Ground-based Remote Sensing of Corn Evapotranspiration under Limited Irrigation Practices

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Abstract. Irrigated agriculture is the largest user of fresh water resources in arid/semi-arid parts of the world, where water is highly-demanded and usually over-allocated. Therefore, it is of crucial importance to accurately identify irrigation requirement of agricultural crops, known as evapotranspiration (ET). In this study, ground-based remotely sensed data were used in two major approaches to estimate crop coefficient (K_c) and ET over two treatments of limited-irrigation corn in northeastern Colorado. The first approach was the reflectance-based K_c, while the second approach was more complex and based on the surface energy balance equation. Implemented methods resulted in K_c values similar to what is reported in the literature for corn in the semi-arid climate of the study area. During a 4-week period, total corn ET averaged for all methods and treatments was 192 mm, similar to the reference alfalfa ET over the same period. The results showed that reflectance-based K_c methods are capable of estimating corn water consumption rates very similar to those of energy balance models during the period considered in the study.

1. Introduction

With a continuous increase in world population, an efficient management of fresh water resources to meet all of the urban, industrial, environmental, and agricultural requirements is becoming extremely challenging. Such a challenge is more pronounced in arid/semi-arid parts of the world, where water scarcity can turn competitions into conflicts. In these regions, irrigated agriculture is responsible for the single greatest consumptive use of water. Hence, a sustainable water resources management in these areas is not possible without having a comprehensive knowledge on the amount of water that is used by crops during the evapotranspiration (ET) process. Traditionally, crop ET is estimated through multiplying reference ET by the so-called crop coefficients, which represent the ratio of water consumption by the crop under consideration to that of a reference crop. Crop coefficients change with crop type and growth stage. Since the method and frequency of water application can have a significant effect on water evaporation from soil and crop surfaces, two types of crop coefficients have been developed. The first type is called the basal crop coefficient (K_{cb}) and accounts for just the crop transpiration, while the other type, known as the single crop coefficient (K_c), includes both transpiration and evaporation. Due to its simplicity, the K_c/K_{cb} approach is used by farmers and irrigation managers and continues to be the most common method of identifying crop water requirements.

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Clearly, the accuracy of crop coefficient approach depends on the accuracy of its components, namely the K_c/K_{cb} and the reference ET. The calculation of reference ET from basic weather parameters measured at weather stations has been investigated thoroughly and the existing standardized methods are satisfactorily accurate. However, crop coefficients vary significantly with agro-climatological conditions, as well as physiological anomalies among different varieties. Thus, tabulated K_c/K_{cb} values developed under pristine conditions of well-managed and stress-free crops are not representative of actual and often sub-optimal conditions. To account for the effect of stress factors, which are rarely absent in agricultural systems, the multiplication of an adjusting stress coefficient (K_s) has been recommended in the literature (Allen et al. 1998). However, the estimation of K_s requires a comprehensive knowledge on soil/water/crop characteristics and becomes extremely cumbersome as the area of interest expands from a single field to canal command area and irrigation district.

With significant improvements in remote sensing instruments and techniques over the past few decades, many researchers have investigated the relationships between spectral characteristics of crop canopies and some of their agronomic parameters, such as canopy cover, leaf area index, and crop height. In addition, promising studies have been conducted to model crop coefficients from remotely sensed Vegetation Indices (VIs), estimated as mathematical combinations of canopy reflectance in different visible and infra-red wavebands (Glenn et al. 2011). Among pioneer works in this field are the research projects conducted by Bausch and Neale (1987), Neale et al. (1989), and Bausch (1993), which have established such relationships for corn planted under semi-arid climate of Colorado. Bausch and Neale (1987) reported that several agronomic parameters of well-watered corn (e.g., leaf area index, canopy shading, etc.) are strongly related to its reflectance properties. They found a linear relationship between tabulated corn K_{cb} suggested by Wright (1982) and remotely sensed estimates of Normalized Difference Vegetation Index (NDVI). Using NDVI to predict corn K_{cb} eliminated the need to manually adjust crop coefficients to account for variations in the onset and duration of different growth stages.

Neale et al. (1989) further advanced the results of previous research by replacing tabulated K_{cb} with values measured by lysimeter at two research sites. The first site (near Greeley, CO) was the same as the one in experiment by Bausch and Neale (1987). Hence, it was not surprising that the new NDVI-K_{cb} relationship was identical to the previous one, especially since the corn was kept under stress-free conditions. However, a slightly different relationship was developed for the second site (near Fruita, CO) and the difference was attributed to the difference in reflectance properties of the background soils at these two locations. The sensitivity of NDVI to the conditions of underlying soil was later investigated in more details by Bausch (1993). He used two types of soils (light- and dark-colored) at two levels of moisture (dry and wet), and found a variation of over 40% in $K_{cb\text{-}NDVI}$ when the background soil changed from light-dry to dark-wet. To overcome this issue, Bausch (1993) suggested that NDVI should be replaced with the Soil Adjusted Vegetation Index (SAVI), which was developed by Huete (1988) in a fashion to be more resilient to fluctuations in soil reflectance. Such a replacement resulted in estimates of $K_{cb\text{-}SAVI}$ that varied less than 6% between the two extreme soil conditions. SAVI-based models have other advantages over NDVI too. For example, both VIs become asymptotic (saturated) at high levels of canopy development, but NDVI saturates sooner than SAVI, making the latter VI to be more sensitive to crop physiological changes after reaching the effective cover (Glenn et al. 2011). SAVI has been also reported to be more stable under varying sun angle and cloudiness conditions (Bausch 1993).

Although VI-based methods have been successfully implemented in the past to compute crop water use, they have a major caveat and that is their slow response to stress development. Since it takes time for stress factors to cause a detectable change in crop spectral characteristics (Neale et al. 1989), VI-K_c models tend to overestimate ET at early stages of stress occurrence. One way to improve model performance under such circumstances is to take advantage of canopy temperature, which is very sensitive to (i.e., able to capture) stress presence. Remotely sensed energy balance (RSEB) models, for example, integrate canopy reflectance, canopy temperature, and some key weather parameters to estimate the portioning of available energy (net radiation minus soil heat flux) into latent and sensible heat fluxes. As a result, they are among the most accurate available methods of approximating crop ET, with errors of less than 6% for seasonal ET estimates (Gowda et al. 2008). However, since RSEB models are data intensive and rely on expert knowledge in several steps of the model, they have been mainly applied in research experiments and not for more practical purposes such as irrigation management and scheduling at the farm or district level. In this study, ground-based remotely sensed data are used as input data to several existing VI-K_c/K_{cb} models to estimate corn water consumption. Two RSEB models were also implemented to evaluate the performance of VI-K_c/K_{cb} methods under water stress conditions. The results of this study will help water managers to have a better understanding of the amount of water that can be salvaged under limited irrigation practices.

2. Methods

2.1. Experimental layout

This study was conducted in one of the Lower South Platte Project Research Farms near the city of Iliff in northeastern Colorado (Lat: 40º 46.05' N, Long: 103º 2.55' W, Elev: 1166 m), which has the South Platte River to the South direction at a close proximity. The predominant soil texture at this location is Clay Loam, similar to the soil type at one of the research sites (Greeley, CO) of Neale et al. (1989). Corn (*Zea mays* L.) was planted in early May and harvested in mid-October, 2011, and received two treatments of limited (deficit) irrigation, using a linear-move sprinkler system. The total irrigation depth over the growing season was 114.3 mm (4.5 in) and 88.9 mm (3.5 in) at the first (L-1) and second (L-2) treatments, respectively. During the same period, 400 mm (15.75 in) of precipitation fell in the area. Each treatment had two replicates, resulting in the total number of four study plots (L-1.1, L-1.2, L-2.1, and L-2.2, hereafter). A hand-held, multi-spectral radiometer (model MSR5, CROPSCAN, Inc., Rochester, MN) was used to measure surface reflectance in five wavebands similar to the bands of Landsat 5 Thematic Mapper (TM) satellite. These bands were in the blue (TM1), green (TM2), red (TM3), near infra-red (TM4) and short-wave infra-red (TM5) portions of the electro-magnetic (EM) spectrum. The MSR5 has two sets of sensors with 28° field of view (FOV). One set of sensors (five bands) is looking downward to detect the radiance reflected from the surface and the other is looking upward, through an opal glass cosine diffuser, to estimate the incoming radiance in the same bands. The fraction of radiation that is reflected by the surface can then be estimated by dividing the downward and upward measurements at each of the five bands.

Since the knowledge of surface temperature is required in running RSEB models, the MSR5 radiometer was equipped with an infra-red thermometer (model IRt/c.2, Exergen Corp., Watertown, MA) with a 35° FOV. The reflectance and temperature of corn canopy were measured by holding the combined MSR5-IRt/c.2 sensors above the top of the canopy at a nadir angle. All measurements were taken within 2 hours from solar noon, on 4 dates over a 4-week period after the corn had reached effective cover. Hourly estimates of key weather parameters were obtained from the measurements of an alfalfa-based weather station adjacent to the study site. This station is owned and managed by the "Colorado Agricultural Meteorological Network (CoAgMet)" program at the Colorado Climate Center, Colorado State University. Measured weather data are published online and are freely available at: http://climate.colostate.edu/~coagmet/. Measured weather parameters were further analyzed to calculate reference alfalfa ET, using the standardized Penman-Monteith method (ASCE-EWRI 2005).

2.2. VI-based crop coefficient

NDVI and SAVI were estimated through the following equations, using canopy reflectance measurements made with the multispectral radiometer:

$$\mathrm{NDVI} = \frac{(\mathrm{TM4}-\mathrm{TM3})}{(\mathrm{TM4}+\mathrm{TM3})} \tag{1}$$

$$\mathrm{SAVI} = \frac{(1.0+\mathrm{L})\times(\mathrm{TM4}-\mathrm{TM3})}{(\mathrm{TM4}+\mathrm{TM3}+\mathrm{L})} \tag{2}$$

where TM3 and TM4 are reflectance (in decimals) in the red and the near infra-red (NIR) portions of the EM spectrum, respectively, and L is a coefficient that decreases with the increase in vegetation density. Huete (1988) suggested that a constant value of L = 0.5 can be used as an average throughout the growing season. Thus, the same value was used in this study. Estimated VIs were then used to calculate corn crop coefficients, based on several previously developed models, presented in Table 1.

Table 1. Implemented methods for estimating corn crop coefficient.

Method	Publication	Study area	Irrigation	Relationship
Neale	Neale et al. (1989)	North CO	Irrigated	$K_{cb} = 1.181\times\mathrm{NDVI}-0.026$
Bausch	Bausch (1993)	North CO	Irrigated	$K_{cb} = 1.416\times\mathrm{SAVI}+0.017$
S&I-I	Singh & Irmak (2009)	South NE	Irrigated	$K_c = 1.317\times\mathrm{NDVI}+0.023$
S&I-D	Singh & Irmak (2009)	South NE	Dry-land	$K_c = 1.213\times\mathrm{NDVI}+0.042$

The first VI-K_c/K_{cb} model was the one developed by Neale et al. (1989) for irrigated corn planted at a site near the city of Greeley, CO. They also developed a slightly different relationship for corn planted near Fruita, CO, and the difference was due to the difference in spectral characteristics of the soil at these two locations. Since the soil type at the research farm of this study was similar to the one at the Greeley site (Nunn clay loam), only the equation developed for this location was used in our analyses. The second approach implemented in this study was the SAVI-based model of Bausch (1993), developed under varying soil color/water content conditions. Since both of the Neale and Bausch methods rely on tabulated basal crop coefficients suggested by Wright (1982), a maximum threshold of 0.93 was applied to their estimates as per recommendation of Bausch (1993), in order to avoid exceeding the maximum K_{cb} of Wright (1982).

Finally, the last approach was based on the results of a study by Singh and Irmak (2009). Unlike the previous two experiments, corn K_c in this study was estimated by running a RSEB model known as SEBAL (Surface Energy Balance Algorithm for Lands, Bastiaanssen et al. 1998). SEBAL-based K_c was then related to NDVI on a distributed basis. Applying SEBAL model made it possible to include several irrigated and dry-land corn fields in the analyses to develop a relationship that covers a wider range of cultural practices. However, the major difference between the first two approaches and the latter one is in the type of crop coefficients they approximate. Neale and Bausch methods compute K_{cb}, while S&I-I and S&I-D models provide an estimate of K_c. As explained before, K_{cb} does not account for evaporation from the soil surface, so its values are expected to be smaller than K_c values. Since VIs were estimated only on 4 dates, the results of all approaches were interpolated linearly for the days in between. Daily crop coefficients were then multiplied by the reference ET to calculate daily rates of corn water use.

2.3. Remotely sensed energy balance model

In general, RSEB models are based on the simple form of energy balance equation at studied surfaces:

$$R_n = G + H + LE \qquad (3)$$

where R_n is net radiation, G is soil heat flux, H is sensible heat flux, and LE is the latent heat flux in units of energy (W m^{-2}) or depth of water (mm d^{-1}). R_n, G, and H components are modeled by integrating remotely sensed and in-situ data, and LE is calculated as the residual of the above equation. In this study, two RSEB models were applied to independently estimate corn water use. The first model is known as METRIC (Allen et al. 2007) and takes advantage of an innovative H estimation approach, which was originally introduced in SEBAL model. According to this approach, H is approximated iteratively by identifying two pixels at near-extreme condition. One of the extreme pixels is a hot (dry) pixel, with a negligible vapor pressure gradient. Over such a pixel, all of the available energy is used for heating the soil and the air above the surface, thus LE could be assumed zero. The other extreme pixel is a cold (wet) pixel, where a well-watered crop uses all of the available energy in the ET process, resulting in a negligible sensible heat flux. The value of H over all other pixels could be interpolated between these two extreme conditions (Allen et al. 2007).

The second implemented RSEB model was specifically developed and validated for corn and soybean by Chávez et al. (2005). Unlike the METRIC model, which was developed to use satellite imagery as input data, the Chávez model was based on the use of aircraft multispectral digital imagery. This model, however, may be applied to any remote sensing platform. In this study, we applied both of the METRIC and Chávez models to the remotely sensed data collected at ground level, which has some differences with air- and space-borne applications. One difference is that unlike satellite – and to a less extent aircraft – imagery, the ground-based data are not affected by the optical thickness of the atmosphere between the sensor and the target. Thus, corrections for atmospheric scattering and attenuation are not required. Another difference is that the canopy reflectance data over studied treatments were collected at slightly different times, since the MSR5-IR/tc.2 needed to be carried from one plot to the other, while in a satellite or aircraft image, all of the remotely sensed data (pixel values in an image) are acquired at the same instance of overpass. To account for this issue, the corresponding hourly weather parameters (from CoAgMet station) were identified in a fashion to represent a time period closest to the time of each remote sensing measurement. For example, if the remote sensing data were taken around 1030 AM, the weather parameters reported at hour 1100 AM was assigned to it. If the remote sensing data were taken close to 1100, the associated weather parameters were averaged for hours 1100 and 1200. Note that weather parameters were measured at time intervals shorter than hourly, but they were averaged over one hour period and reported at the end of that hour.

Although the METRIC model can be applied over any type of agricultural crops, some of its internal sub-models (e.g., the roughness length function) are developed for short crops with a height of less than 1.0 m (Allen et al. 2007). Therefore, the model was further modified to better represent heat and water dynamics over the tall canopy of corn. This modification was made by the use of actual crop height measurements for estimation of zero-plane displacement height, as well as roughness length for heat and momentum transfer. To be consistent, the same height measurements were used in running the Chávez model. ET results of both RSEB models were divided by the reference ET (from CoAgMet Station) to obtain K_c on each of the 4 dates of data acquisition. For the days in between these 4 dates, values were interpolated linearly. Finally, daily corn ET was estimated by multiplying daily K_c by the corresponding reference ET.

3. Results and Discussion

3.1. Spectral characteristics of corn canopy

Since surface reflectance data are the major input data to all of the implemented approaches in this study, it is of crucial importance to control their quality prior to any further analyses. All of the reflectance values detected by MSR5 had a behavior very similar to what is expected for the viewed surfaces. Estimated VIs were also within the expected range reported in the literature. Figure 1 demonstrates the spectral reflectance of two corn canopies and a bare soil in visible and infra-red wave-bands.

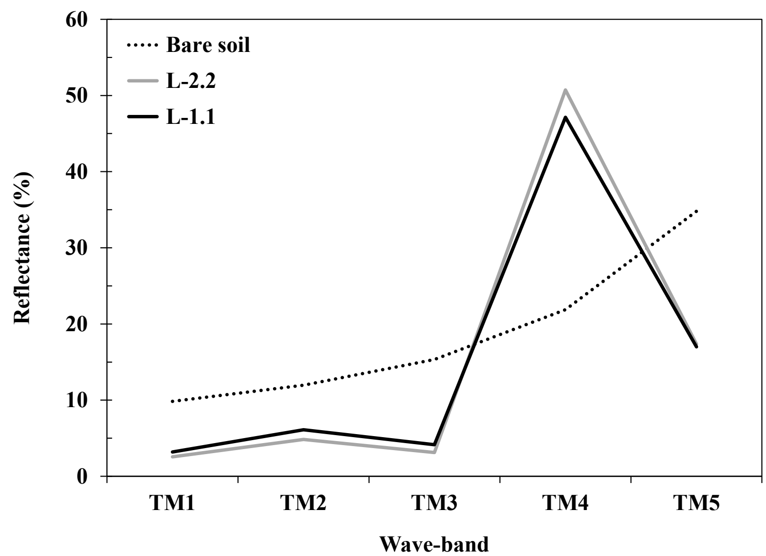

Figure 1. The reflectance of corn canopy at treatments L-1.1 (solid black), L-2.2 (solid gray), and the bare soil of a fallow field (dotted black), captured by MSR5 on Aug. 5th, within 30 minutes of 1200 PM (MST).

According to this figure, the reflectance of corn was below 10% in the three visible bands, with a local peak in the green band (TM2). Such a low reflectance is due to the fact that green leaves absorb most of the radiation in the visible part of the EM spectrum. At the NIR band (TM4), however, the corn canopy reflected about half of the incident radiation. This high reflectance is caused by the cellular structures and by the arrangements of multiple layers of leaves. Finally, the reflectance in the short-wave infra-red band (TM5) is inversely related to the water content of vegetation.

Interestingly, treatment L-2.2 had a higher reflectance in NIR and slightly lower reflectance in visible bands compared to treatment L-1.1, meaning that the corn at L-2.2 was at a better condition compared to the corn at L-1.1. This is mainly due to the fact that the second treatment received only 25 mm less irrigation water compared to the first one. This small difference in irrigation water was even less significant since the amount of precipitation during the growing season was considerably larger than the average, probably enough to meet the entire crop water requirement. In addition to crop reflectance, the bare soil of a fallow field had an expected reflectance signature, with values increasing with the wave length. This fallow field represented the hot pixel, required in the METRIC model. The cold pixel was selected over a well-watered and healthy patch of alfalfa, located within adjacent alfalfa fields. Since these alfalfa fields were harvested and irrigated on different dates, the location of the cold pixel did not remain the same throughout the considered study period.

3.2. VI-based crop coefficient

NDVI and SAVI were computed for each of the four treatments, based on equations 1 and 2 and the measured canopy reflectance. Estimated VIs were then used as input data into implemented VI-K_c/K_{cb} approaches. For the days in between the four measurement dates, the values were interpolated linearly to achieve one value per day. Table 2 summarizes some of the statistical characteristics of daily K_c/K_{cb} for a 4-week period (Aug 5th to Sep 2nd, 2011).

Table 2. Statistical characteristics of VI-based corn K_c/K_{cb}, n = 29.

Treatments		Neale	Bausch	S&I-I	S&I-D
L-1.1	**Min.**	0.76	0.69	0.90	0.85
	Max.	0.93	0.93	1.13	1.06
	Mean	0.89	0.87	1.07	1.01
	Median	0.91	0.89	1.10	1.03
L-1.2	**Min.**	0.72	0.63	0.85	0.80
	Max.	0.93	0.93	1.21	1.14
	Mean	0.88	0.83	1.08	1.02
	Median	0.90	0.86	1.10	1.03
L-2.1	**Min.**	0.59	0.50	0.71	0.68
	Max.	0.93	0.93	1.19	1.12
	Mean	0.83	0.76	1.01	0.96
	Median	0.86	0.80	1.04	0.99
L-2.2	**Min.**	0.85	0.76	1.00	0.95
	Max.	0.93	0.93	1.18	1.11
	Mean	0.92	0.86	1.10	1.04
	Median	0.93	0.86	1.10	1.04

As mentioned, unusually high amount of precipitation replenished soil water content and prevented noticeable water-stress-induced reduction in corn growth (crop height was about the same for all treatments). The difference in irrigation depths among the two treatments was also not significant enough. Hence, the observed variation in VIs and consequently K_c/K_{cb} values were more a result of spatial variations in soil conditions and plant population, rather than the differences in the amount of applied water. As expected, K_c values of S&I-I method, developed for irrigated corn, were about 6% larger than the results of S&I-D, developed for dry-land corn. S&I-I results were also larger than K_{cb} estimates of Neale and Bausch methods by 21 and 29% on average, respectively. This difference mainly represents the portion of corn ET that is evaporated from soil and plant surfaces, assuming other factors (e.g., experimental differences in developing these methods) do not play a significant role. In general, all of the K_c estimates suggest that corn water use during the study period was very close to that of the reference alfalfa.

3.3. Remotely sensed energy balance model

Hourly estimates of corn ET based on the two RSEB models, calculated for the time of remote sensing data acquisition, were divided by the corresponding hourly alfalfa reference ET to obtain RSEB-based K_c of corn. This hourly computed K_c value was assumed to represent the 24-hour K_c for the day of measurement. Crop coefficients for the days in between the four measurement dates were linearly interpolated. Over the four weeks of study period, average daily K_c values based on the METRIC model were 1.01, 1.00, 0.96, and 1.02 for treatments L-1.1, L-1.2, L-2.1, and L-2.2, respectively. The same values based on the Chávez model were slightly smaller at 0.94, 0.97, 0.94, and 0.93 for treatments L-1.1, L-1.2, L-2.1, and L-2.2, respectively. Figure 2 shows the evolution of corn crop coefficient for plot L-2.1, resulted from all of the implemented VI- and RSEB-based approaches, in addition to the K_c values reported by the CoAgMet.

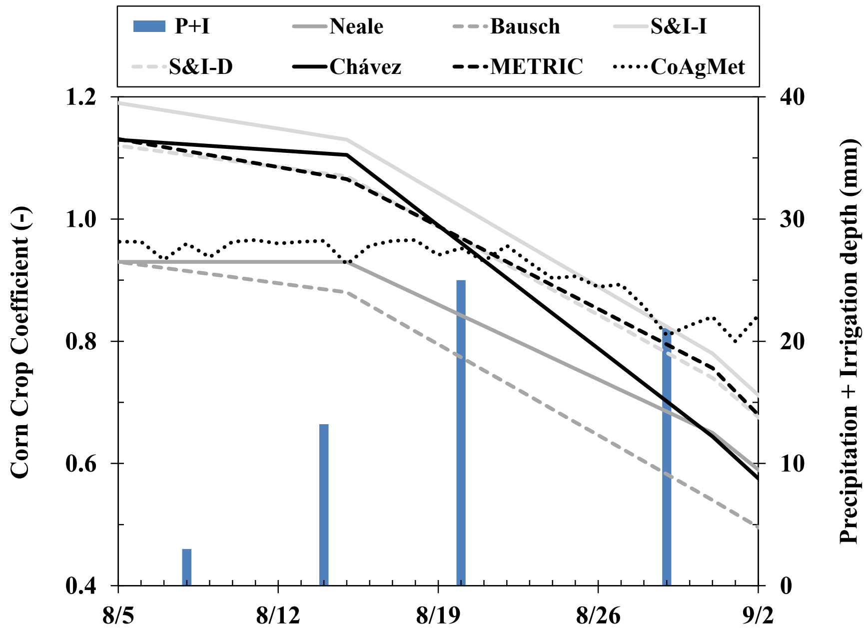

Figure 2. Corn crop coefficients for treatment L-2.1, along with the depth of applied water (irrigation or precipitation) represented as vertical bars on a separate axis.

As demonstrated in Figure 2, S&I-I and S&I-D results had a very similar pattern, with the former being slightly larger than the latter. The S&I-D and METRIC estimates were essentially the same over the entire study period. This is not surprising as the S&I-D method was developed using the K_c estimates of SEBAL model, which is very similar to METRIC, especially over flat terrains. In addition, S&I-D results represent dry-land condition, which is also very similar to the conditions of this study, where irrigation water accounted for only 20% of the total applied water by irrigation and precipitation. The results of Chávez model were similar to the previous two methods for the first half of the study period, but they dropped to values close to the Bausch estimates by the end of the 4-week period. Neale and Bausch estimates of K_{cb} were closer to each other at the beginning of the period, but they diverged as the time passed. It appears that this pattern is due to the corn senescence, which started in late August. SAVI and NDVI have different sensitivities to the change in leaves chlorophyll content, as well as the wetness of background soil, which is more pronounced at later stages of the growth.

Another point to notice in Figure 2 is that the 25-mm irrigation event of Aug. 20th was not detected by any of the methods. This is because no measurement was taken on or shortly after this event. The next measurement occurred 11 days later, allowing the soil surface evaporation to cease. Having a measurement on or close to this irrigation event would have eliminated the underestimation error, but it may have also caused an overestimation error on the dates when the surface became dry, especially since the next measurement was after a wetting event too. The best solution to this issue would be taking readings on every single day, which is not feasible for most practical purposes such as irrigation scheduling and management. Under realistic conditions, decision makers need to rely on a few discrete measurements. Therefore, it seems that the solution lies in improving the interpolation method employed to estimate the intermediate values of crop coefficient and water use.

3.4. Corn water consumption

Identified crop coefficients were multiplied by daily alfalfa reference ET to calculate daily corn ET. Figure 3 shows the resulted values for treatment L-2.1, as an example of other treatments. At this treatment, the variation among daily ET estimates of implemented methods reached 2.0 mm on some days. However, it was smaller on other days, especially when the alfalfa reference ET was small due to a lower atmospheric demand.

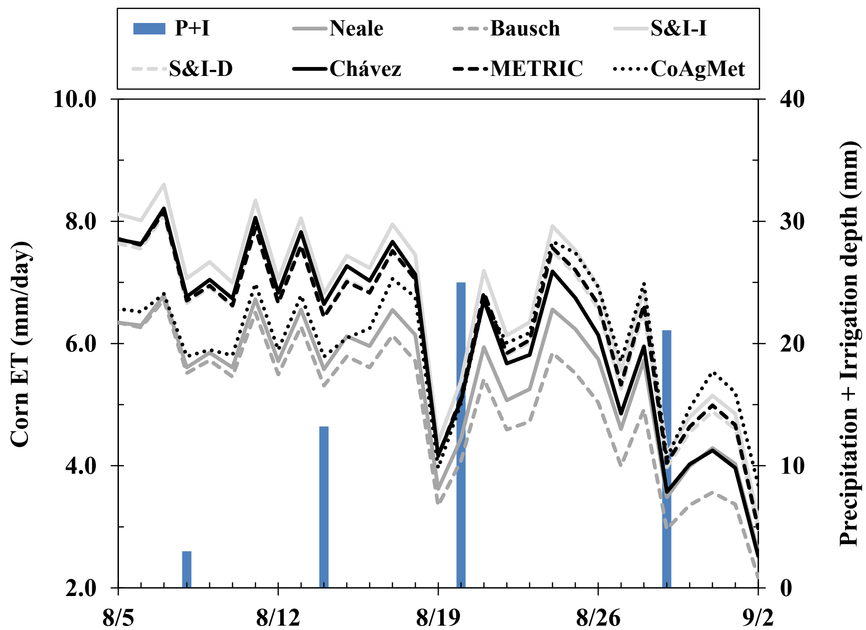

Figure 3. Corn ET for treatment L-2.1, along with the depth of water application (irrigation or precipitation) represented as vertical bars on a separate axis.

In general, crop transpiration estimates based on the two K_{cb} approaches of Neale and Bausch were smallest and the ET results of S&I-I were the largest during the study period. Estimates of crop ET made by the Chávez model followed that of S&I-I, S&I-D, and METRIC methods during the first 2 weeks of the study, but they dropped to smaller values by early September. Corn ET estimates resulted from applying K_c values of CoAgMet were among the smallest for the first half, and largest for the second half of the 4-week period. Based on this method, minimum, maximum, mean, and total corn ET were 3.7, 7.7, 6.0, and 175 mm during the study period, respectively. The same parameters for the reference crop (alfalfa) were 4.2, 8.5, 6.6, and 190 mm, respectively. Table 3 presents some of the statistical characteristics of calculated corn water use for all of the treatments and methods.

Table 3. Statistical characteristics of corn water use (mm), n = 29.

Treatments		Neale	Bausch	S&I-I	S&I-D	Chávez	METRIC
L-1.1	**Min.**	3.3	3.0	3.9	3.7	2.9	3.7
	Max.	7.5	7.1	8.9	8.4	8.1	8.3
	Mean	5.9	5.7	7.1	6.7	6.2	6.7
	Sum	*171*	*165*	*205*	*193*	*180*	*193*
L-1.2	**Min.**	3.1	2.8	3.7	3.5	2.6	3.3
	Max.	7.3	6.8	8.8	8.3	8.2	8.1
	Mean	5.8	5.5	7.1	6.7	6.4	6.6
	Sum	*167*	*159*	*206*	*194*	*184*	*191*
L-2.1	**Min.**	2.6	2.2	3.1	3.0	2.5	3.0
	Max.	6.8	6.7	8.6	8.1	8.2	8.2
	Mean	5.4	5.0	6.6	6.3	6.2	6.3
	Sum	*157*	*146*	*193*	*182*	*179*	*183*
L-2.2	**Min.**	3.7	3.3	4.4	4.2	2.7	3.6
	Max.	7.8	7.1	9.2	8.7	7.6	8.6
	Mean	6.1	5.7	7.3	6.8	6.1	6.7
	Sum	*176*	*164*	*210*	*199*	*177*	*195*

Total corn ET, averaged over all four treatments, was 204, 192, 180, and 191 mm, based on S&I-I, S&I-D, Chávez, and METRIC methods, respectively. These values are very close (95-107%) to the reference alfalfa ET during the same period. Corn water use is expected to be close to the reference rates during mid-season growth stage. However, since the study period of this experiment expanded to the beginning of the late-season growth stage (corn senescence), corn ET estimates were expected to be slightly smaller than the reference values. The only method that met this expectation was the Chávez RSEB model. Therefore, this model was used as the reference model for evaluating the performance of the other methods. Based on this approach, daily corn ET estimates of S&I-I, S&I-D, and METRIC methods had a Mean Bias Error (MBE) of 0.8, 0.4, and 0.4 mm day^{-1}, respectively. However, it should be noted that calculated errors are significantly affected by the estimates of the last two weeks of the study, when the results of Chávez model dropped below the results of other methods. Limiting the performance evaluation to the first two weeks of the study, when corn was still at mid-season growth stage, decreased MBE values to 0.4, –0.1, and –0.1 mm day^{-1} based on the same methods, respectively. The results of CoAgMet method had an opposite behavior. Daily corn ET based on tabulated K_c values of CoAgMet had a smaller MBE (–0.2 mm day^{-1}) when the entire study period was considered. Excluding the last two weeks of study increased the MBE to –0.8 mm day^{-1}. This different behavior is due to the fact that the underestimation error of this method during the first half of study was compensated by its overestimation error during the second half, suggesting that the results of tabulated K_c values are more reliable over longer (monthly and seasonal) rather than shorter (daily and weekly) periods. Among the two methods of estimating corn transpiration, NDVI-based model of Neale et al. (1989) resulted in values that were 3-8% larger than the SAVI-based model of Bausch (1993). Since NDVI is more sensitive to the color and water content of the underlying soil, Bausch model is more accurate for approximating corn transpiration. The results of this method were 88% of the ET estimates of Chávez model, meaning that only 12% of water use was through evaporation from soil and crop surfaces.

4. Conclusion

Two types of remote sensing approaches were implemented in this study to estimate corn crop coefficients. The first approach consisted of four previously developed VI-K_c/K_{cb} models, while the second approach included two RSEB models. As expected, K_{cb} values were smaller than K_c values. Estimated K_{cb} and K_c values were then used to calculate corn transpiration and evapotranspiration, respectively. The results showed that the two limited-irrigation treatments did not have a significant difference in water use. This was mainly due to the fact that precipitation events were larger in amounts compared to irrigation events, which most probably prevented water stress from developing and impacting corn growth. Total corn ET estimates over a 4-week period were similar to the alfalfa reference ET (from weather station), confirming that the unusually high rates of precipitation provided the entire corn water requirement. Taking the Chávez RSEB model (developed specifically for corn) as the reference, the performance of S&I-D method (developed for dry-land corn) was similar to the METRIC model, and better than the S&I-I method. Although S&I-D and METRIC methods had similar accuracies, the former approach is less complicated and requires far less data, so farmers and the technical staff of irrigation districts can be easily trained to use this method. Tabulated K_c values suggested by CoAgMet resulted in corn ET estimates that were smaller than all other ET estimates and close to the corn transpiration estimates. The error in this method was larger when the study period was reduced to periods shorter than 4 weeks.

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