surface used while developing the model, corresponding ETref (grass or alfalfa) should be used for the model to work well.

1.3 Previous Studies on Vegetation Indices

Tucker (1979) conducted studies to relate RED, GREEN, and NIR bands with canopy biomass, water content, and chlorophyll content using a hand-held radiometer. He found that Simple Ratio (SR) - ratio of surface reflectance in the NIR and RED bandwidths, Difference Vegetation Index (DVI), NDVI, and Transformed Vegetation Index (TVI) were sensitive to the amount of photosynthetically active vegetation present in the plant canopy. Also, he concluded that NIR and RED linear combinations were superior to GREEN and RED linear combinations for monitoring vegetation. All combinations of different bandwidths investigated were found to produce very similar results when monitoring vegetation.

Idso et al. (1980) studied the use of the Transformed Vegetation Index (TVI) to estimate crop yield using a hand-held multispectral radiometer. In their study, the surface spectral reflectance was measured in the RED and NIR bands with a hand-held radiometer. They concluded that remote sensing could be a reliable and useful technique to predict and monitor crop yield.

Jackson et al. (1983) compared the SR, NDVI, DVI, and DVI Difference (DD) vegetation indices for their abilities to discriminate vegetation from soil and to detect stress. A hand-held radiometer having bands similar to the Landsat satellite Multispectral Scanner System (MSS) was used. None of the examined vegetation indices were able to meet the criteria for an “ideal” vegetation index. For example, the SR was insensitive to vegetation when green cover was less than 50% but was found to be the most sensitive index when green cover was above 70%. They concluded that the use of a single vegetation index could not adequately assess vegetation over an entire growing season, thus, using two or more indices may be required.

Huete (1988) developed the Soil Adjusted Vegetation Index (SAVI), which was derived from NDVI. SAVI introduced the vegetation density constant (L) to address the soil background effect on vegetation index results. “L” was a function of vegetation density with values of 1, 0.5, and 0.25 for very low, intermediate, and high-density crops respectively.

Crippen (1990) proposed the Infrared Percentage Vegetation Index (IPVI), which was similar to NDVI, but with increased computational speed and a non-negative range. It measures the percentage of near-infrared radiance in relation to the combined radiance from both the NIR and RED bands.

According to Yoder and Waring (1994), the visible band used for computation of NDVI plays an essential role in establishing correlations between the vegetation index and canopy properties. The study was conducted in a greenhouse / laboratory setting with "miniature" canopies of Douglas-fir (*Pseudotsuga menziesii*). The Canopy reflectance was measured using the hemispheric illumination system. The normalized difference vegetation index had a high correlation with canopy properties when using a narrow red band (671-674 nm) while the case was opposite when computed using a narrow green band (565-575 nm). This study points out the need for careful selection of bands when calculating vegetation indices.

Qi et al. (1994) introduced the Modified Soil Adjusted Vegetation Index (MSAVI) based on the original SAVI function. The ground-based and airborne remote sensing data was collected from a cotton canopy (*Gossypium hirsutum*) for this purpose. The vegetation density function L does not appear in the MSAVI equation as it was incorporated into coefficients used in the equation. Performance of MSAVI was found like NDVI at higher vegetation densities and like SAVI for intermediate densities, to result in higher vegetation sensitivity.

In an effort to establish an index not affected by soil reflectance and sun/view geometry, Roujean and Breon (1995) found that soil background had a significant effect on NDVI. The effect of soil background was more significant when the surface cover was lower. Since DVI was less affected than NDVI by soil background, they developed the Renormalized Difference Vegetation Index (RDVI) by utilizing the positive qualities of NDVI and DVI.

Gitelson et al. (1996) developed the Green Normalized Vegetation Index (GNDVI). GNDVI is based on NDVI but uses the GREEN bandwidth instead of RED. The experiments were performed on horse chestnut leaves (*Aesculus hilypocastanum*) and on Norway maple leaves (*Acer platanoides*) using the hemispheric illumination spectrum. This vegetation index was introduced because of its sensitivity to chlorophyll concentration in leaves. GNDVI was found to be more sensitive to a wide range of chlorophyll concentrations than the original NDVI.

Rondeaux et al. (1996) introduced the Optimized Soil Adjusted Vegetation Index (OSAVI) by incorporating an optimum adjust factor which was calculated as 0.16. Rondeaux et al. (1996) suggested that OSAVI can be specifically used for agricultural applications.

Gao (1996) introduced the vegetation index, Normalized Difference Water Index (NDWI), by combining the NIR and SWIR bands. The NIR bands are affected by leaf structure and dry matter but not by moisture content. On the other hand, SWIR bands reflect changes in both canopy water content and vegetation structure. The combination of both these bands helps to eliminate variations produced by vegetation structure and dry matter content, hence improving the accuracy in determining vegetation water content (Ceccato et al., 2001).

In a study conducted by Payero et al. (2003), several vegetation indices were evaluated to estimate canopy heights for alfalfa and grass using a hand-held multispectral radiometer. They established good logistic growth relationships to predict plant height of alfalfa. They concluded that selection of the proper vegetation index is important for higher accuracy for plants like alfalfa and grass.

Tasumi et al. (2005) evaluated the vegetation index based crop coefficient performance for crops like alfalfa, soybean, corn, peas (*Pisum sativum*), potato, sugar beet (*Beta vulgaris*), and wheat in south-central Idaho using satellite images from Landsat 5 and 7. Their study concluded that Kc had a strong relationship to NDVI during the mid-season crop period.

Johnson et al. (2012) conducted a study to monitor vegetable crop evapotranspiration using NDVI. A ground based digital camera was used to measure fractional vegetation cover (Fc). A strong relationship between NDVI and Fc was found with a coefficient of determination (r^2) of 0.96. These Fc data were then converted to actual crop evapotranspiration rates using grass reference evapotranspiration (ETo). They found minimal uncertainty associated with the model for both daily (< 0.5 mm/d) and seasonal (6-10%) evapotranspiration estimates. They conclude this approach can facilitate the timely estimation of crop water use.

Kamble et al. (2013) developed a combined model to estimate crop coefficient based on NDVI for irrigated and rain-fed crops like maize, grass, and soybean from three different study sites using images from the MODIS satellite. Their study also found that a strong linear correlation exists between NDVI estimated Kc and measured Kc with r^2 value of 0.91.

1.4 Multispectral Radiometer Vegetation Indices

Five spectral bandwidths, recorded using a handheld multispectral radiometer, were used to calculate vegetation indices. Table 2 provides the list of vegetation indices evaluated in this study and their corresponding equation. The vegetation indices listed in Table 2 below are commonly used and each are an improvement over previous vegetation index, ranging from a simple NIR to RED bandwidth ratio to indices involving SWIR bandwidths.

Table 2. List of vegetation indices evaluated in this study

Vegetation Index	Abbrev.	Equation	Reference
Simple Ratio	SR	(NIR/RED)	Tucker, 1979
Normalized difference vegetation index	NDVI	(NIR-RED)/(NIR+RED)	Tucker, 1979
Transformed vegetation index	TVI	$(NDVI + 0.5)^{0.5}$	Tucker, 1979
Infrared percentage vegetation index	IPVI	NIR/(NIR+RED)	Crippen, 1990
Soil adjusted vegetation index	SAVI	[(NIR-RED) /(NIR+RED+L)] ×(1+L)	Huete, 1988

Modified soil adjusted vegetation index	MSAVI	$(2NIR+1-[(2NIR+1)^2-8(NIR-RED)]^{0.5})/2$	Qi et al., 1994
Difference vegetation index	DVI	NIR-RED	Roujean and Breon,1995
Renormalized difference vegetation index	RDVI	$(NDVI\times DVI)^{0.5}$	Roujean and Breon,1995
Optimized soil adjusted vegetation index	OSAVI	1.16×(NIR-RED)/(NIR+RED+0.16)	Rondeaux et al., 1996
Green normalized difference vegetation index	GNDVI	(NIR-GREEN)/(NIR+GREEN)	Gitelson and Merzlyak, 1998
Normalized difference water index	NDWI	(NIR-SWIR)/(NIR+SWIR)	Gao, 1996

Note: All vegetation indices listed above are in decimal units.
Where, NIR = surface reflectance in the near infrared band, RED = surface reflectance in the red band, GREEN = surface reflectance in the green band, SWIR = surface reflectance in the short-wave infrared band, L = vegetation density constant (1, 0.5, and 0.25 for very low, intermediate, and high crop densities respectively).

1.5 Problem Statement

It is estimated that nearly 90 percent of agricultural land in the Colorado River Basin requires irrigation, with about 60% of the land exclusively growing forage crops (Cohen, 2013). Irrigated agriculture consumes more than 70% of the Colorado River water supply (Cohen, 2013).

The concept of Water banking is gaining popularity in the western slope of Colorado. Water banking is an approach where water is “stored” or “banked” for later use. Established under Colorado law in 2003, a water bank is a market-based approach to address shortages of water supply by compensating agricultural water users for allowing their water to be temporarily used for another purpose (Cabot et al., 2017). This approach can be used as part of a demand management plan to prevent flow at Lee’s Ferry from declining below minimum levels or to address local water supply issues in Colorado.

A total of 623,295 acres (252,238 hectares) of grass hay production fields were identified suitable for water banking as it is the primary water user on the Western Slope (Natural Resources Consulting Engineers, 2012). It is therefore essential to make accurate estimations of actual grass pasture evapotranspiration. The conserved consumptive use (CU) can be used for water supply management as the demand for water increases and sources are limited. Also, this can be a beneficial strategy (conserving CU) during drought to protect junior water right holders whose water rights are uninterruptible – e.g., domestic use, health use, etc.

Studies have recognized remote sensing as an effective means of overcoming issues of conventional crop coefficient approaches with the potential of developing locally calibrated crop coefficients (Singh et al., 2009). However, the complex agro-environmental conditions, including the use of conventional surface irrigation methods, small to medium field sizes, complex topography, and cloud cover during a growing season affects the accuracy of the remote sensing approach conducted using Earth Observation Satellites (EOS) like Landsat, Sentinel, etc. A ground-based Kca(VI) model for grass pasture, developed using a handheld multispectral radiometer (MSR5, Cropscan®), is proposed for the Western Slope of Colorado to overcome the limitations of remote sensing conducted using Earth Observation Satellites (EOS). A handheld multispectral radiometer is easier to use, data processing is simple as opposed to other EOS based methods, can be used on all field sizes and topography, and useful readings can be obtained even during somewhat cloudy conditions (Cropscan, 2011).

1.6 Objectives

The overall goal of this project was to develop quantitative relationships to improve the estimation of actual crop coefficients (average single Kca) from multispectral radiometer data, measured at point scale on the field, for grass hay/pastures on the Western Slope of Colorado. The objectives of this study were to:

1) Develop local calibration equations for soil water content sensors.
2) Use the soil water balance approach to determine actual evapotranspiration rates of grass hay/pastures based on data from Montrose and Gunnison county study sites.
3) Develop Kca(VI) models for grass pastures.
4) Evaluate the performance of Kca(VI) models.

CHAPTER 2: MATERIALS AND METHODOLOGY

2.1 Study Area

The study was conducted at two grass hay/pasture sites, one at the Lower Gunnison and one at the Upper Gunnison River Basin. Figure 1 below shows the location of study sites.

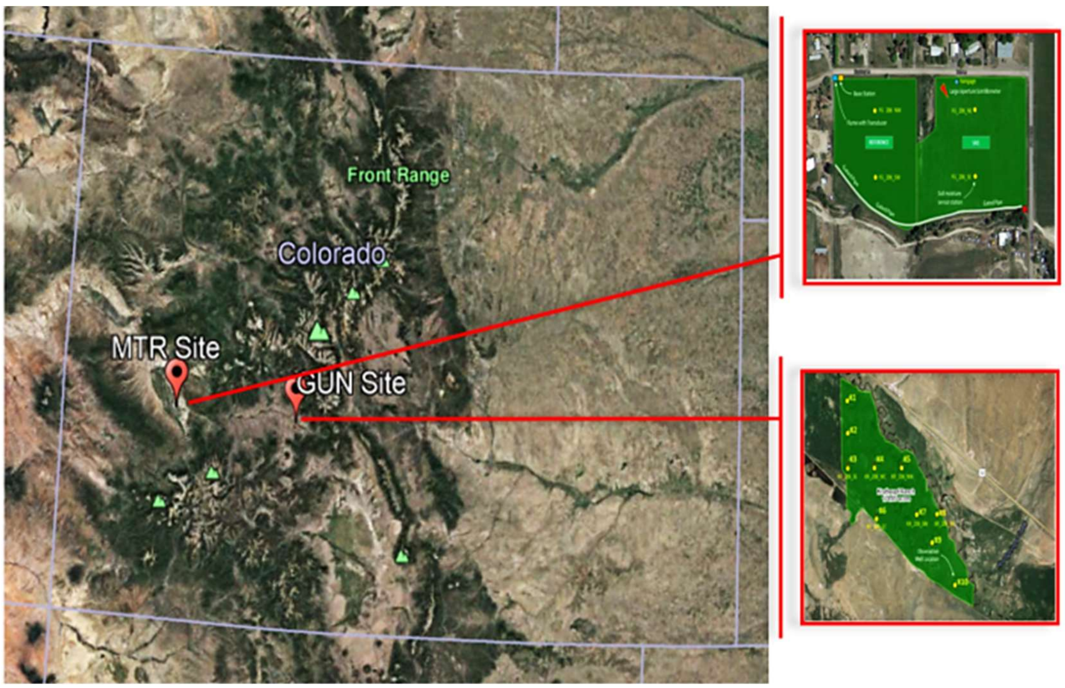

Figure 1. Montrose and Gunnison County Study Sites

2.1.1 Grass Hay/Pasture Site #1 (Montrose, CO)

One of the two grass hay/pasture sites was at approximately 38.509˚ N and -107.874˚ W, elevation ~1765 m at Montrose County, Colorado (MTR). This site has been historically furrow-irrigated using gated pipe along the south side of the property. The site (Figure 2) is 14.50 ac (5.86 ha), was divided into two treatments: 1) Reference (REF) irrigation conditions under typical management and historical water diversion, and; 2) Treatment (TRT) irrigation replicating a potential water bank scenario where irrigation is applied for part of the season up until a specific date. The full irrigation (REF) and reduced irrigation (TRT) fields were 6.30 ac (2.54 ha) and 8.20

ac (3.31 ha), respectively. The Montrose reference plot (MTR REF) was irrigated throughout the season, while the Montrose treatment plot (MTR TRT) received no water after May 12 in 2016. Grass coverage is dominantly (~40%) fescue (*Festuca arundinace*), with minor coverage of smooth bromegrass (*Bromus inermis*) and bluegrass (*Poa pratensis*). Interspersed coverage (<10%) of plantago (*Plantago lanceolate*), chicory (*Cichorium intybus*) and some volunteer alfalfa (*Medicago sativa*) was also noted. Plant species composition data were collected using a modified step-point method (Owensby, 1973). Soils are described by the Natural Resources Conservation Service (NRCS) Soil Survey Geographic (SSURGO) Database as Loutzenheiser silty clay loam. Soil field capacity, wilting point, and textural class analyses from several cores (0-30 cm) on the MTR REF and MTR TRT fields were also conducted by Midwest Laboratories (Omaha, NE). Table 3 lists the results of the lab analysis, which was also used for soil water balance calculations (discussed later).

Table 3. Soil Characteristics at the Montrose (grass hay/pasture) field site

Irrigation	Abbrev	Area	Field Capacity	Wilting Point	Available Moisture	Textural Class
Full	REF-MTR	6.3 ac	31.29 %	17.47 %	13.82 %	Clay
Full	REF-MTR	6.3 ac	26.62 %	11.61 %	15.01 %	
Full	REF-MTR	6.3 ac	27.10 %	11.59 %	15.51 %	
Partial-Season	TRT-MTR	8.2 ac	33.33 %	12.44 %	20.89 %	Clay Loam
Partial-Season	TRT-MTR	8.2 ac	30.57 %	21.49 %	9.08 %	
Partial-Season	TRT-MTR	8.2 ac	24.79 %	14.16 %	10.63 %	
Partial-Season	TRT-MTR	8.2 ac	33.98 %	14.02 %	19.96 %	
Partial-Season	TRT-MTR	8.2 ac	37.41 %	14.88 %	22.53 %	

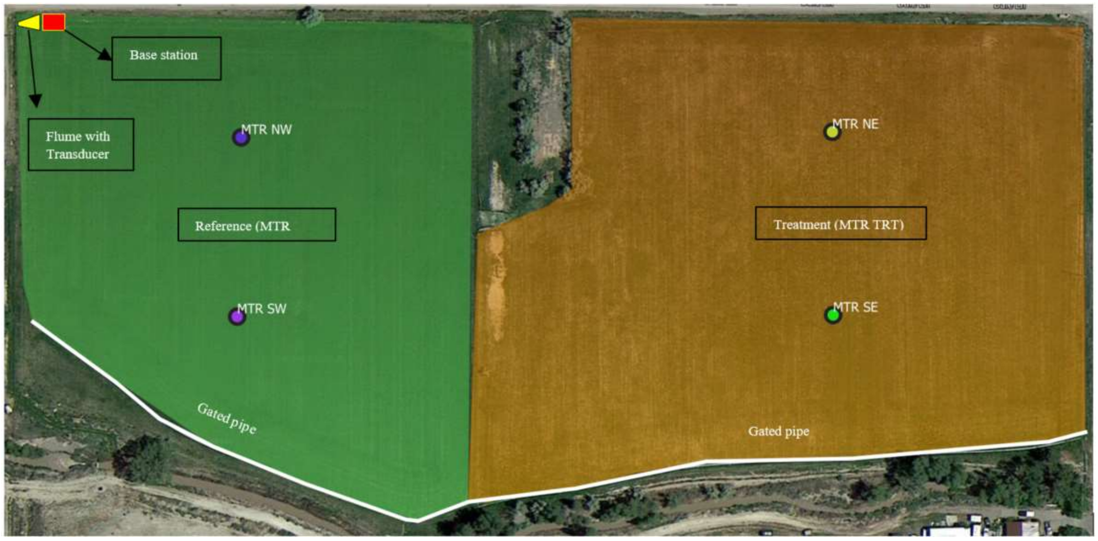

Figure 2. Montrose field site layout with instrumentation

2.1.2 Grass Hay/Pasture Site #2 (Gunnison, CO)

The other grass hay/pasture site was located at approximately 38.458˚ N and 106.634˚ W, elevation ~2448 m in Gunnison County, Colorado (GUN). This site has been historically wild-flood irrigated (water flows across the field freely). Irrigation water is supplied from a shared diversion structure along the Coats Brothers Ditch, which takes water from Tomichi Creek. The study site (Figure 3) is 178 ac (72.03 ha). In 2016, the entire 178 ac was entered into a short-term lease with the Colorado Water Conservation Board (CWCB), to use decreed water as an instream flow. The uneven topography of the field suggested that some portion of the field would receive much less irrigation than others.

Grass coverage consists of a mix of common meadow foxtail (*Alopecurus pratensis*), timothy (*Phleum pratense*), smooth bromegrass (*Bromus inermis*), and orchard grass (*Dactylis glomerata*). Plant species composition data were gathered from the producer. Soils are described by the NRCS Soil Survey Geographic (SSURGO) Database as silty clay loam with slightly decomposed plant material in the top 15 cm and very gravelly loam at greater depths . From field observations, the soils and root zone on these fields were found to be very shallow, underlain by river cobble. Table 4 below provides information of groundwater well locations and depths corresponding to Figure 3. Transducers were installed at the observation points K3, K4, K5, K6, K7, and K8 to record the fluctuation in groundwater table.

Table 4. Groundwater observation well locations at Gunnison site

ID	Longitude	Latitude	Elevation		Depth (inches)
K1*	-106.63683542666982	38.4621987270425	2442.5	m	---
K2	-106.63683542666982	38.4603841143088	2443.5	m	37.00
K3	-106.63683542666982	38.4586870740551	2444.3	m	45.00
K4	-106.63449654042319	38.4586870740551	2443.7	m	37.50
K5	-106.63383135257986	38.4558305795152	2445.5	m	40.25
K6	-106.63071999012634	38.4586870740551	2443.6	m	41.00
K7	-106.6290892070379	38.4558305795152	2445.7	m	52.00
K8	-106.62685760914582	38.4558305795152	2446.1	m	37.00
K9	-106.62743696628749	38.4541502357754	2446.1	m	46.00
K10	-106.62486204563383	38.4517976887909	2450.5	m	64.00

"*" no observation well

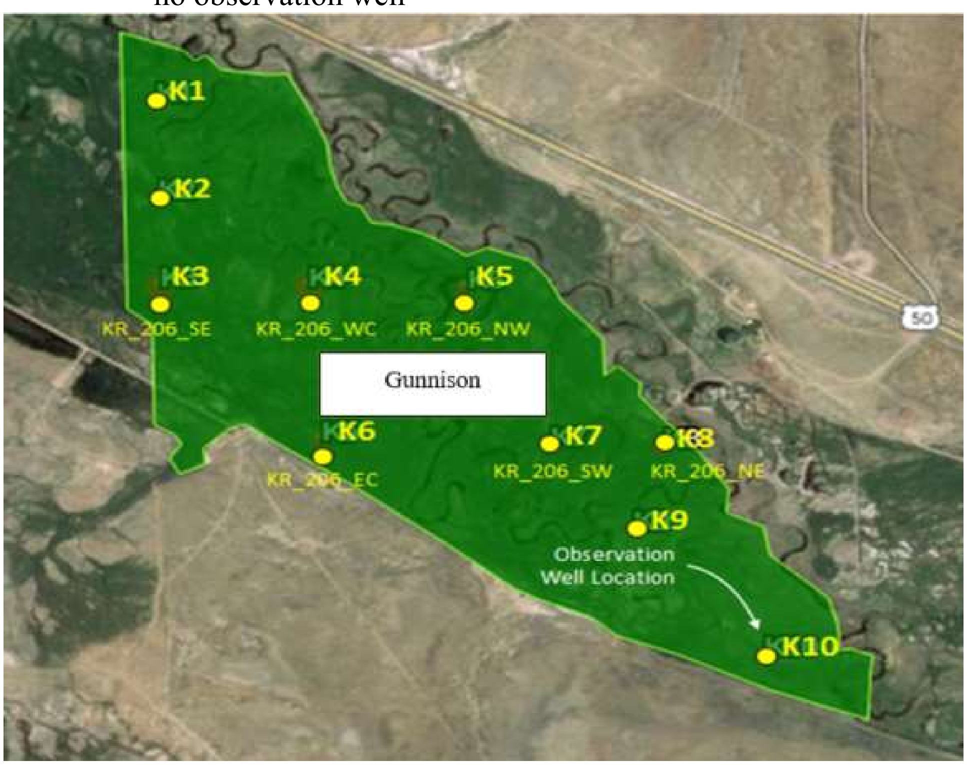

Figure 3. Gunnison field site layout with instrumentation

2.2 Soil Water Balance Instrumentation

Irrigation water volumes diverted to the MTR site were measured using a McPropeller (McCrometer, Hemet, CA) flow meter. Irrigation water volume was not measured at the GUN site due to the type of irrigation used (wild flood). Flow meter data were recorded using a CR206X data logger (Campbell Scientific, Logan, UT). Tailwater flow at MTR was recorded using an EZ Flow Nu-Way ramp flume (Welfelt Fabrication, Delta, Colorado) equipped with a stilling well. A pressure transducer, CS451 (Campbell Scientific, Logan, UT), and a CR206X data logger (Campbell Scientific, Logan, UT) were used to measure and record flow volume at the flume. Precipitation amount was obtained from the nearest (Montrose, MTR01 and Gunnison, GUN01) CoAgMet weather station (www.coagmet.edu).

Soil moisture was measured at MTR and GUN sites using CS655 (Campbell Scientific, Logan, UT) volumetric water content sensors – installed in 2015 at 6 in (15 cm), 18 in (45 cm), and 24 in (60 cm) depths from the ground level. These sensors collected data at 30-minutes intervals. The Montrose site was equipped with two soil moisture sensing stations in each plot (REF and TRT). The position of these stations was located at 25% and 75% along the distance of the furrow and at the center of each plot. The Gunnison site had six soil moisture sensing stations at locations representing low, middle, and high points in the field to include the topographical variations in the study area.

Subsurface movement of water was tracked to assess the potential upflux due to capillary rise (U) and loss of water to deep percolation (DP). A one-dimensional soil water balance model was applied at the study sites; lateral flow of water was not measured. The occurrence of U and DP was assessed relative to the change in depth of the groundwater table. Groundwater levels were recorded using 1 in (2.5 cm) PVC observation wells equipped with Level logger pressure transducers (Solinst®, Georgetown, ON) at both sites. Barometric pressure correction was done for the transducers installed using separate onsite barometric loggers (Solinst®, Georgetown, ON).

2.3 Soil moisture sensor calibration

Calibration of the CS655 (Campbell Scientific, Logan, UT) sensor is necessary for accurate characterization of soil water content. These sensors estimate the volumetric water content of soil using electromagnetic soil properties. In a performance evaluation study of similar sensors (CS616/625) by Varble et al., (2011), it was found that factory-based calibration of volumetric water content did not achieve the required accuracy in sandy clay loam, loamy sand, and clay loam soils near Greeley in north eastern Colorado. They further recommended using locally (in-situ) calibrated equations over factory-based equations, since field data are more representative of the actual conditions in which sensors operate. For field-based calibration, 107 gravimetric soil samples were taken at locations near the sensing stations using a Madera Probe (Precision Machine Inc., Lincoln, NE) at depths of 6 in (15 cm), 12 in (30 cm), and 18 in (45 cm). Soil samples were collected extensively for the 2016 and 2017 field seasons from Montrose site, and five other study sites (located at Fruita, Orchard Mesa, Eckert, Delta, and Yellow Jacket) not included in this study. Due to the location of the Gunnison site, it was not possible to perform regular soil sampling. Soil samples were collected to capture the drying curve of soil moisture. All collected samples were used to develop local calibration equations for the CS655 (Campbell Scientific, Logan, UT) sensors. The soil samples were oven dried for 24 hours at 105 ^{o}C (California test 226, 1999). The change in mass was used to compute soil volumetric water content (VWC). These gravimetrically derived VWC data were plotted against the soil water content readings from the CS655 (Campbell Scientific, Logan, UT) sensors to obtain calibration curves. Sensors were calibrated according to the soil type, plus a general equation was also developed to represent different soil types for the Western Slope of Colorado.

2.4 Weather Data

Weather data was downloaded from Colorado Agricultural Meteorological (CoAgMet) weather stations listed in Table 5 below. The research sites selected were in close proximity of these weather stations. The Montrose and Gunnison sites were 3.4 miles and 17.6 miles away from the nearest weather stations respectively. The weather stations collected various meteorological variables like solar radiation, air temperature, humidity, wind speed, vapor pressure and precipitation. For this study, 2016 and 2017 meteorological data were accessed from these stations.

Table 5. List of weather stations with elevation and reference crop type

Station (Code)	Elevation (m)	Reference crop type
Montrose (MTR)	1722	Grass
Gunnison (GUN)	2406	Grass

2.5 Soil Water Balance

Soil water balance (SWB) was performed to calculate actual crop evapotranspiration (ETa) rates. Generally, SWB is only a function of the change in soil water content throughout the plant rooting depth, given that there are no infrequent irrigations and negligible upflux or capillary rise. The general SWB equation can be written as below (Andales et al., 2011):

$$Dc = Dp + ETa - P - Irr - U + SRO + DP \qquad (1)$$

Where,

Dc = Soil water deficit or depletion at current day (mm)

Dp = Soil water deficit or depletion at previous day (mm)

ETa = Crop evapotranspiration rate at current day (mm)

P = Effective precipitation (mm)

Irr = Gross irrigation amount (mm)

U = Groundwater upflux (mm)

SRO = Surface runoff volume (mm)

DP = Deep percolation (mm)

A crop extracts water from the soil to satisfy its evapotranspiration requirements. Hence, stored soil water is gradually depleted from the root zone of the crop. The difference between the volumetric water content at field capacity and current soil volumetric water content is considered as the soil water deficit (D). Tracking this change can help us understand the ETa rate. The soil water deficit is defined mathematically by Equation 2 below:

$$\text{Soil water deficit (D)} = (\theta_{FC} - \theta_i) \times Rz \qquad (2)$$

Where,

θ_{FC} = soil water content at field capacity (mm/m)

θ_i = soil water content at current day (mm/m)

Rz = root zone depth (m)

The root zone depth of a crop plays a vital role in determining crop ETa rates. The rootzone depth and upflux possibility were analyzed based on data from crop season 2016. Giddings soil core sample observations and auguring indicated that the root zone was not likely to penetrate the depth of 30 in (75 cm) at MTR site. Also, the groundwater table at the MTR site was mostly deeper than 30 in (75 cm) below the surface for the entire season (see appendix). The groundwater table was found at the level of rootzone at MTR NE sensing station; however, there was no noticeable change in volumetric soil water content readings in the deeper sensors to confirm the possibility of roots extracting water from that depth. This indicates that the rootzone might be shallower than 30 inches as well. The rootzone depth of 30 in (75 cm) was used for SWB for MTR site. The GUN site had a much shallower root zone depth. A previous study in the high mountain meadows of Colorado also suggests that there is a sharp reduction in root matter at the interface of rocky layers found close to the surface and approximately 6 in (15 cm) above the water table (Walter et al., 1990). The groundwater table at GUN was at a constant 24 in (60 cm) depth from the surface except for during irrigation events. Thus, the rootzone was estimated at 18 in (45 cm) for this study site.

The soil water upflux was negligible at MTR based on a very deep groundwater level from the surface, presence of a impermeable layer at depth of 30 in (75 cm) from the soil surface, and electrical conductivity (EC) measured by deep sensors. In the event of soil water upflux, the EC is expected to increase as the movement of salts would occur upward. However, no such movement was observed (appendix Figure 33). Similarly, at GUN, the possibility of upflux was neglected due to the presence of rocky soils, which had no potential of creating capillary rise of groundwater. Prior studies of intermountain meadows also state that those rocky soil layers imposed significant restrictions on capillary rise of water into the root zone (Walter et al., 1990).

Based on the approaches and assumptions considered, the SWB equation was further simplified and re-arranged to calculate ETa as presented in the Equation 3 below:

$$ETa = (Dc - Dp) + P + Irr - SRO \quad (3)$$

Equation 3 was further simplified by calculating the terms Irr and SRO as one single term, which was represented by the change in volumetric soil water content level in the rootzone between previous and current day at the particular sensing station.

2.6 Forage Yields

Forage yields data were recorded for Montrose and Gunnison study sites for each cutting cycle. Ten forage samples were collected at each treatment prior to harvest to calculate yield. Yield samples were collected using a 0.25 m^2 frame, hand clipped at 7.5 cm to simulate approximate cutter-bar height of a harvester. Plant material was dried in a forced-air oven at 55°C for 72 hours. The dry weights were then converted to mega-grams per hectare (Mg/ha). In instances when the forage samples were not collected, the bale count number was obtained from the producer and was converted to mega-grams per hectare.

2.7 Actual Crop Coefficients Estimation

Alfalfa reference evapotranspiration (ET_r) based on the ASCE standardized reference evapotranspiration equation (ASCE EWRI, 2005), on a daily time step, was used in this study. The reason for selecting the alfalfa reference surface for this study is basically because the weather stations (CoAgMET), which are very commonly used in Colorado, calculates reference evapotranspiration rates based on the alfalfa reference surface. Thus, models developed using alfalfa reference surface is expected to save time and avoid complicated calculations of reference evapotranspiration rates for the end users. The ASCE standardized reference evapotranspiration equation to estimate ET_r is given by Equation 4 below:

$$ET_{sz} = \frac{0.408\Delta(R_n - G) + \gamma \frac{Cn}{T + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + Cd u_2)} \quad (4)$$

Where,

ETsz = standardized reference crop evapotranspiration for reference surfaces

[mm day^{-1}],

R_n = calculated net radiation at the crop surface [MJ m^{-2} day^{-1}],

G = soil heat flux density at soil surface [MJ m^{-2} day^{-1}],

T = mean daily air temperature at 1.5 to 2 m height [°C],

u_2 = mean daily wind speed at 2 m height [m s^{-1}],

e_s = saturation vapor pressure at 1.5 to 2 m height[kPa],

e_a = mean actual vapor pressure at 1.5 to 2m height[kPa],

$e_s - e_a$ = saturation vapor pressure deficit [kPa],

Δ = slope vapor pressure-temperature curve [kPa °C^{-1}],

γ = psychrometric constant [kPa °C^{-1}],

Cn = numerator constant that is a function of reference type and calculation time step [K mm s^3 Mg-1],

Cd = denominator constant that is a function of reference type and calculation time step [s m^{-1}].

The ETr obtained using Equation 4, and ETa using Equation 3 were used to calculate actual crop coefficients (Kca). Actual crop coefficient (Kca) is defined as the ratio of ETa and ETr (Allen et al., 1998) and is given by Equation 5 below:

$$Kca = ETa/ETr \qquad (5)$$

2.8 Surface Reflectance Measurements

Surface reflectance and temperature data were collected using a multispectral radiometer MSR5 (Cropscan, Rochester, MN). The MSR5 is housed in an 8 x 8 x 8 cm casing, made of anodized aluminum. It consists of an upward and downward facing set of sensors that measure both incoming and reflected radiation from the surface, which allows taking reflectance readings of the crop surface. The MSR5 measures surface reflectance in 5 bandwidths between 460 and 1750 nanometers. The field (ground diameter) view of the sensor is 28 degrees, which allows for a field diameter equal to half the height at which the radiometer is held from the ground. The data collected were stored in the instrument's data logger controller (DLC) in millivolt format, which was later processed using Cropscan software to obtain the surface reflectance in percentages.

The MSR5 was used to collect ground-based remote sensing data during the crop growing seasons of 2016 and 2017. Measurements were taken at approximately solar noon and timed to coincide with dates of Landsat 7 and Landsat 8 overpasses. The surface reflectance readings were taken near the locations of soil water content sensing stations. Table 6 below lists the data collection days for the study sites.

Table 6. MSR5 data collection days for 2016 and 2017 field season

MTR		GUN	
2016	2017	2016	2017
6/28/2016	5/30/2017	6/21/2016	6/16/2017
7/14/2016	6/7/2017	7/7/2016	6/24/2017
7/30/2016	6/15/2017	7/23/2016	7/10/2017
8/7/2016	7/11/2017		7/18/2017
8/15/2016	7/17/2017		9/12/2017
8/23/2016	7/26/2017		9/20/2017
9/8/2016	8/2/2017		
	8/10/2017		
	8/24/2017		
	9/3/2017		

2.9 Reflectance Based Model Evaluation

The calculated Vegetation Indices (VI) listed in Table 2 were regressed against the crop coefficients (Kca) obtained from Equation 5 for each date listed in Table 6 above. Eleven different Kca(VI) models were developed for grass hay/pasture. Multiple surface reflectance readings were recorded at each sensing station on every data collection day. A total of 402 surface reflectance data points were collected using MSR5 for developing the Kc(VI) models. However, only 108 surface reflectance data points were found useful because of technical issues related to soil water content sensors. In addition, 26 surface reflectance data points were collected and used to validate the Kca(VI) models developed. Since multiple surface reflectance readings were collected at areas surrounding the sensors, their average value was used in validation.

The surface reflectance data were collected for the crop season of 2016 and 2017 for both study sites. Due to the limited amount of data collected, it was decided to separate the data from these study sites into two categories: model development and model validation. Since each water content sensing station was treated as a separate unit (not influenced by surrounding sensing stations), data collected from the MRT NW sensing station in 2017 was separated as an independent dataset to validate the Kca(VI) models. The rest of the data collected from all sensing stations from both study sites in 2016 and 2017 were used to develop the Kca(VI) models.

Surface reflectance readings collected around the MTR NW sensing station in 2017 were used in the Kc(VI) models developed. The estimated crop coefficients were then multiplied by ETr to obtain model estimated actual crop evapotrasnpiration rates for grass hay/pastures. The modeled and measured crop evapotranspiration were linearly regressed to evaluate the relationship between them. The modeled and measured crop evapotranspiration rates for a cutting cycle (from 7/11/17 to 9/3/17) were linearly regressed to evaluate the Kc(VI) model's performance.

2.10 Statistical Evaluation

The main statistics used to evaluate the performance of the Kca(VI) models were the Root Mean Square Error (RMSE), Mean Biased Error (MBE), and Nash Sutcliffe Coefficient of Efficiency (NSCE) calculated using Equation 6, Equation 7, and Equation 8. RMSE measures the average magnitude of the error. It is the square root of the average of squared differences between predicted and observed values. MBE describes the model bias. A negative MBE indicates that predicted values are smaller than the actual observed values. The NSCE is used to assess the predictive power of a model. The value of NSCE ranges from negative infinity to 1, with negative values indicating unacceptable model performance while values closer to 1 indicate an increase in the model's accuracy.

$$RMSE = [N^{-1}\sum_{i=1}^{N}(P_i - O_i)^2]^{0.5} \tag{6}$$

$$MBE = N^{-1}\sum_{i}^{N}(P_i - O_i) \tag{7}$$

$$NSCE = 1 - \frac{\sum_i^n (P_i - O_i)^2}{\sum_i^n (O_i - O_o)^2} \tag{8}$$

Where Pi, Oi, O_o, and n are predicted value, observed value, mean of observed values, and total number of observations respectively.

In addition to the above-mentioned statistics, one-way analysis of variance (ANOVA) was also performed to determine whether there were any statistically significant differences between means of the crop evapotranspiration rates estimated by the developed Kca(VI) models and actual measured rates. The ANOVA compares the means between the groups (Ott et al., 2010). ANOVA tests the null hypothesis given by Equation 9 below:

$$Ho = \mu_1 = \mu_2 = \mu_3 = \ldots\ldots = \mu_k \tag{9}$$

where μ = mean of the group and k = number of groups. However, if the ANOVA returns a statistically significant result, the null hypothesis is rejected, and the alternative hypothesis (Ha) is accepted, which means that there are at least two groups whose means are significantly different from each other.

CHAPTER 3: RESULT AND ANALYSIS

3.1 Soil Water Content Sensors Calibration

Two calibration equations were developed for CS655 (Campbell Scientific, Logan, UT) soil volumetric water content sensors from the field gravimetric soil samples collected. Figure 4 below shows the general calibration equation developed using all gravimetric soil samples collected from five different study sites. It represents the general calibration equation for the Western Slope. These sensors were also calibrated based on the soil type. Figure 5 below shows the calibration equation for silty clay loam soils. The Montrose site was identified as silty clay loam, whereas, a general calibration equation was applied to the Gunnison site. The volumetric soil water content (VWC) measured by CS655 sensors were then calibrated using these equations and the calibrated VWC measurements were used to perform the soil water balance. These sensors were found to give more accurate readings when the recorded soil VWC is less than 20 m^3/m^3 (RMSE = 4.05% and MBE = 2.15%), whereas, the sensor's soil VWC was found to be higher when the recorded soil VWC was higher than 20 m^3/m^3 (RMSE = 11.43% and MBE = 10.44%).

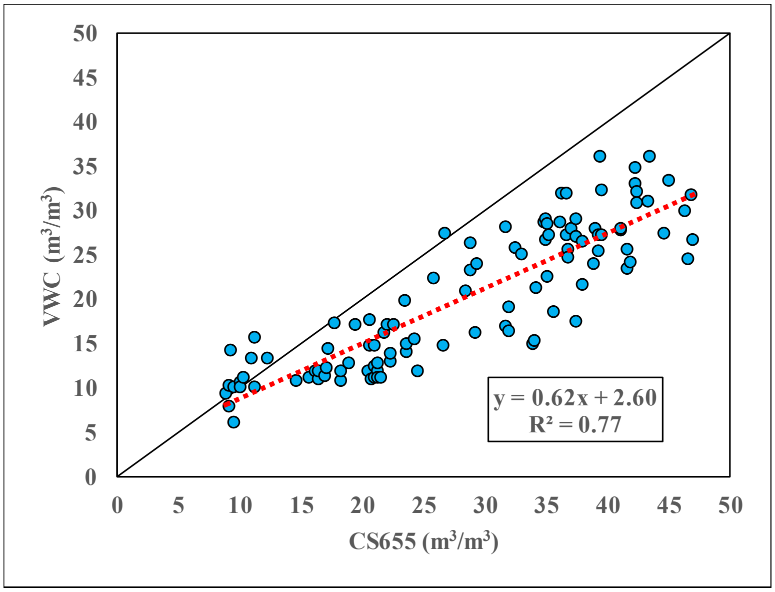

Figure 4. CS655 general calibration equation

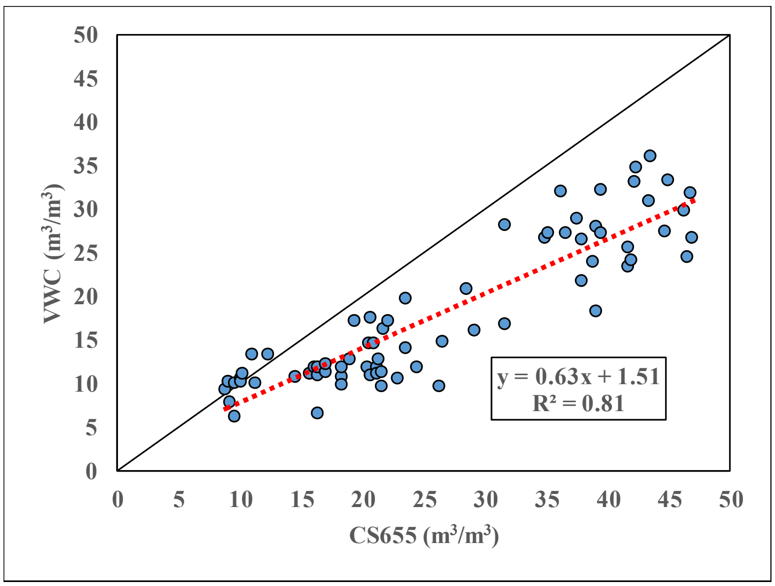

Figure 5. CS655 calibration equation for silty clay loam soil

3.2 Soil Water Balance

Soil Water Balance (SWB) was performed for crop growing seasons of 2016 and 2017 to calculate actual evapotranspiration (ETa) rates. Figure 6 shows the seasonal ETa calculated for grass hay/pasture for the Montrose and Gunnison sites. The Montrose reference (MTR REF) field was not subjected to any water stress for the entire study period. The seasonal ETa for MTR REF in 2016 was calculated at 471.8 mm while it was 425.3 mm in 2017. However, the yields remained fairly similar for both years. The average yield recorded for the MTR REF field was 1.21 Mg/ha in 2016 and 1.28 Mg/ha in 2017 for each cutting cycle.

The Montrose treatment (MTR TRT) field, which was subjected to partial season stress in 2016, showed an increase in ETa in 2017. The seasonal ETa calculated for 2016 was 300 mm while it increased to 363.1 mm in 2017. Also, the recorded yield was higher when compared to the previous year's yield data. The average yield recorded for the MTR TRT field was 0.84 Mg/ha in 2016 with no yield in the second cutting cycle. However, in 2017 the yield was 0.96 Mg/ha in the first cutting and 0.79 Mg/ha in the second cutting cycle. This result shows that grass hay/pasture can withstand occasional water stress, without significant long-term effect, and makes it a suitable crop to be included in water banking.

The Gunnison (GUN) site showed slightly decreased ETa between 2016 and 2017 (Figure 6). The seasonal ETa was calculated at 296.6 mm in 2016 and 250.7 mm in 2017. Yield data were not available from this field. Similar irrigation practices were used for both years. Irrigation was stopped certain time before the cutting to allow the field to drain down the standing water.

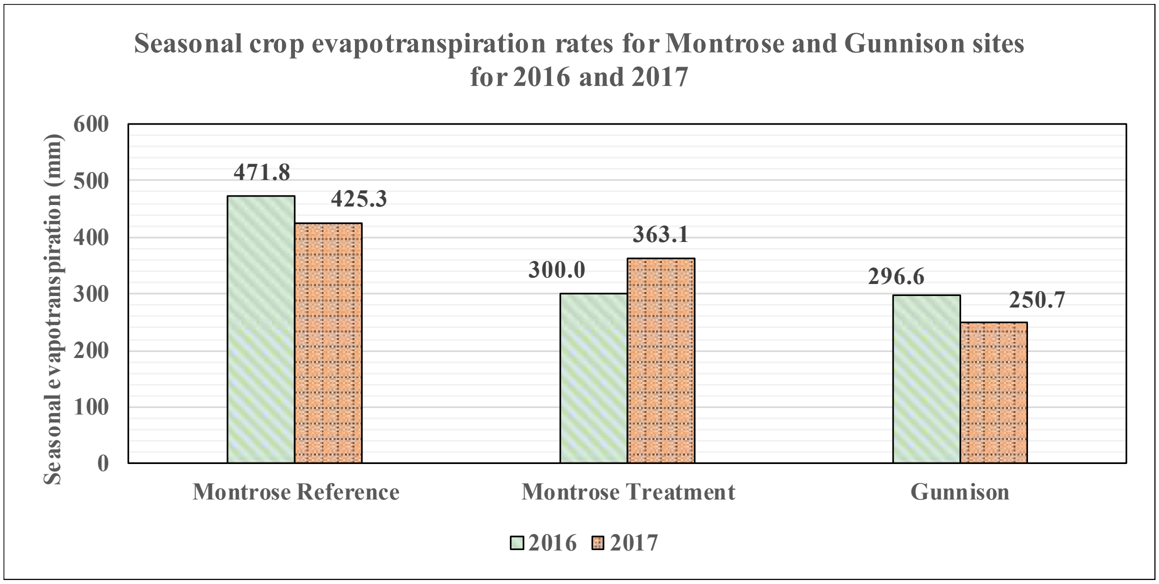

Figure 6. Seasonal crop evapotranspiration rates for Montrose and Gunnison sites for 2016 and 2017

Table 7 below shows the average weather conditions and number of days in the crop season for both the MTR and GUN study sites. On average, there was a slight increase in mean temperature for both sites. A decrease (99.39 mm) in precipitation amount was recorded at the Gunnison site while the precipitation increased by 6.35 mm in 2017 at the Montrose site.

Table 7. Study sites and average weather conditions for crop seasons

Site	Year	Mean Temp. (°F)	Max Temp. (°F)	Min Temp. (°F)	Total Precipitation (mm)	Number of days in crop season
MTR	2016	62.3	79.8	44.8	84.58	141
MTR	2017	65.0	82.1	48.0	90.93	141
GUN	2016	51.3	72.1	32.6	199.39	169
GUN	2017	52	71.6	32.5	100.33	169

Figures 7 through 10 below shows the actual evapotranspiration rates (ETa) and volume soil water content (VWC) for the Montrose and Gunnison sites for 2016 and 2017. The calculated ETa values for both sites were much lower than the ASCE standardized ETr. For the fully irrigated condition at the Montrose site, ETa was found to be 44% of ETr while it was only 30% of ETr for the Gunnison site. Thus, using average published crop coefficients to calculate ETa might not be representative of actual field evapotranspiration rates. One possible solution to this problem could be using the dual crop coefficient method, which takes into account the single crop coefficient (Kcb), crop water stress coefficient (Ks), and soil evaporation coefficient (Ke) (Hoffman et al., 2007). The limitation to the dual crop coefficient method is in properly modeling Ks and Ke.

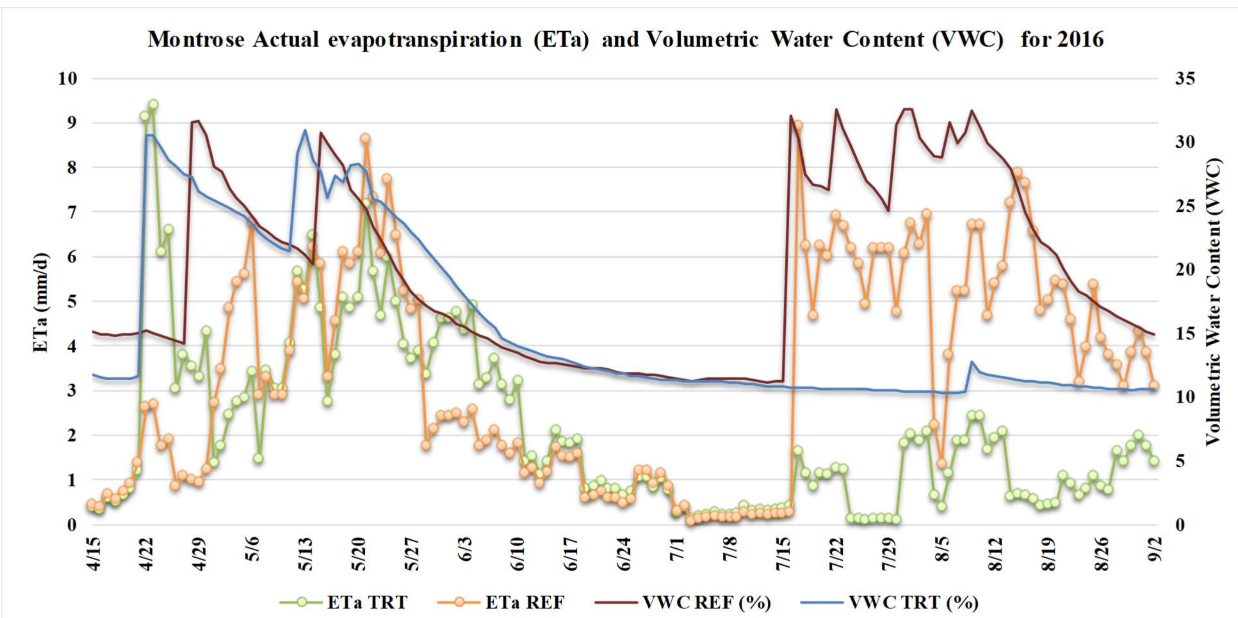

Figure 7. Actual evapotranspiration (ETa) and volumetric water content (VWC) graph for Montrose reference and treatment fields (2016)

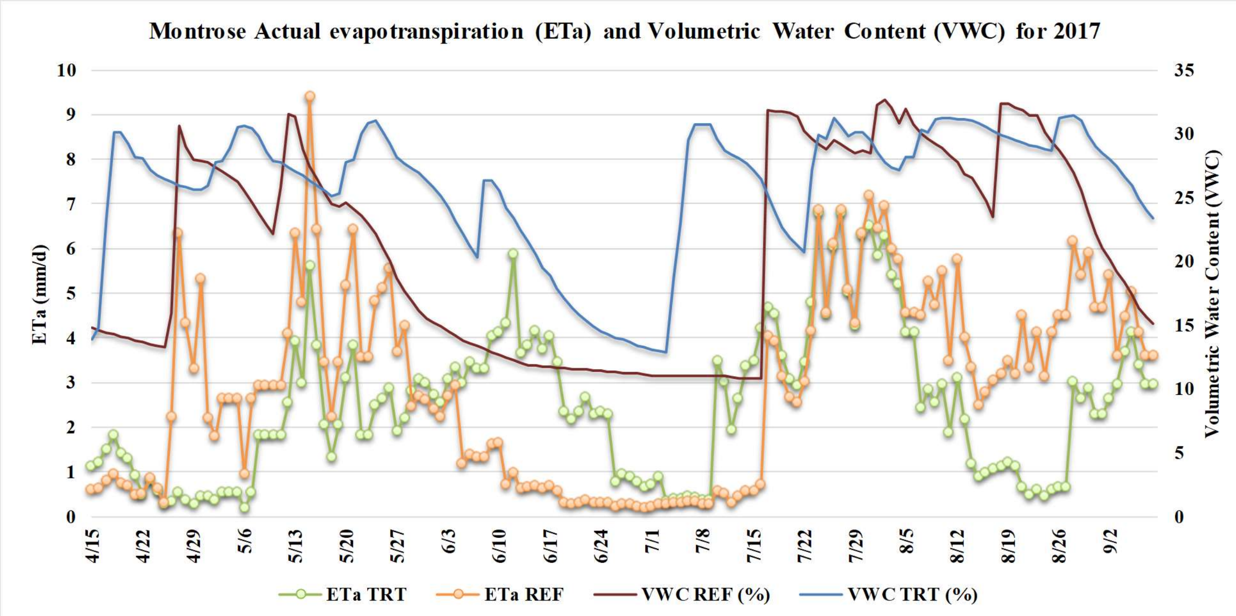

Figure 8. Actual evapotranspiration (ETa) and volumetric water content (VWC) graph for Montrose reference and treatment fields (2017)

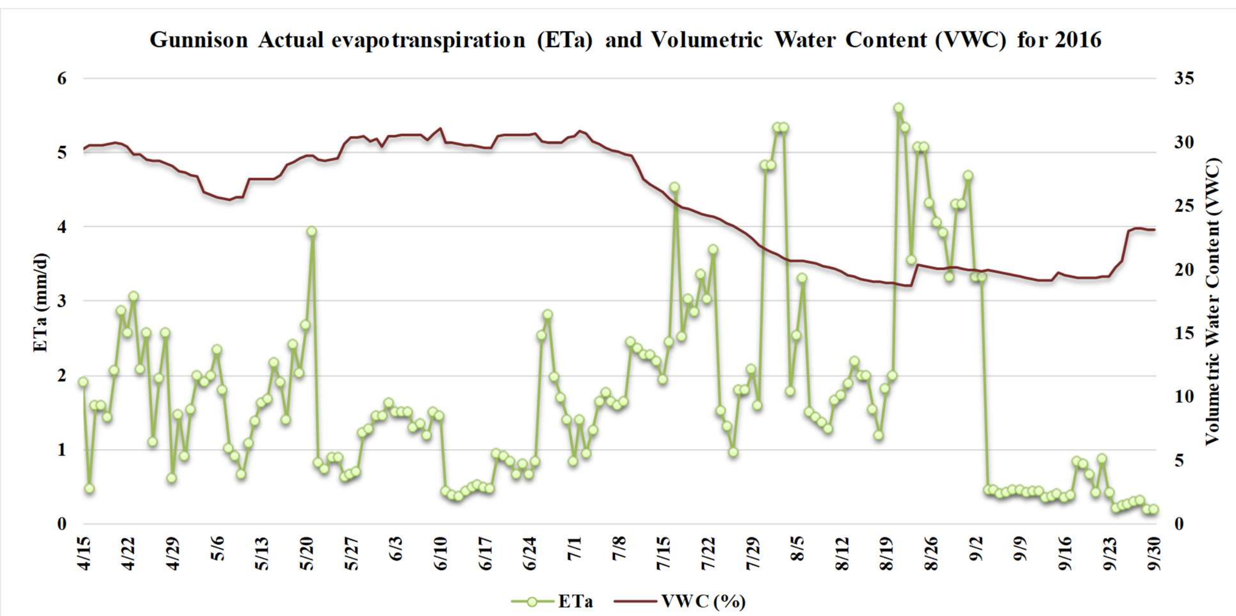

Figure 9. Actual evapotranspiration (ETa) and volumetric water content (VWC) graph for Gunnison site (2016)

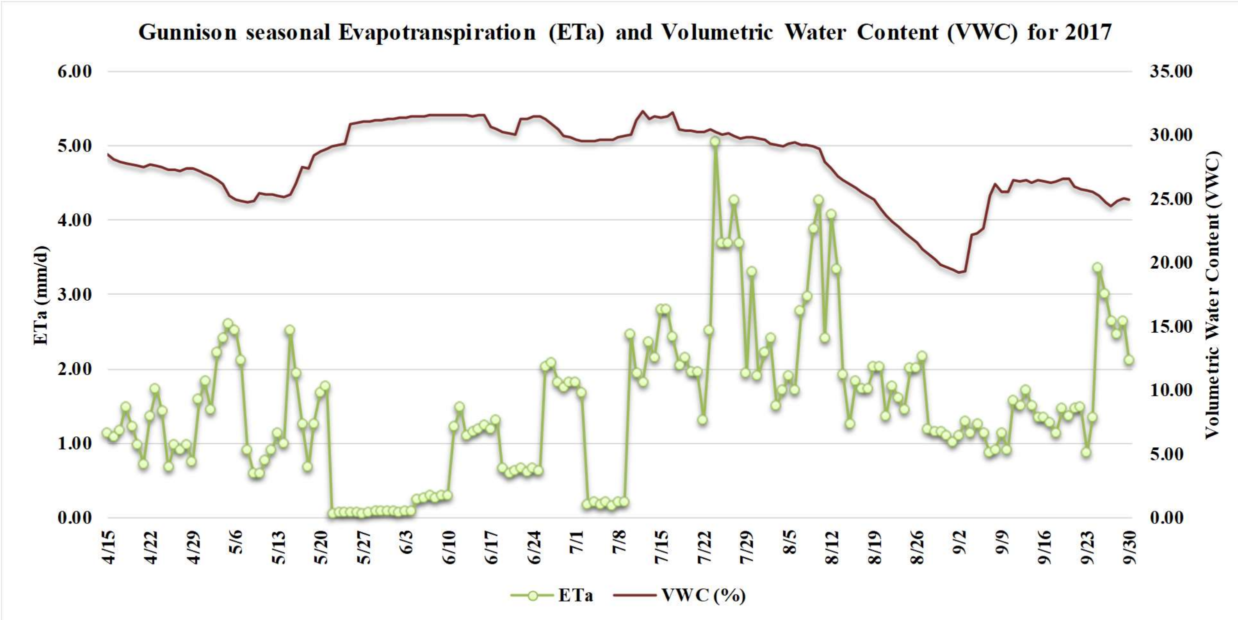

Figure 10. Actual evapotranspiration (ETa) and volumetric water content (VWC) graph for Gunnison site (2017)

Results from the soil water balance were used to calculate actual crop coefficients (Kca) for grass hay/pastures. Crop coefficients were calculated as described in section 2.7 using the ETa and ETr values. These crop coefficients were then related to surface reflectance readings to develop reflectance-based crop coefficient models, described in section 3.3.

3.3 Reflectance-Based Crop Coefficient Models

An empirical regression model was developed utilizing the surface reflectance, and actual crop coefficient data for each vegetation index evaluated. The reflectance-based crop coefficient models are shown in Figures 11 through 21 for grass hay/pasture. The actual crop coefficient (Kca) estimated here is a single crop coefficient. Crop coefficients are related to vegetation indices by Equation 10 as:

$$Kca = a \times (VI) + b \qquad (10)$$

Where a and b are constants.

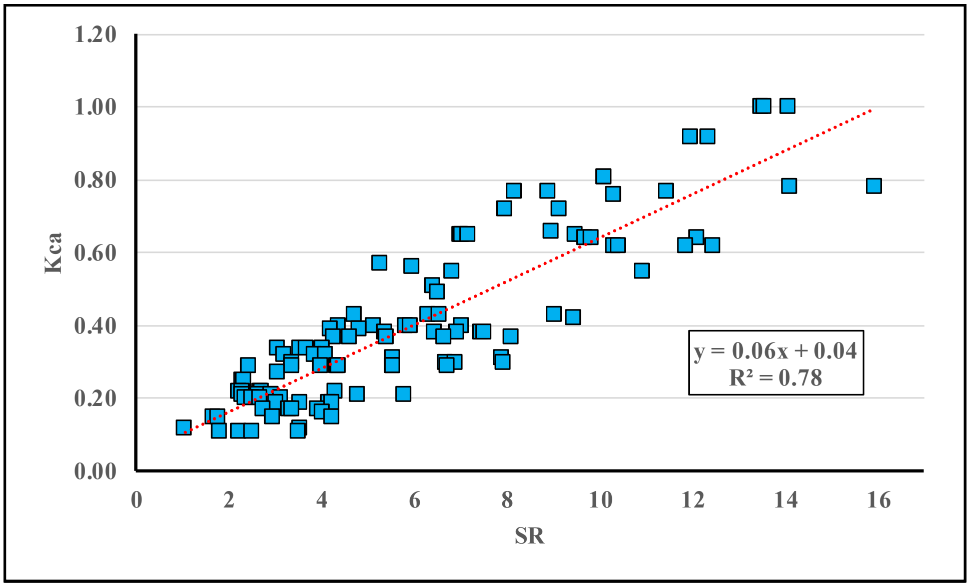

Figure 11. Simple ratio (SR) versus actual crop coefficient (Kca)

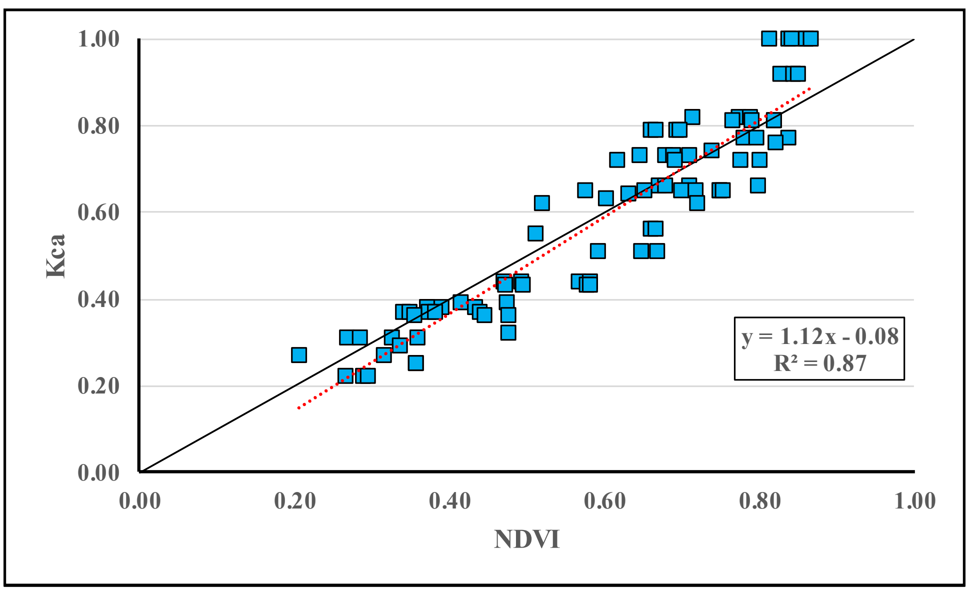

Figure 12. Normalized difference vegetation index (NDVI) versus actual crop coefficient (Kca)

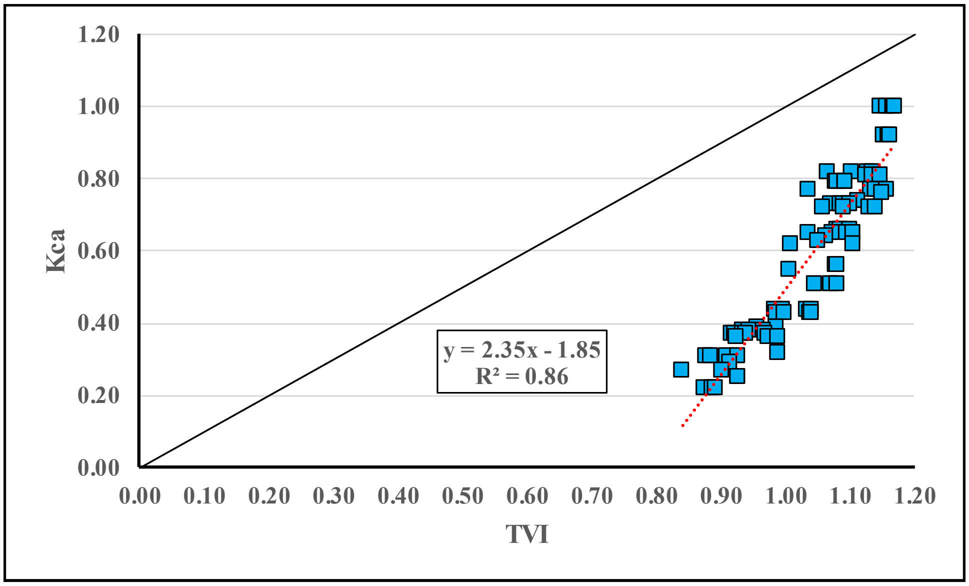

Figure 13. Transformed vegetation index (TVI) versus actual crop coefficient (Kca)

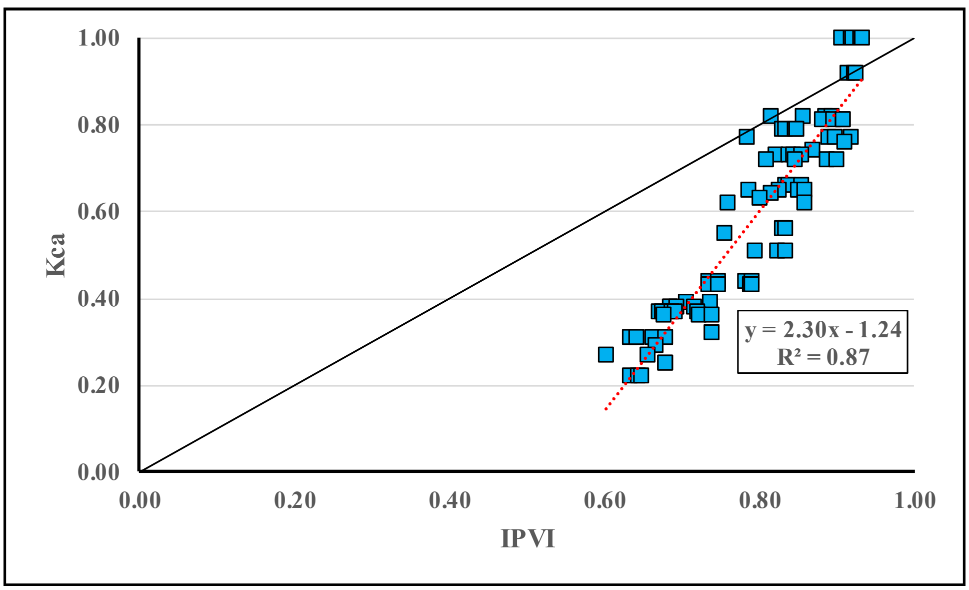

Figure 14. Infrared percentage vegetation index (IPVI) versus actual crop coefficient (Kca)

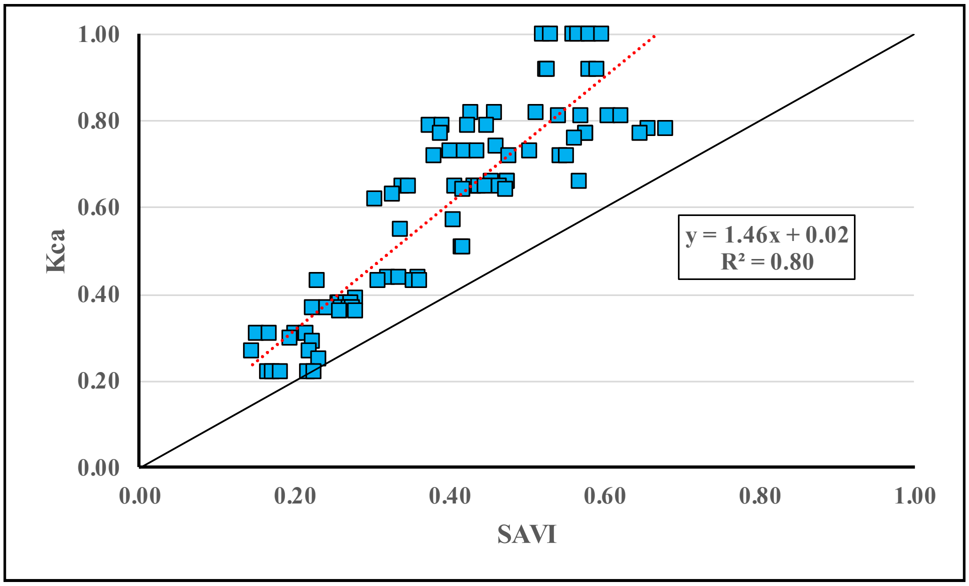

Figure 15. Soil adjusted vegetation index (SAVI) versus actual crop coefficient (Kca)

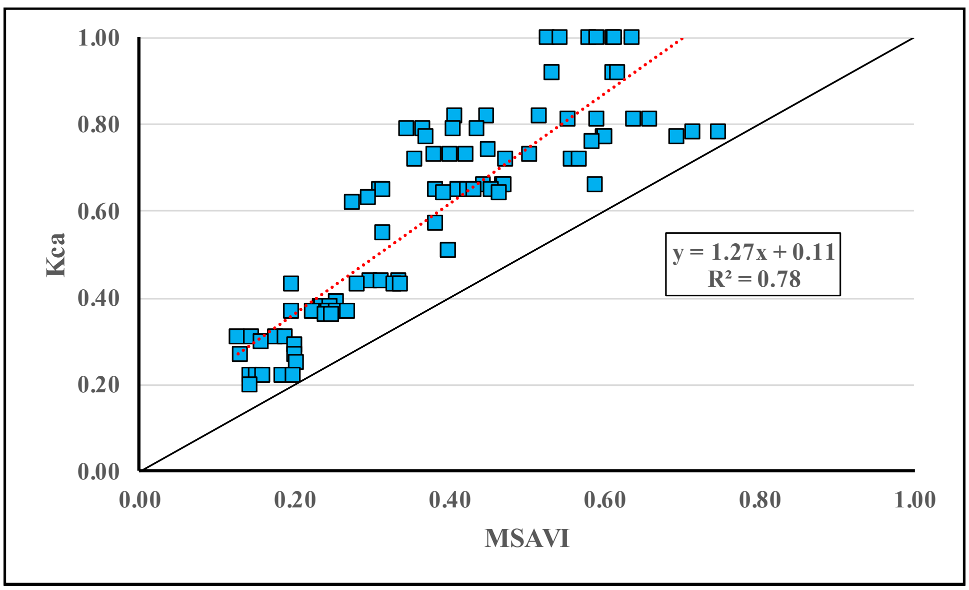

Figure 16. Modified soil adjusted vegetation index (MSAVI) versus actual crop coefficient (Kca)

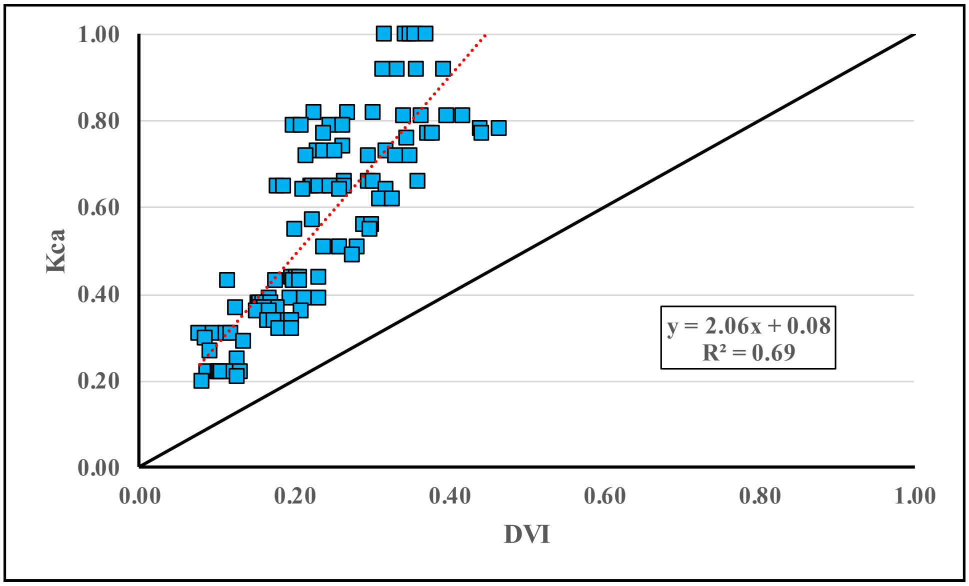

Figure 17. Difference vegetation index (DVI) versus actual crop coefficient (Kca)

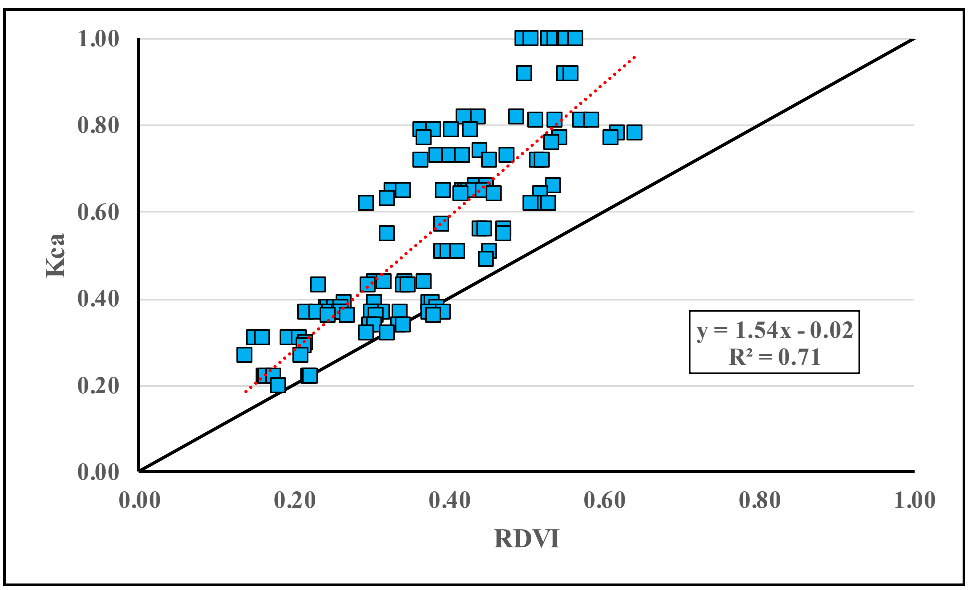

Figure 18. Renormalized difference vegetation index (RDVI) versus actual crop coefficient (Kca)

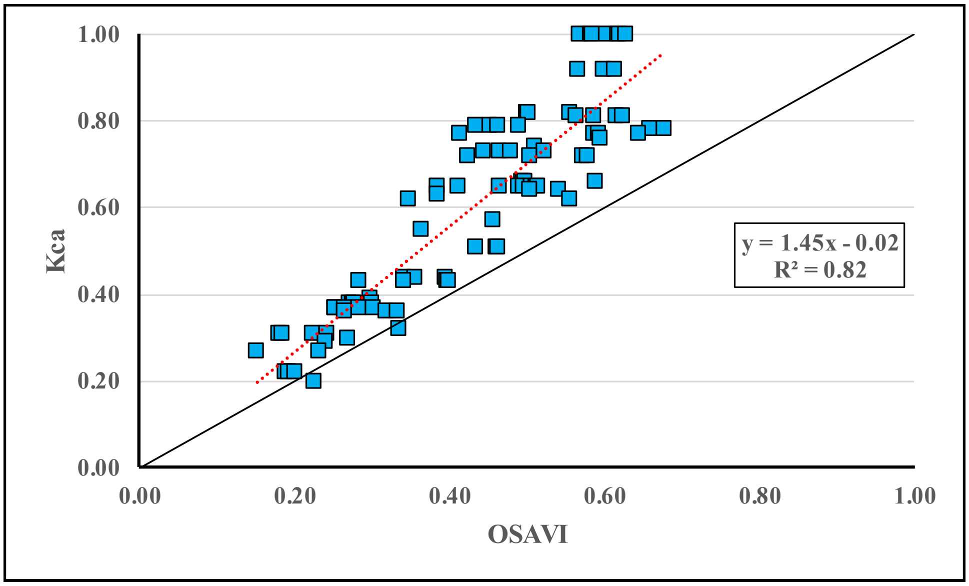

Figure 19. Optimized soil adjusted vegetation index (OSAVI) versus actual crop coefficient (Kca)

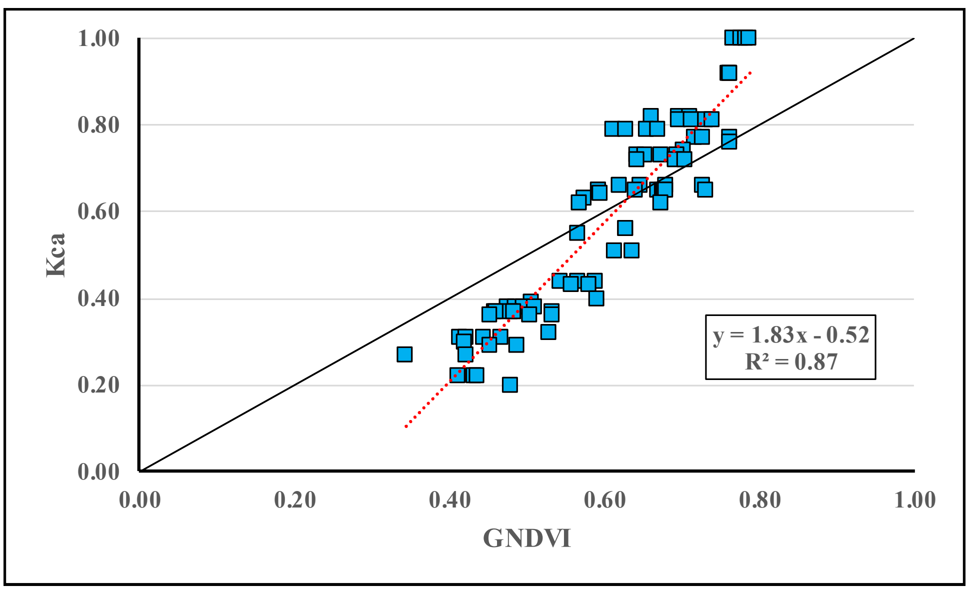

Figure 20. Green normalized difference vegetation index (GNDVI) versus actual crop coefficient (Kca)

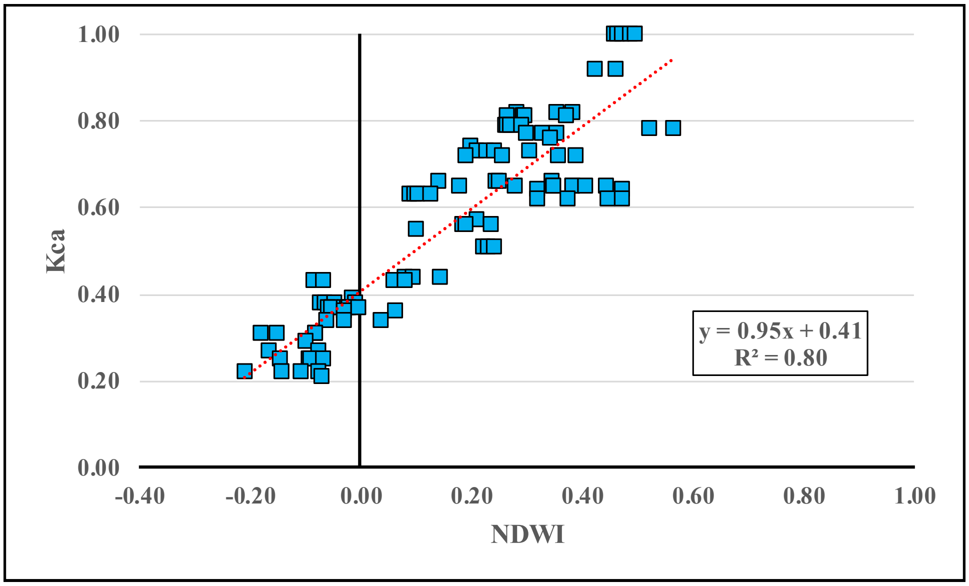

Figure 21. Normalized difference water index (NDWI) versus actual crop coefficient (Kca)

From Figures 11 to 21, it can be seen that most of the indices have a strong correlation with Kca. All models developed have a linear relationship between Kca and VI. Normalized difference vegetation index (NDVI), Transformed vegetation index (TVI), Infrared percentage vegetation index (IPVI), and Green normalized difference vegetation index (GNDVI) had the highest coefficients of determination (0.87) while Difference vegetation index (DVI) had the lowest (0.69). The fitted function seen on each Figures 11 to 21 were used to estimate Kca to validate the Kca(VI) models. Figure 22 below shows the estimated Kca values calculated using the Kca(VI) models for the collected validation data. The validation data was collected since the beginning of second cutting cycle at MTR NW sensing station in 2017.

The change in crop coefficients can be observed in the second cutting cycle where the development stage began on 7/11/17 and stabilized around 8/24/17, which corresponded to plant maturity. The second cutting was done around 9/4/2017 with the second cycle being approximately 54 days long. The crop coefficient estimated by SR model was lower than the estimates from other Kca(VI) models. The detailed performance analysis of these models is discussed in section 3.4.

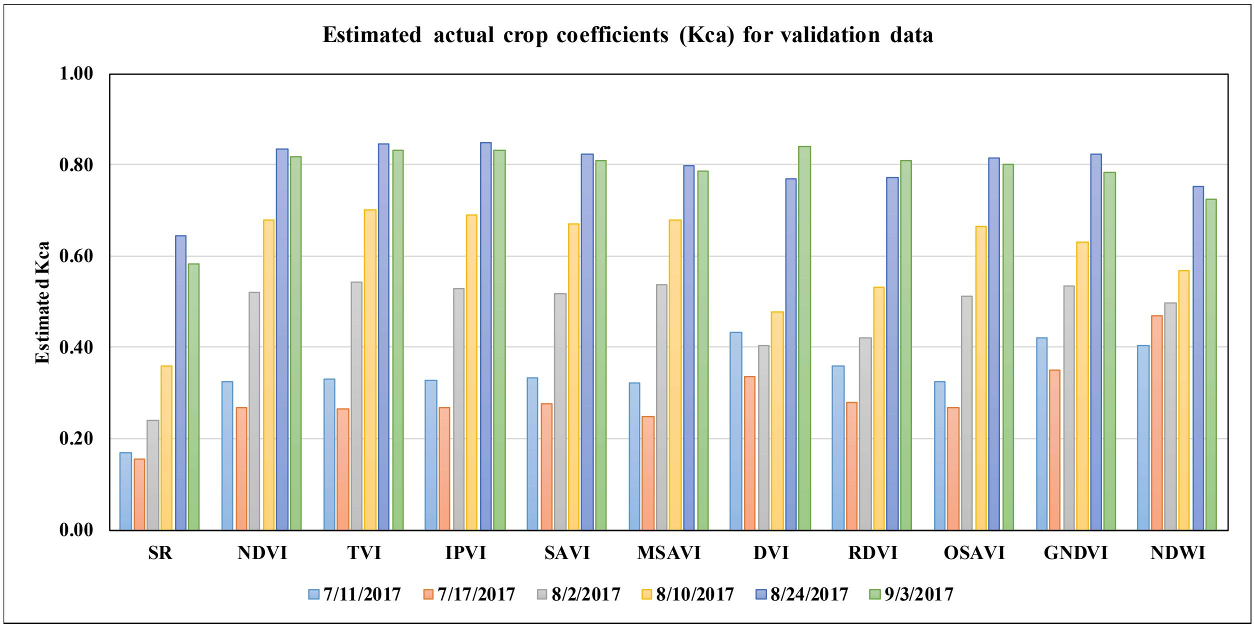

Figure 22. Estimated reflectance-based crop coefficients for 2017 at the MTR NW sensing station.

3.4 Performance Evaluation of the Models

Table 8 below shows the summary of statistical evaluations done for each of the Kca(VI) models developed in section 3.3. In the table below, Kca is the actual crop coefficient, a and b are constants, and VI is the surface reflectance based vegetation index.

Table 8. Statistical evaluation summary of the Kca(VI) models

VI	Kca = a × (VI) + b					
	a	b	R^2	RMSE	MBE	NSCE
SR	0.06	0.04	0.78	0.10	-0.001	0.78
NDVI	1.12	-0.08	0.87	0.08	0.004	0.87
TVI	2.35	-1.85	0.86	0.08	0.007	0.86
IPVI	2.30	-1.24	0.87	0.08	0.001	0.87
SAVI	1.46	0.02	0.80	0.10	-0.004	0.80
MSAVI	1.27	0.11	0.78	0.11	0.002	0.78
DVI	2.06	0.08	0.69	0.12	0.004	0.69
RDVI	1.54	-0.02	0.71	0.11	0.005	0.71
OSAVI	1.45	-0.02	0.82	0.08	0.002	0.82
GNDVI	1.83	-0.52	0.87	0.09	0.004	0.87
NDWI	0.95	0.41	0.80	0.09	0.003	0.80

As discussed earlier in section 3.3, NDVI, TVI, IPVI and GNDVI had the highest coefficient of determination (R^2 = 0.87) while DVI had the lowest R^2 value at 0.69. Similarly, RMSE was used to evaluate the difference in estimation error between the estimated Kca and calculated Kca. Among the Kca(VI) models evaluated, the NDVI, TVI, IPVI and GNDVI indices had the lowest RMSE at 0.08. This indicates that these Kca(VI) models performed well with minimal error between estimated and calculated ETa. The DVI had the highest RMSE at 0.12. The mean bias error (MBE) was very low and close to zero for all models. The NSCE values were equal to the coefficient of determination. The NSCE value indicates the efficiency of the model. Among the models evaluated, NDVI, TVI, IPVI, and GNDVI had the highest NSCE values (about 0.87), compared to other indices, while the DVI was found to have the lowest at 0.69.

In addition to the above-discussed statistics, the ability of the models to estimate ETa (ETa = Kca × ETr) on a daily basis was also evaluated. Figure 23 below shows the relationship between estimated and calculated ETa for each Kca(VI) model. The estimated ETa, using the model, was plotted against calculated ETa from the soil water balance, and regression analysis was performed to determine the relationship between them. The coefficient of determination (R^2) was used to interpret the results. A higher value of R^2 (closer to 1) would suggest that the estimated ETa is very close/equal to calculated ETa and vice-versa. GNDVI had the highest R^2 value of 0.79, while DVI had the lowest value of R^2 (0). Based on the results, GNDVI performed better than other Kca(VI) models. The NDVI, TVI, and IPVI also performed reasonably well (R^2=0.70) when compared to the other models. The DVI model performed the worst with no relationship between the estimated and calculated ETa. The performance of all other Kca(VI) models, except NDVI, TVI, IPVI, and GNDVI, were not satisfactory. Hence, they were not analyzed further.

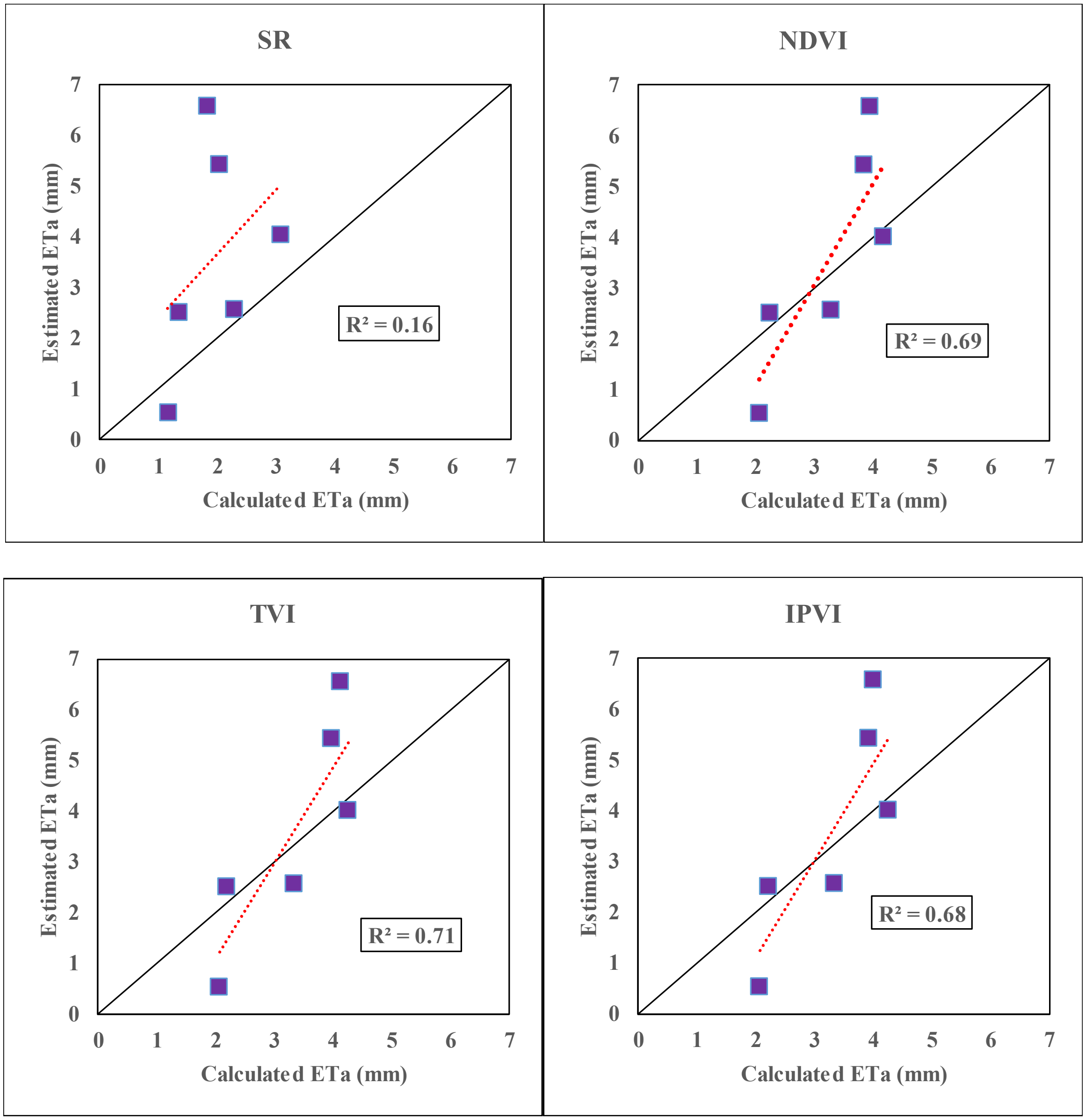

Figure 23. Validation of vegetation index (VI) – actual crop coefficient (Kca) models. The graph depicts regression scatter plots of estimated versus calculated actual evapotranspiration (ETa) rates for each vegetation index based model

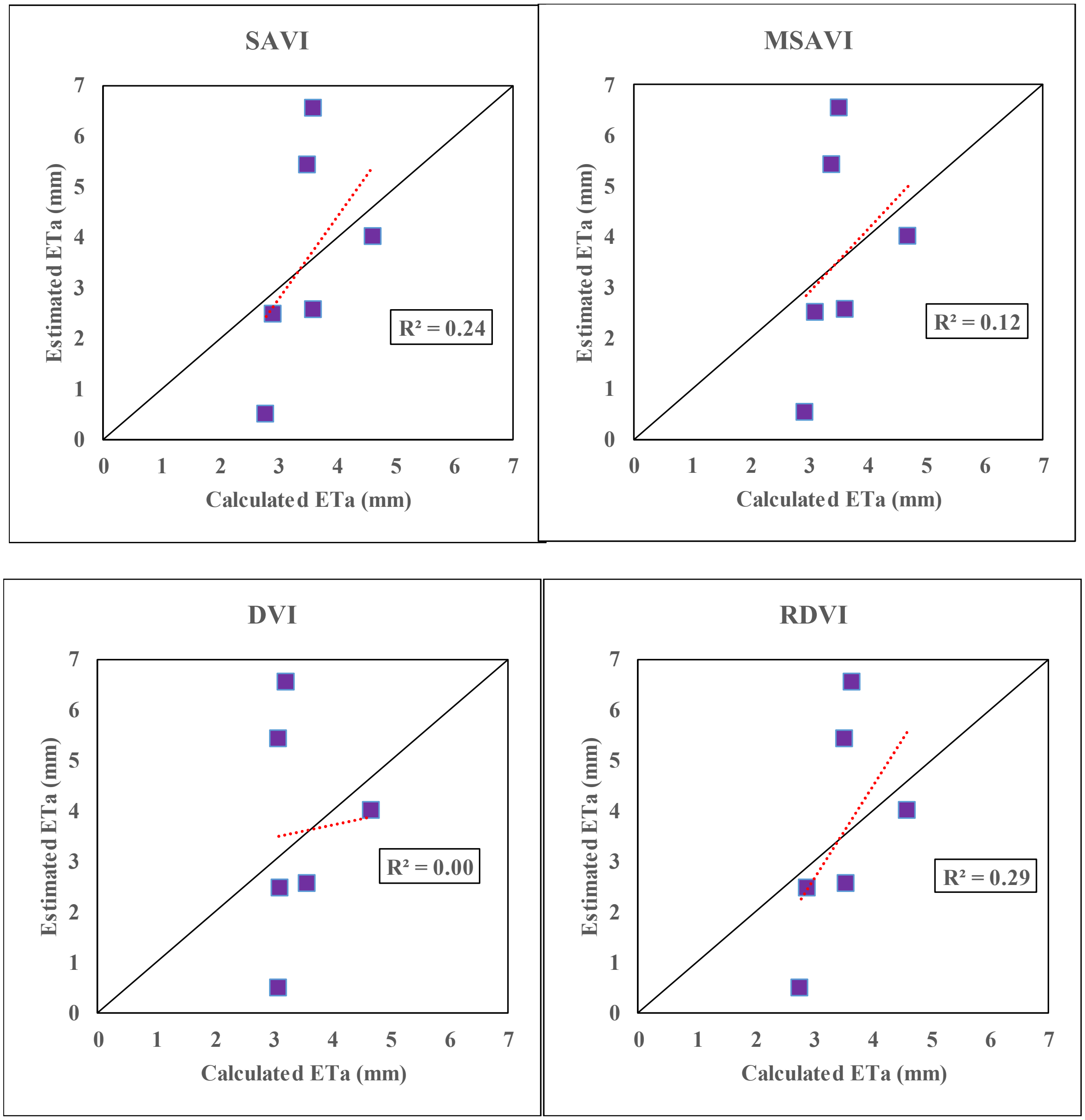

Figure 23 (continued). Validation of vegetation index (VI) – actual crop coefficient (Kca) models. The graph depicts regression scatter plots of estimated versus calculated actual evapotranspiration (ETa) rates for each vegetation index based model

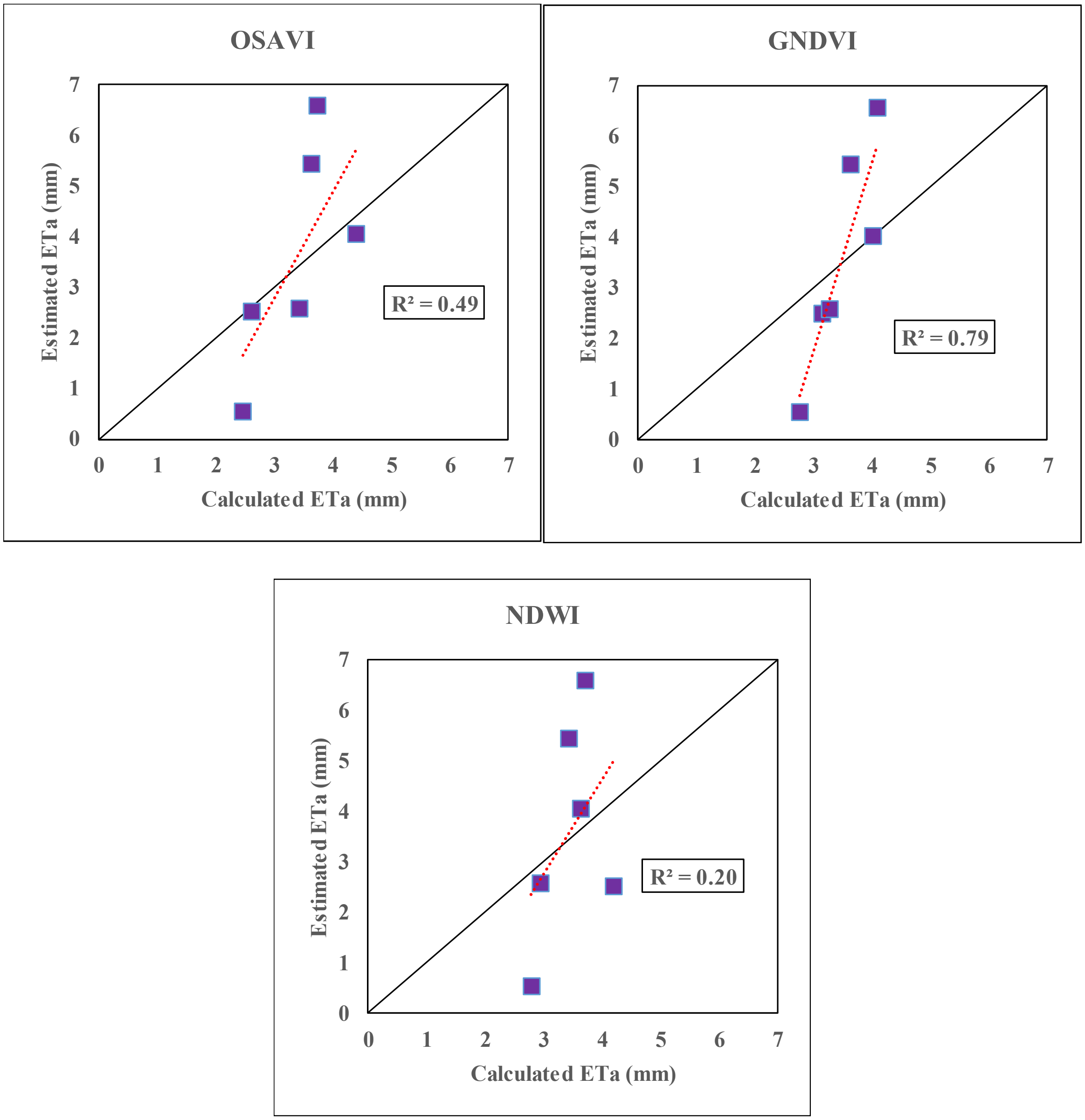

Figure 23 (continued). Validation of vegetation index (VI) – actual crop coefficient (Kca) models. The graph depicts regression scatter plots of estimated versus calculated actual evapotranspiration (ETa) rates for each vegetation index based model

Root mean squared error (RMSE) and mean bias error (MBE) analysis was done for NDVI, TVI, IPVI, and GNDVI. The results are presented in Table 9 below.

Table 9. Statistical evaluation of Kca(VI) model performance

Kca(VI) model	RMSE (mm/d)	MBE (mm/d)
NDVI	1.43	-0.33
TVI	1.36	-0.27
IPVI	1.41	-0.29
GNDVI	1.60	-0.09

TVI had the lowest RMSE value at 1.36 mm/d while GNDVI had the highest RMSE value at 1.60 mm/d. The performance of NDVI and IPVI models were similar with calculated RMSE of 1.43 and 1.41 mm/d. However, the GNDVI model was least biased, while other Kca(VI) models were negatively biased. This suggests that NDVI, TVI, and IPVI models were under-predicting ETa rates.

Analysis of Variance (ANOVA) can be a useful method to study variations between means of calculated and estimated ETa. As described in section 2.10, an ANOVA test was conducted to check whether there were statistically significant differences between the means of calculated and estimated ETa. For this purpose, the estimated ETa values were used from NDVI, TVI, IPVI, and GNDVI based Kca(VI) models. The confidence interval was set at 95%. Table 10 below shows the results of one-way ANOVA.

Table 10. Analysis of variance between calculated and estimated evapotranspiration rates.

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.48	4.00	0.12	0.08	0.99	2.76
Within Groups	38.86	25.00	1.55			
Total	39.35	29.00				

The important things to note in above Table 10 are F ratio (F) and critical F ratio (Fcrit) values. If the F value is larger than Fcrit, we reject our null hypothesis. In this case, the Fcrit value was larger than our F value. Hence, the result from the ANOVA test suggests that there was no significant variation in means between the groups. Thus, the selection of vegetation index does not have a significant impact on our actual ETa estimate.

Figure 24 below shows estimated Kca values for the second cutting cycle at the MTR NW sensing station using different Kca(VI) models. The NDVI and GNDVI models were developed in this study, while Vashisht (2016), Alam (2018), and Johnson (2012) are previously developed models. The METRIC EEFLUX estimate is from an online platform (https://eeflux-level1.appspot.com/). It can be observed that the METRIC based Kca estimate is much higher than the other methods used. A recent study by Hydrologic Engineering Inc. (2016) to assess the agricultural consumptive use in Upper Colorado River Basin also confirms that the METRIC based crop evapotranspiration estimate was much higher than the other method used. The Alam (2018) and Johnson (2012) based Kca estimates were very similar to each other and lower than NDVI, GNDVI, and Vashisht (2016) based models. One possible reason for this could be the Alam (2018), and Johnson (2012) models are based on the short reference surface (grass) while other models are based on the tall reference surface (alfalfa). There were only small differences between Kca estimates based on NDVI, GNDVI, and Vashisht (2016) models. The Vashisht (2016) model was found to slightly overestimate Kca compared to NDVI and GNDVI based models.

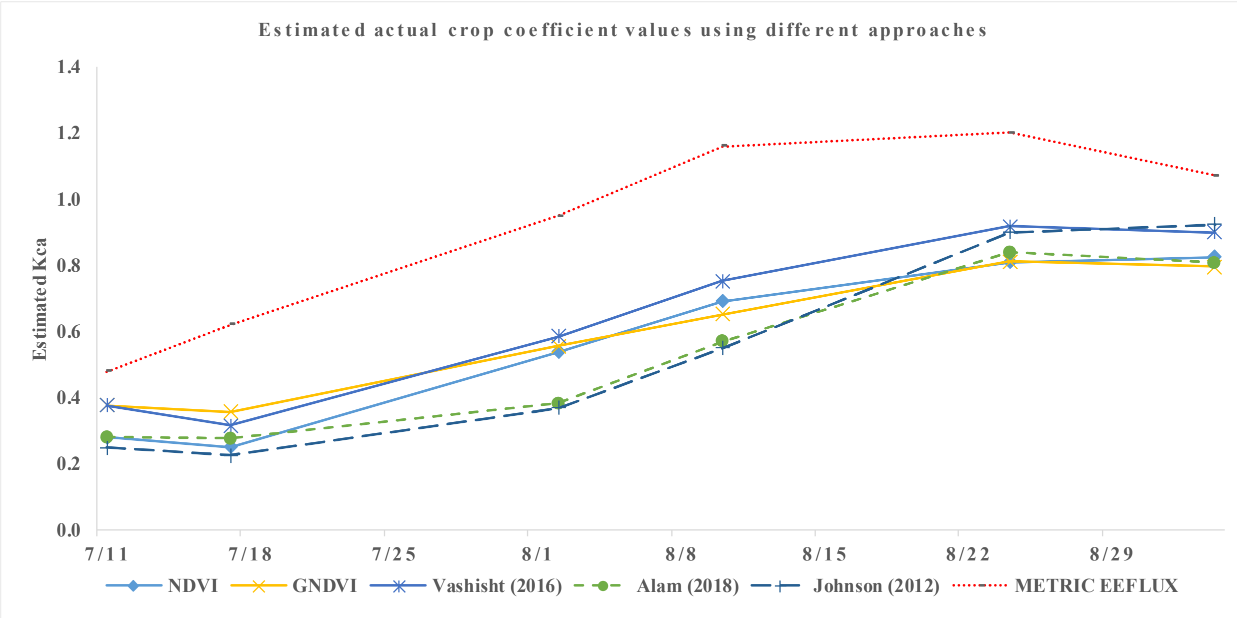

Figure 24. Estimated actual crop coefficient values using different approaches

Considering all the statistical analyses performed in section 3.4, it can be concluded that there is no significant difference between NDVI, TVI, IPVI, and GNDVI based models. However, the GNDVI model was found to perform better when compared to other models in predicting daily actual ETa. Hence, it is recommended that the GNDVI based Kca(VI) model be used to estimate daily actual Kca and ETa rates for grass hay/pastures in western Colorado.

CHAPTER 4: CONCLUSION AND RECOMMENDATIONS

This study compared and evaluated the performance of eleven different Kca(VI) based models, developed for estimating actual crop coefficients and evapotranspiration rates for the Western Slope of Colorado.

The calibration equation developed for CS655 sensors characterized different soil types found in western Colorado. As suggested by a previous study on similar sensors, CS655 sensors also tend to overestimate the volumetric water content when moisture levels in the soil are above 20% VWC. The calibration equations developed aim to reduce this problem and can be applied to future research as well.

One dimensional soil water balance was performed to estimate the ETa rate for grass hay/pasture. The soil water balance suggested that the ETa rate can follow the different trend when compared to reference evapotranspiration rates. ETa calculated for the Montrose site was only about 44% of ETr, while only about 30% at the Gunnison site. The soil water balance at the Montrose treatment field (MTR TRT) showed that there was no carryover stress present in 2017 from the previous year's partial-season irrigation practice. An increase in yield was recorded for that field in 2017 (0.12 Mg/ha for first cutting and 0.79 Mg/ha in the second cutting cycle). This result can be useful to support the concept of using grass hay/pastures for water banking purpose).

Surface reflectance readings from a hand-held multispectral radiometer were processed and related to Kca to develop Kca(VI) models.

Among the models developed and evaluated, GNDVI, TVI, NDVI, and IPVI based Kca(VI) models were most accurate when estimating the daily ETa rates for grass hay/pastures. All other

Kca(VI) models developed did not perform well. The DVI was found to give the worst result with no relationship between estimated and calculated ETa on a daily basis.

Analysis of Variance suggested that there was no statistically significant difference among the GNDVI, TVI, NDVI, and IPVI based Kca(VI) models. This suggests that selection of any one of the models should not significantly affect ETa estimates. Performance evaluation of the models also suggests that the GNDVI based model is most accurate while estimating ETa of grass hay/pasture on a daily time step. We can conclude that depending upon the availability of surface reflectance readings, user can use either of the four models (GNDVI, TVI, NDVI, or IPVI) to estimate ETa. However, it is recommended to use the GNDVI based Kca(VI) model for increased accuracy.

While this research has shown positive results, there is still room for improvement. Future studies should focus on improving the calibration equation of CS655 sensors by conducting more gravimetric soil sampling and including samples from greater depths. Since it is challenging to install the soil moisture sensors at greater depth, use of instruments like neutron probes can be beneficial. The limitation of one-dimensional soil water balance is that lateral flow of water towards the sensor cannot be properly tracked. Use of instruments like weighing lysimeters can also help us to get a better understanding of crop evapotranspiration rates and refine the models. Also, further research can focus on evaluating the relationships between the vegetation index based models and fractional crop cover.

The results from this study can be used as an inexpensive and fast method to estimate actual crop coefficients and actual evapotranspiration rates for the Western Slope of Colorado.

REFERENCES

Alam, S. M., Lamb, W. D., & Rahman, M. M. (2018). A refined method for rapidly determining the relationship between canopy NDVI and the pasture evapotranspiration coefficient.

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop requirements. Irrigation and Drainage Paper No. 56, FAO, (56), 300. https://doi.org/10.1016/j.eja.2010.12.001

Andales, A. A., Chavez, J. L., & Bauder, T. A. (n.d.). Irrigation Scheduling: The Water Balance Approach. Network, (4), 1–6.

ASCE-EWRI. (2005) The ASCE standardized reference evapotranspiration equation. In: Allen RG, Walter IA, Elliot RL, et al. (eds.) Environmental and Water Resources Institute (EWRI) of the American Society of Civil. Engineers, ASCE, Standardization of Reference Evapotranspiration Task Committee Final Report, 213pp. Reston, VA: American Society of Civil Engineers (ASCE).

Bannari, A., Morin, D., Bonn, F., & Huete, A. R. (1995). A review of vegetation indices. Remote Sensing Reviews, 13(1), 95–120. https://doi.org/10.1080/02757259509532298

Bausch, W.C. (1993). Soil background effects on reflectance-based crop coefficients for corn. Remote Sensing of Environment, 46(1), 213-222

Blaney, H.F. and W.D. Criddle. (1962). Determining consumptive use and irrigation water requirements. USDA Technical Bulletin 1275, US Department of Agriculture, Beltsville, MD.

Cabot, P., Vashisht, A., Chávez, J.L. (2017). Using Remote Sensing Assessments to Document Historical and Current Saved Consumptive Use (CU) on Alfalfa and Grass Hayfields Managed Under Full and Partial-Season Irrigation Regimes.

California Test 226. (1999). Method for determining moisture content by oven drying. Department of Transport Engineering Service Center, State of California-Business, Transportation and Housing Agency, (November), 1–2.

Ceccato, P., Flasse, S., Tarantola, S., Jacquemoud, S., & Grégoire, J. M. (2001). Detecting vegetation leaf water content using reflectance in the optical domain. Remote Sensing of Environment, 77(1), 22–33. https://doi.org/10.1016/S0034-4257(01)00191-2

Cohen, M., Christian-smith, J., Berggren, J. (2013). Water To Supply The Land. Pacific Institue. 2013.

Colorado Division of Water Resources (CDWR). (2008). State of Colorado's CDSS Consumptive Use Model. StateCU. s.l., Colorado, United States: Colorado's Decision Support Systems, September 2008.

Crippen, R. E. (1990). Calculating the vegetation index faster. Remote Sensing of Environment, 34(1), 71–73. https://doi.org/10.1016/0034-4257(90)90085-Z

Cropscan. (2001). Multispectral radiometer user's manual.

Doorenbos, J. and W.O. Pruitt. (1977). Crop water requirements. FAO Irrigation and Drainage Paper No. 24. 1977.

Engman, E. T. (1995). Recent advances in remote sensing in hydrology. US National Report to International Union of Geodesy and Geophysics 1991–1994. Reviews of Geophysics (supplement). American Geophysical Union. 967–975.

Er-Raki, S., Chehbouni, A., Guemouria, N., Duchemin, B., Ezzahar, J., & Hadria, R. (2007). Combining FAO-56 model and ground-based remote sensing to estimate water consumptions of wheat crops in a semi-arid region. Agricultural water management, 87(1), 41-54.

Gao, B. C. (1996). NDWI-A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of. Environment, 58(April 1995), 257–266.

Genc, L., Inalpulat, M., Kizil, U., Mirik, M., Smith, S. E., & Mendes, M. (2013). Determination of water stress with spectral reflectance on sweet corn (Zea mays L.) using classification tree (CT) analysis. Zemdirbyste-Agriculture, 100(1), 81–90.

Gitelson, A. A. (2013). Remote estimation of crop fractional vegetation cover: the use of noise equivalent as an indicator of performance of vegetation indices. International Journal of Remote Sensing, 34(17), 6054–6066. https://doi.org/10.1080/01431161.2013.793868

Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment, 58(3), 289–298. https://doi.org/10.1016/S0034-4257(96)00072-7

Gowda, P. H., Chavez, J. L., Colaizzi, P. D., Evett, S. R., Howell, T. A., & Tolk, J. A. (2008). ET mapping for agricultural water management: present status and challenges. Irrigation science, 26(3), 223-237.

Hoffman, G. J (2007). Design and Operation of Farm Irrigation Systems. American Society of Agricultural and Biological Engineers.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X.

Hunsaker, D. J.; Pinter, P.J.; Jr.; Kimball, B.A. (2005). Wheat basal crop coefficients determined by normalized difference vegetation index. Irrigation Science, 24(1), 1–14.

Hydrologic Engineering Incorporation (2016). Assessing agricultural consumptive use including remote sensing of actual evapotranspiration in the upper Colorado river basin.

Idso, S. B., Pinter, P. J., Jackson, R. D., & Reginato, R. J. (1980). Estimation of grain yields by remote sensing of crop senescence rates. Remote Sensing of Environment, 9(1), 87–91. https://doi.org/10.1016/0034-4257(80)90049-8

Jackson, R. D., Slater, P. N., & Pinter, P. J. (1983). Discrimination of growth and water stress in wheat by various vegetation indices through clear and turbid atmospheres. Remote Sensing of Environment, 13(3), 187–208. https://doi.org/10.1016/0034-4257(83)90039-1

Jayanthi, H., Neale, C. M., & Wright, J. L. (2007). Development and validation of canopy

Johnson, L.F., Trout, T.J. (2012). Satellite NDVI assisted monitoring of vegetable crop evapotranspiration in California's San Joaquin valley. Remote Sensing. 2012, 439–455.

Juday, D.G., J.E. Brummer and D.H. Smith. (2011). Use of alternative temperature expressions with Blaney-Criddle. ASCE Journal of Irrigation and Drainage Engineering. 137: 573–584.

Kamble, B., Kilic, A., & Hubbard, K. (2013). Estimating crop coefficients using remote sensing-based vegetation index. Remote Sensing, 5(4), 1588–1602. https://doi.org/10.3390/rs5041588

Ley, T.W., Allen, R.G., Jensen, M.E. (2010). Translating Wind Speed Measured Over Alfalfa for Use in the ASCE Standardized Reference ET Equation. An ASABE Conference Presentation. 2010, Number: IRR10-8725

METRIC EEFLUX (2017). https://eeflux-level1.appspot.com/

Montgomery, D. M. (2005). Legal consequences of evapotranspiration measurement. Colorado Water Newsletter. Colorado Water. Newsletter of the Water Center of Colorado State University. 22(2), 25–28.

Natural Resources Consulting Engineers. (2012). Colorado River Compact Colorado Water Bank Feasibility Study Water Supply Technical Memorandum.

Neale, C. M., Bausch, W. C., & Heermann, D. F. (1989). Development of reflectance-based crop coefficients for corn. Transactions of the ASAE,32(6), 1891-1900.

Neale, C. M., Jayanthi, H., & Wright, J. L. (2003). Crop and irrigation water management using high resolution airborne remote sensing. In Proceedings of 54th IEC meeting of the international commission on irrigation and drainage (ICID) workshop remote sensing of ET for large regions (Vol. 17).

Norviel, W. S., W. F. McClure, D. E. Carpenter, J. G. Scrugham, S. B. Davis, R. E. Caldwell,

Ott, L.R., Longnecker, M. (2010). An Introduction to Statistical Methods and Data Analysis. Brooks/Cole CENGAGE Learning. 2010. 402-410.

Payero, J. O., Neale, C. M. U., & Wright, J. L. (2004). Comparison of eleven vegetation indices for estimating plant height of alfalfa and grass. Applied Engineering in Agriculture, 20(3), 385–393. https://doi.org/10.1017/CBO9781107415324.004

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). a Modified Soil Adjusted Vegetation Index. Remote Sensing of Environment, 48, 119–126. https://doi.org/10.1016/0034-4257(94)90134-1

Rafn, E.B., B. Contor and D.P. Ames. (2008). Evaluation of a method for estimating irrigated crop-evapotranspiration coefficients from remotely sensed data in Idaho. ASCE Journal of Irrigation and Drainage Engineering 134: 722–729.

Rafn, E.B., B. Contor and D.P. Ames. (2008). Evaluation of a method for estimating irrigated crop-evapotranspiration coefficients from remotely sensed data in Idaho. ASCE Journal of Irrigation and Drainage Engineering 134: 722–729.

Ray, S. S., & Dadhwal, V. K. (2001). Estimation of crop evapotranspiration of irrigation reflectance-based crop coefficient for potato. Agricultural water management, 88(1), 235-246.

Rondeaux, G., M. Steven, and F. Baret. 1996. Optimization of Soil-Adjusted Vegetation Indices. Remote Sensing of Environment 55: 95-107.

Roujean, J. L., & Breon, F. M. (1995). Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sensing of Environment, 51(3), 375–384. https://doi.org/10.1016/0034-4257(94)00114-3.

Sammis T. W., J. Wang, and D. R. Miller. (2011). The transition of the Blaney-Criddle formula to the Penman-Monteith equation in the Western United States. Journal of Service Climatology. 5(1): 1-11.

Seevers, P. M. and R.W Ottmann. (1994). Evapotranspiration estimation using a normalized difference vegetation index transformation of satellite data.'' Hydrol. Sci. J. 39: 333–345.

Senay, G.B., S. Leake, P.L. Nagler, G. Artan, J. Dickinson, J.T. Cordova and E.P. Glenn. (2011). Estimating basin scale evapotranspiration (ET) by water balance and remote sensing methods. Hydrological Processes. 25: 4037–4049.

Singh, R. K., & Irmak, A. (2009). Estimation of crop coefficients using satellite remote sensing. Journal of irrigation and drainage engineering,135(5), 597-608.

Smith, D. H. (2008). Consumptive Irrigation Water Use Intermountain Meadows of Colorado. Colorado Water. Newsletter of the Water Center of Colorado State University. 25(1): 18-22. http://wsnet.colostate.edu/cwis31/ColoradoWater/Images/Newsletters/2008/CW_25_1.pdf.

Tasumi, M.; Allen, R.; Trezza, R.; Wright, J. (2005). Satellite-Based energy balance to assess within-population variance of crop coefficient curves. Journal of Irrigation and Drainage Engineering, 131(1), 94–109.

Taylor, S. A., Ashcroft, G. L., Brady, N. C., Baver, L. D., Gardner, W. R., Brady, N. C., & Weil, R. R. (1972). Physical edaphology: the physics of irrigated and nonirrigated soils (No. 631.43 T246). Centro Regional de Ayuda Técnica, México, DF (México).

Taylor, S. A., Ashcroft, G. L., Brady, N. C., Baver, L. D., Gardner, W. R., Brady, N. C., & Weil, R. R. (1972). Physical edaphology: the physics of irrigated and nonirrigated soils (No. 631.43 T246). Centro Regional de Ayuda Técnica, México, DF (México).

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0

Varble, J.L. and J.L. Chávez. (2011). Performance evaluation and calibration of soil water content and potential sensors for agricultural soils in eastern Colorado. Agricultural Water Management 101: 93– 106.

Vashisht, A. (2016). Remote sensing assessments of consumptive use of agricultural water in western slope of Colorado. M.S. Thesis. Colorado State University.

Viña, A., A.A. Gitelson, A.L. Nguy-Robertson and Y. Peng, Y. (2011). Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. Remote Sensing of Environment. 115(12): 3468-3478.

Walter, I. A. (2004). Strengths and weaknesses of the modified Blaney- Criddle method. Determination of consumptive use in water rights (course manual), Colorado Bar Association, Denver.

Walter, I.A., E.G. Siemer, J.P. Quinlan and R.D. Burman. (1990). Evapotranspiration and Agronomic Responses in Formerly Irrigated Mountain Meadows, South Park, Colorado. Report for the Denver Board of Water Commissioners, City and County of Denver, CO. March 1, 1990. 216 pp.

Wright, J.L. (1982) New evapotranspiration crop coefficients. Proceedings of the American Society of Civil Engineers, Journal of the Irrigation and Drainage Division. 108(IR2): 57-74.

Yoder, B. J., & Waring, R. H. (1994). the Normalized Difference Vegetation Index of Small Douglas-Fir Canopies with Varying Chlorophyll Concentrations. Remote Sensing of Environment, 49(February), 81–91.

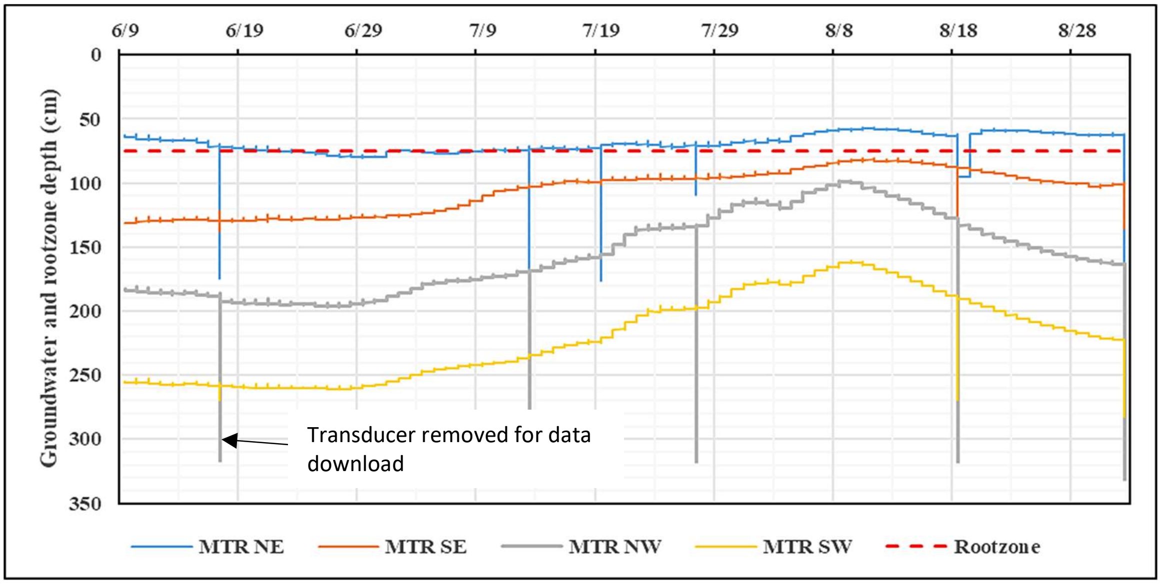

Figure 25. Ground water depths at Montrose site (2016) and assumed Rootzone depth

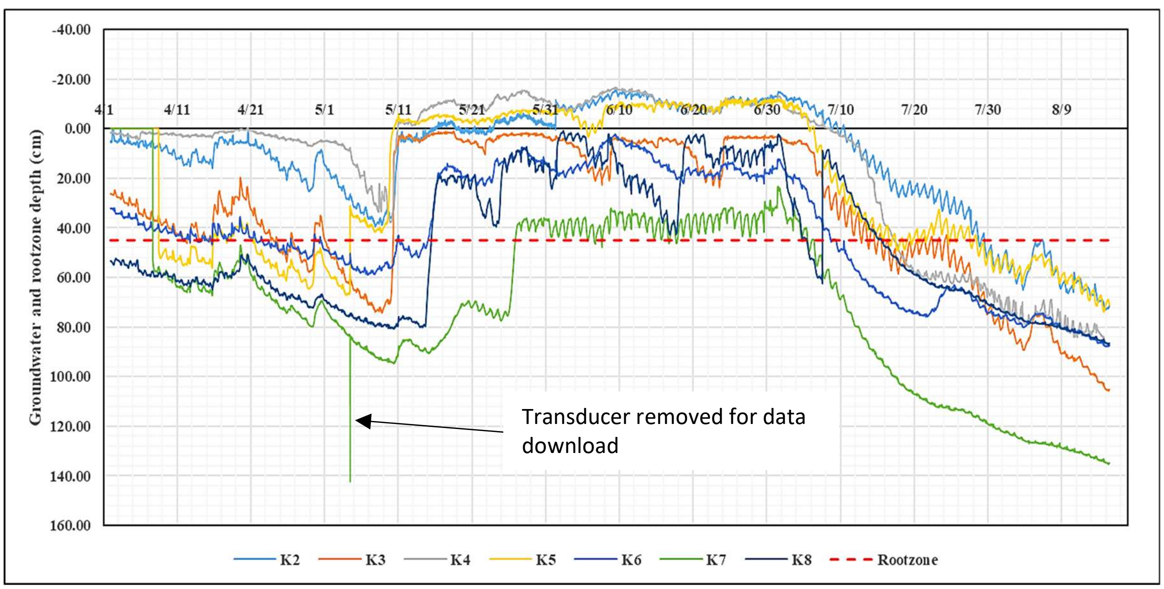

Figure 26. Ground water depths at Gunnison site (2016) and assumed Rootzone depth

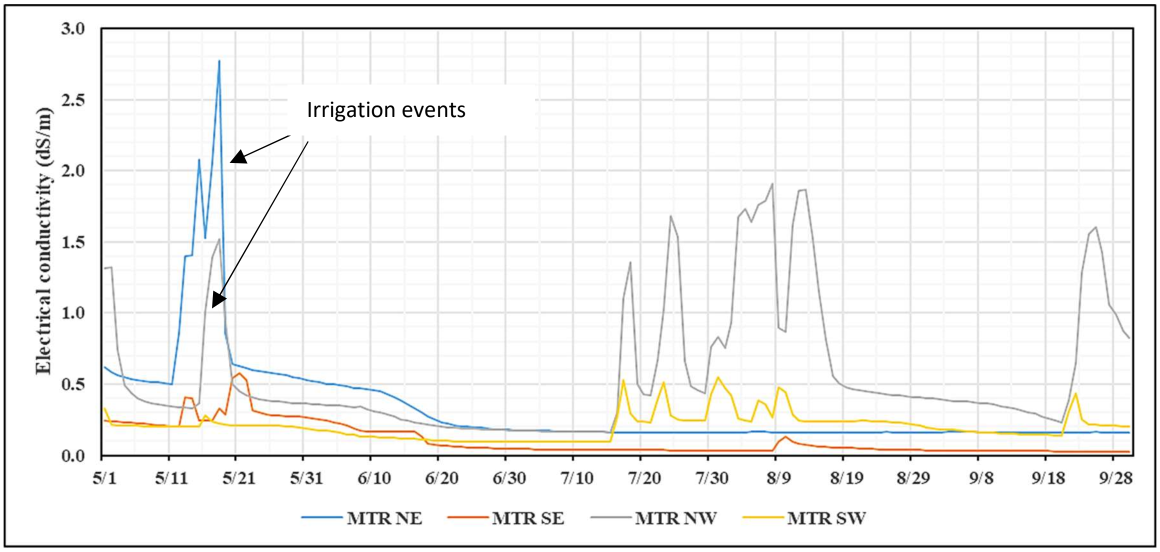

Figure 27. Electrical conductivity recorded by deep sensors at Montrose site (2016)

APPENDIX 2

Table 11: Some previously developed models listed in Table 1 and their corresponding reference surface, reference evapotranspiration (ETr) measurement approach, actual evapotranspiration (ETa) measurement approach, and remote sensing instrument used

Study	Reference surface	ETref measured using	ETa measured using	Remote sensing instrument
Neale et al. (1989)	Alfalfa	Lysimeter	Lysimeter	Hand-held radiometer
Bausch et al. (1993)	Alfalfa	Lysimeter	Lysimeter	Multispectral radiometer mounted on a structure
Singh & Irmak (2009)	Alfalfa	Penman-Monteith	Surface energy balance	Landsat 5 and 7 satellites
Johnson et al. (2012)	Grass	Lysimeter	Lysimeter	Landsat 5 satellite and ground based digital camera to measure fractional vegetation cover
Kamble et al. (2013)	Grass	Hargreaves and Samani model	Surface energy balance	MODIS satellite
Vashisht (2016)	Alfalfa	Penman-Monteith	Surface energy balance	Landsat 7 and 8 satellites
Alam et al. (2018)	Grass	Penman-Monteith	Evaporation dome	Hand-held radiometer

LIST OF ABBREVIATIONS

CU	Consumptive use
DVI	Difference vegetation index
ET	Evapotranspiration
ET_a	Actual evapotranspiration
ET_r	Alfalfa based reference evapotranspiration
GNDVI	Green normalized vegetation index
GREEN	Green bandwidth
IPVI	Infrared percentage vegetation index
Kca	Actual crop coefficient
Kcb	Basal crop coefficient
L	Vegetation density constant
Fc	Fractional cover
MSAVI	Modified soil adjusted vegetation index
NDVI	Normalized difference vegetation index
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
NIR	Near Infra-Red
OSAVI	Optimized soil adjusted vegetation index
RDVI	Renormalized difference vegetation index
RED	Red bandwidth
SAVI	Soil Adjusted Vegetation Index

SAVI	Soil adjusted vegetation index
SR	Simple Ratio
SWIR	Shortwave infra-red bandwidth
TVI	Transformed vegetation index
VI	Vegetation Index
MTR	Montrose study site
TRT	Treatment field
REF	Reference field
GUN	Gunnison study site