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UTILIZING DIGITAL IMAGE PROCESSING AND TSEB MODEL FOR THE ESTIMATION OF ET

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ABSTRACT

Having an accurate yet simple method to estimate crop evapotranspiration (ET_C) is a vital component of reliable irrigation scheduling. In this study, two versions of the two-source energy balance (TSEB) model: the TSEB model with the Priestley-Taylor equation (TSEB-PT) and the Penman-Monteith equation (TSEB-PM), were used to estimate ET_C of dry edible beans in western Nebraska. Compared with previous studies, this study is unique in that a Visual Basic software - Crop Canopy Image Analyzer (CCIA) was developed to process digitally-captured RGB canopy images to obtain necessary canopy cover (CC) parameters for the TSEB models such as CC percentage and leaf shape factor (leaf area divided by its perimeter). Both TSEB-PT and TSEB-PM models were able to estimate ET_C well for fully-irrigated dry edible bean by having root mean square error (RMSE) of ranged from 0.03 to 0.05 in/day in 2019, as compared to ET_C estimated from FAO56. Furthermore, ET_C from TSEB-PT and TSEB-PM were compared with soil water balance derived ET_C and the RMSE ranged from 0.08 to 0.38 inches in roughly one-week period under four irrigation treatments ranged from dry land to fully irrigated. The proposed methods in this study, by uniting digital image processing with TSEB models, have great potential to be automated and used in field-scale for various irrigation management scenarios of many crops.

INTRODUCTION

Water scarcity is one of the main factors constraining agricultural production in arid and semiarid areas. The knowledge of crop evapotranspiration (ET_C), as well as the mechanism of ET_C partitioning into surface evaporation (E) and crop transpiration (T), is very important for precise quantification of the water balance in irrigation scheduling and management, optimizing crop production, identifying crop stress and drought impacts. Nebraska is the predominant irrigated agriculture state in the United States, with 3.3 million ha of irrigated lands which accounts for 14.9% of total irrigated lands in the U.S. (USDA 2013). In western Nebraska, where rainfall is much less than eastern part of the state, irrigation is critical since ET_C for regional crops always exceeds in-season precipitation. Particularly for dry edible bean (*Phaseolus vulgaris L.*) production in western Nebraska, 90% of its production is on irrigated lands (Yonts et al., 2018). Depending on the source of water, irrigated lands in western Nebraska are subject to unstable and variable surface water supply or ground water allocation of 70 acre-inches per certified irrigated acre per consecutive 5 years (https://www.npnrd.org/water-management/integrated-management-plan.html). The cutoff of surface water supply to eastern Wyoming and western Nebraska in 2019 due to a tunnel collapse (https://extension.unl.edu/statewide/panhandle/canal-break/) further emphasizes the importance of understanding and quantifying crop consumptive use (loss of water through ET) when water supply is limited.

There are many methods available to quantify ET_C. One simple method to determine crop ET is by solving the soil water balance equation:

$$ET_c = -\Delta S + P + I - R - D \quad (1)$$

where during the time period, ΔS is change in soil water storage; P is precipitation; I is irrigation applied; R is runoff; D is deep percolation. Since P and I can be straightforwardly obtained and recorded, and runoff or deep percolation can be minimized by management, determination of ΔS is most critical when using soil water balance to calculate ET. Soil water content can be measured by taking soil gravimetric samples, or by using variety of soil moisture sensors such as neutron probe and electromagnetic sensors (Evett et al., 2006; Singh et al., 2018). However, measuring soil water content below the root zone can be quite challenging depending on the crop root depth and is critically important for accuracy of ET_C estimation using soil water balance method (Evett et al., 2012). If soil water content below root zone is measured and remain relatively constant, it verifies no deep percolation has happened and ET estimation is accurate. To the contrary, deep percolation will have to be estimated if soil water content below root zone constantly fluctuates.

The FAO Irrigation and Drainage Paper No. 56 (Allen et al., 1998) is widely adopted worldwide to estimate ET_C by using concept of reference evapotranspiration (ET_o) and crop-specific coefficient (K_C). Application of the FAO56 method requires accurate and representative weather data, specifically on-site temperature, humidity, solar radiation, and wind speed, as well as proper siting (Pereira et al., 2015). However, such information are not always available for individual fields and incomplete, inaccurate, or interpolation of proximate weather data to calculate ET_C can lead to erroneous results (Benli et al., 2010; Kwon and Choi, 2011). FAO56 method estimates ET_C for plants that on under optimal and well-watered conditions, and for plants that are under stress or in non-standard conditions, K_C will have to be adjusted accordingly (Allen et al., 1998). In reality, plants grown at a large commercial production field are often subjected to various soil types, elevations, and slopes, which combination of these conditions can be unfavorable for plants. Therefore, application of FAO56 method under such condition will have to be adjusted according to actual conditions. Since ET_o remains the same, K_C can be adjusted and scaled by remotely-sensed vegetation indexes (Neale et al., 1990; Kamble et al., 2013).

The TSEB model has been proposed to estimate ET_C, where sensible heat and latent heat flux for both soil (T_S) and canopy (T_C) temperatures can be calculated separately using a single measurement of composite surface (soil and canopy) temperature (T_R), meteorological variables (air temperature, wind speed, solar radiation, relative humidity), and vegetation information (crop height, CC percentage, leaf area index) (Norman et al., 1995). T_R is assumed that the sum of T_c and T_s weighted by CC (Norman et al., 1995):

$$T_R^4 = f_S T_c^4 + (1 - f_S) T_s^4 \quad (2)$$

where f_S is the fraction of CC appearing in the field of view of Infrared Radiometry Thermometer (IRT). The fraction of the field of view of IRT can be related to view zenith angle (θ) and leaf area index (LAI) (Eqn. 3).

$$f_S = 1 - \exp\left(\frac{-0.5LAI}{\cos\theta}\right) \quad (3)$$

Previous TSEB studies have used commercial plant canopy analyzers such as LAI-2000 (LI-COR Biosciences, Lincoln, NE, USA) to obtain LAI (Norman et al., 1995; Colaizzi et al., 2010, 2012; Hoffman et al., 2016). However, such instruments are mostly used by research facilities and infeasible for commercial farm use due to cost and interpretability of data. In addition, several important parameters in TSEB model are hard to acquire, such as aerodynamic resistance, canopy resistance at the boundary layer, and soil resistance (Norman et al., 1995; Kustas and Norman, 1999). The boundary layer of canopy resistance can be estimated by LAI, wind speed, canopy height, and leaf area (A) divided by leaf perimeter (P) (A/P) (Norman et al., 1995). The soil resistance is estimated by canopy height, LAI, wind speed above soil surface, and A/P (Kustas and Norman, 1999). In this study, instead of measuring LAI to estimate f_S, we proposed a new method by using RGB CC picture taken from field and a software modified from a soybean CC software (Liang et al., 2018). A previous study using digital photographs was shown to reduce errors of f_S calculations by 15% compared with the commonly used clumping index approach such as aircraft and Landsat imagery (Colaizzi et al., 2012). However, to our best knowledge, there have been no studies that use digital images to estimate leaf shape factor and subsequently use in calculation of TSEB models.

Hence the objectives of this paper were to: 1) develop a software/algorithm to estimate dry edible bean canopy cover percentage and leaf shape factor; 2) calculate daily ET_C using TSEB models with software determined canopy parameters; 3) compare daily ET_C from TSEB models with FAO56 determined ET_C and soil water balance determined ET_C using neutron probe readings.

MATERIAL AND METHODS

Experiment site and design

The experiment was conducted at the University of Nebraska-Lincoln, Panhandle Research and Extension Center (PHREC) in Scottsbluff, NE (41°53'34.93"N, 103°41'2.04"W, elevation 3900 ft) in 2019. The climate in the region is semi-arid with annual average rainfall of 15.7 inches. Soil in the experimental field is Tripp very fine sandy loam, with up to 3 percent slopes. Great Northern Beans were planted at 22 inches row spacing on June 7th and June 10th in 2018 and 2019, respectively. The experiment was a randomize complete design (RCD) with 4 irrigation treatments (0%, 33%, 66%, and 100% of full irrigation) and 3 replicates. The full irrigation treatment (FIT) was meant to fully satisfy crop water needs which is calculated based on crop evapotranspiration (ET_C) using the method presented in FAO-56 (Allen et al., 1998). Dry edible bean crop coefficients were adopted from growth stage charts from the Nebraska Agricultural Water Management Network (NAWMN) (http://nawmn.unl.edu). Details of NAWMN can be found in Irmak et al. (2010).

Irrigation was applied using a Zimmatic (Lindsay Corporation, Omaha, NE, USA) variable rate linear move sprinkler irrigation system. Irrigation was applied to all treatments when management allowed depletion (MAD) of FIT was at 40%, and irrigation rates of treatments were calculated based on percentage of FIT. An on-site weather station (~0.75 mile from experimental field) from the Automated Weather Data Network (AWDN, http://awdn.unl.edu/classic/home.cgi) collected hourly air temperature, relative humidity, solar radiation, wind speed and precipitation. Plots were 33 ft wide by 50 ft long. Each plot consisted of 18 crop rows and the middle 6 rows were used for sensor installation, image acquisition, and data collection. Composite temperature of crop canopy and soil was measured using infrared thermometers (IRTs) from Apogee Instruments (Apogee Instruments, Inc., Logan, Utah, USA). The model SI-431, which has a field of view of 14° half angle and accuracy of ± 0.3 °C with SDI12 output were used in this study. The IRTs were installed at all three replications of each irrigation treatment. The IRTs were mounted to a metal pole 4 ft above the ground, and were angled 45° below horizon and parallel with the crop row. Heights of IRTs were kept same throughout the season. According to the height of and view angle of the IRTs, the total area seen by the sensor was approximately 6.56 sq. ft^2 at maximum. Data from the IRTs were continuously recorded every 5 minutes using CR300 data-loggers (Campbell Scientific Inc., Logan, Utah, USA). In addition to IRTs, at each plot, a neutron probe access tube was installed at 4 ft depth and a 503 DR Hydroprobe (CPN International, Inc., Concord, CA, USA) was used to measure soil water content at 1 ft increment at weekly basis during the growing seasons. Soil water content data were therefore used to compute ET_C using equation 1.

Crop Canopy Image Analyzer (CCIA)

Canopy cover images of dry beans were taken on four dates in 2019 (July 18th, July 22nd, August 1st and August 14th). Pictures were taken at dry bean canopies nearby IRT of each irrigation treatment with a RGB camera (1500$\times$1125 pixels) on a tablet (Samsung Galaxy Tablet 10, Samsung Group, Seoul, South Korea) at a distance of approximately 12 inches height above the canopy at 45 downward degrees. Twenty representative canopy images from various treatments plots during different growth stages were randomly selected to classify color groups and train the designed software Crop Canopy Image Analyzer (CCIA) for estimating CC percentage. To estimate A and P for calculating soil resistance in TSEB models, three dry bean leaves were randomly taken from each irrigation treatment on July 18th, July 25th, and August 2nd of 2019. CCIA utilizes Mahalanobis distance and Canny edge detection method to estimate canopy cover and leaf shape factor, repectively.

Mahalanobis distance (Devroye et al., 1996) is a classification method for analyzing leaf color, and it has been used to determine soybean A (Liang et al., 2018). The Mahalanobis distance (Md) (Eqn. 4) measures the similarity between an unknown sample group and a known sample group.

$$Md = \sqrt{(X-Y)^T S^{-1} (X-Y)} \quad (4)$$

Where X is a three dimensional vector (R, G, B), which represented pixels from the image to be processed. Y is a three dimensional vector ($\bar{R}$, $\bar{G}$, $\bar{B}$), which represents the average of reference pixels (reference group) for each class to be identified. The Mahalanobis color distance standardizes the influence of the distribution of each feature considering the correlation between each pair of terms. In the case of RGB color images, S is computed as (Eqn. 5):

$$S = \begin{bmatrix} \sigma_{R_{ref}R_{ref}} & \sigma_{R_{ref}G_{ref}} & \sigma_{R_{ref}B_{ref}} \\ \sigma_{G_{ref}R_{ref}} & \sigma_{G_{ref}G_{ref}} & \sigma_{G_{ref}B_{ref}} \\ \sigma_{B_{ref}R_{ref}} & \sigma_{B_{ref}G_{ref}} & \sigma_{B_{ref}B_{ref}} \end{bmatrix} \quad (5)$$

and as an example, the elements of S are calculated as:

$$\sigma_{G_{ref}R_{ref}} = \sigma_{R_{ref}G_{ref}} = \frac{\sum_{i=1}^{n}(R_i-\bar{R})(G_i-\bar{G})}{n-1} \quad (6)$$

where σ is covariance of R, G, B reference group colors, R_i, G_i, B_i are the values of the i^{th} match (i=1, 2, 3, …..n), and $\bar{R}$, $\bar{G}$, $\bar{B}$ are the mean color values for R, G, B in the given image, respectively.

In the proposed methodology of this work, six reference groups of pixels were selected to generate the classification, in which every group represented relevant characteristics of dry bean leaves and background classes. The six groups identified were: leaves (light green leaves, light yellow leaves, dark green leaves) and background (shadow, soil, and silver metal rods which data loggers were mounted to). If any of these classes were not present, or a new class appeared on the image, the number and/or the group labels was modified in the program. To implement the classification and provide graphical interface to the user, the software was developed using Visual Basic 2017 (Figure 1). Details of the identified leaves were shown as green color and background were shown as pink color in the output figures. CC percentage (f_s) was calculated using green area pixel number (N_G) and background pixel number (N_B) (Eqn.7).

$$f_s = \frac{N_G}{N_G + N_B} \times 100\% \tag{7}$$

TSEB Models

The TSEB model was originally developed by Norman et al. (1995) to make use of remotely sensed radiometric surface temperatures to estimate soil evaporation and canopy transpiration. The model was further modified by Kustas and Norman (1999) by improving the soil surface resistance formulation and net radiation partitioning between soil and canopy components. The net radiation is partitioned between the vegetated canopy and soil, and can be expressed as:

$$R_n = R_{ns} + R_{nc} = H + LE + G \tag{16}$$

where R_n is net radiation (W m^{-2}), R_{ns} and R_{nc} are the net radiation for soil and vegetation canopy (W m^{-2}), respectively; H and LE are sensible and latent heat fluxes (W m^{-2}), respectively, and G is the soil heat flux (W m^{-2}). The energy balance for the soil and vegetated canopy can be expressed as:

$$R_{ns} = H_s + LE_s + G \tag{17}$$

$$R_{nc} = H_c + LE_c \tag{18}$$

where H_s and H_c are the sensible heat fluxes for the soil and canopy (W m^{-2}), respectively, LE_s and LE_c are the latent heat fluxes for the soil and canopy (W m^{-2}), respectively. G is parameterized with the phase difference approach:

$$G = R_{ns}\left\{a \cdot \cos\left[\frac{2\pi}{b}(t + c)\right]\right. \tag{19}$$

where t is the solar time angle (s), a is the amplitude parameter (dimensionless), and c is the shift (s). In this study, parameters a, b, and c take the values of 0.3, 86,400, and 10,800 following Colaizzi et al. (2012).

In this study, the series resistance network form was applied, in which H_c, H_s, and the sum of both terms are calculated as:

$$H_c = \rho C_p \frac{T_c - T_{ac}}{r_x} \tag{20}$$

$$H_s = \rho C_p \frac{T_s - T_{ac}}{r_s} \tag{21}$$

$$H = \rho C_p \frac{T_{ac} - T_a}{r_a} \tag{22}$$

Where ρ is the air density (kg m^{-3}), C_p is the specific heat of air (J kg^{-1} K^{-1}), T_s is the soil temperature (K), T_c is the canopy temperature (K), T_{ac} and T_a are the air temperature within the canopy boundary layer and air temperature (K), respectively, r_a is the aerodynamic resistance (s m^{-1}), r_x is the resistance in the boundary layer near the canopy (s m^{-1}), and r_s is the resistance to heat flux in the boundary layer above the soil surface (s m^{-1}). The r_a, r_x, and r_s are calculated according to Norman et al. (1995) and Kustas and Norman (1999). The leaf shape factor was calculated for r_s and r_x. The r_s is calculated as:

$$r_s = \frac{1}{c(T_s - T_c)^{1/3} + bu_s} \quad (23)$$

where c=0.0025, b=0.012, and u_s is wind speed at the height of soil surface, m s^{-1} (Kustas and Norman, 1999).

The u_s is calculated as:

$$u_s = u_c \exp\left(-a\left(1 - \frac{0.05}{h_c}\right)\right) \quad (24)$$

where u_c is the wind speed at top canopy (m s^{-1}), h_c is canopy height (m), and factor a is calculated as:

$$a = 0.28F^{2/3}h_c^{1/3}s^{-1/3} \quad (25)$$

where s called mean leaf size given by four times the leaf area divided by the leaf perimeter (Norman et al., 1995). In this article, leaf area divided by leaf perimeter is defined as leaf shape factor (L_S) (Eqn. 8).

The r_x is calculated as:

$$r_x = \frac{C'}{F}\left(\frac{s}{U_{d+Z_m}}\right)^{1/2} \quad (26)$$

where C' is derived from weighting a coefficient for leaf boundary layer resistance over the height of the canopy (Norman et al., 1995) and equation for calculating U_{d+Z_m} can be found in Norman et al. (1995).

The TSEB-PT model uses a modified Priestley-Taylor formulation to parameterize the canopy transpiration:

$$LE_c = \alpha_{PT} f_S \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (27)$$

Where α_{PT} is the Priestley-Taylor parameter (dimensionless), Δ is the slope of the saturation vapor pressure versus temperature curve (kPa $°C^{-1}$) and γ is the psychrometric constant (kPa $°C^{-1}$). An initial estimate of T_C can be derived as follows:

$$T_c = T_a + \frac{R_{nc} r_a}{\rho C_p}\left[1.0 - \alpha_{PT} f_S \frac{\Delta}{\Delta + \gamma}\right] \quad (28)$$

Accordingly, T_S is calculated with an in initial estimate of T_S, and then r_s can be estimated with the temperature gradient between the soil and canopy described in Kustas and Norman (1999). From Eqn.20 to Eqn. 22, the component H_S can be calculated and the LE_C and the LE_S are solved as residual terms. In order to obtain a realistic estimation of surface heat fluxes under water stressed conditions, the α_{PT} is iteratively decreased until LE_S exceeds zero and the initial α_{PT} is set 1.26 (Kustas and Norman, 1999). The detailed description of the TSEB model and the parameterization of the resistance network can be found in Norman et al. (1995) and Kustas and Norman (1999). The

TSEB model was revised by Colaizzi et al. (2012) using the Penman-Monteith equation instead of the Priestley-Taylor formulation to account for the impact of advection over semiarid environment. This revised version of the TSEB model is termed as TSEB-PM. The effects of varying vapor pressure deficit can thus be taken into account in the TSEB-PM model. The canopy transpiration is characterized using the Penman-Monteith equation:

$$LE_c = f_S\left(\frac{\Delta R_{nc}}{\Delta+\gamma^*} + \frac{\rho C_p(e_s-e_a)}{r_a(\Delta+\gamma^*)}\right) \quad (29)$$

and T_c is initialized as:

$$T_c = T_a + \frac{R_{nc} r_a \gamma^*}{\rho C_p(\Delta+\gamma^*)} - \frac{e_s-e_a}{\Delta+\gamma^*} \quad (30)$$

where $\gamma^*=\gamma(1 + r_c/r_a)$, r_c is the bulk canopy resistance (s m^{-1}), r_a is the aerodynamic resistance between the canopy and the air above the canopy (s m^{-1}), and e_a and e_s are the actual and saturation vapor pressure of the air (kPa), respectively. Similar to TSEB-PT, the TSEB-PM model was iteratively implemented. During the iterative procedure, r_c increases from 10 s m^{-1} with an increment of 20 s m^{-1} and terminates at 1000 s m^{-1}, or until LE_S exceeds zero. Comprehensive details of the TSEB-PM can be found in Colaizzi et al. (2012).

RESULTS AND DISCUSSION

In 2019, average yields of treatment ranged from 538 to 586 kg ha^{-1}. Yields in 2019 were significantly lower than normal, primarily due to two consecutive hailstorms which occurred around 8/15/2019. The hailstorms caused significant canopy defoliation among treatments. The CC percentage at the same sampling date increased with irrigation amounts (Figure 1). CC percentage after hailstorm damage was reduced on average by 43% at 0% treatment, 47% at 33% treatment, 51% at 66% treatment, and 54% at 100% treatment (Figure 1). Crop ET was not computed after the hailstorms. Yields were not significantly different among treatments (P = 0.68). Rain and irrigation are shown in Figure 2.

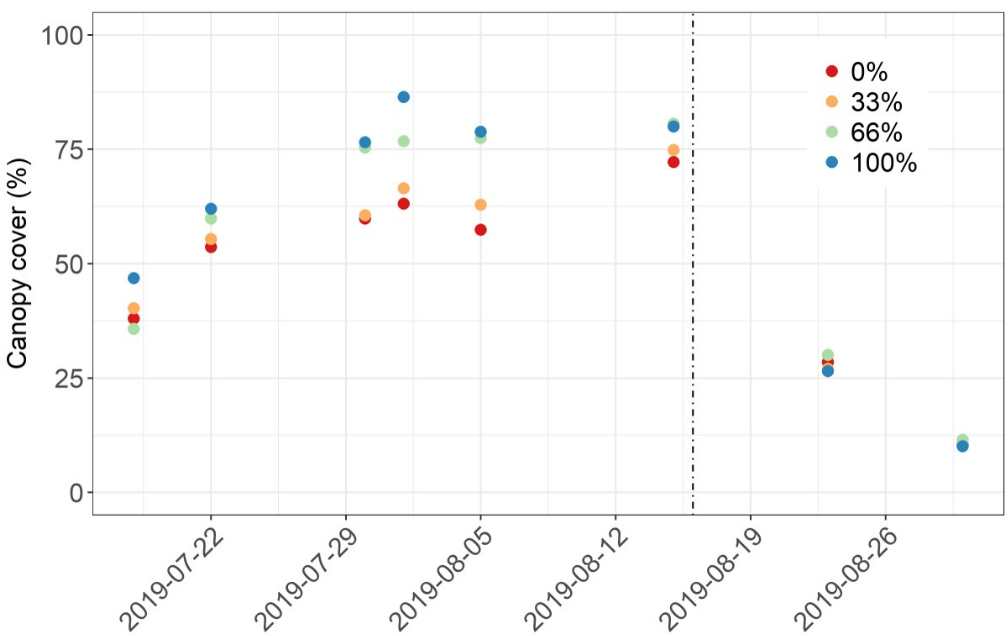

Figure 1. Canopy cover for four irrigation treatments between 7/18/2019 and 8/31/2019. Dashed line indicates when crop was damaged by hailstorms on 8/15/2019.

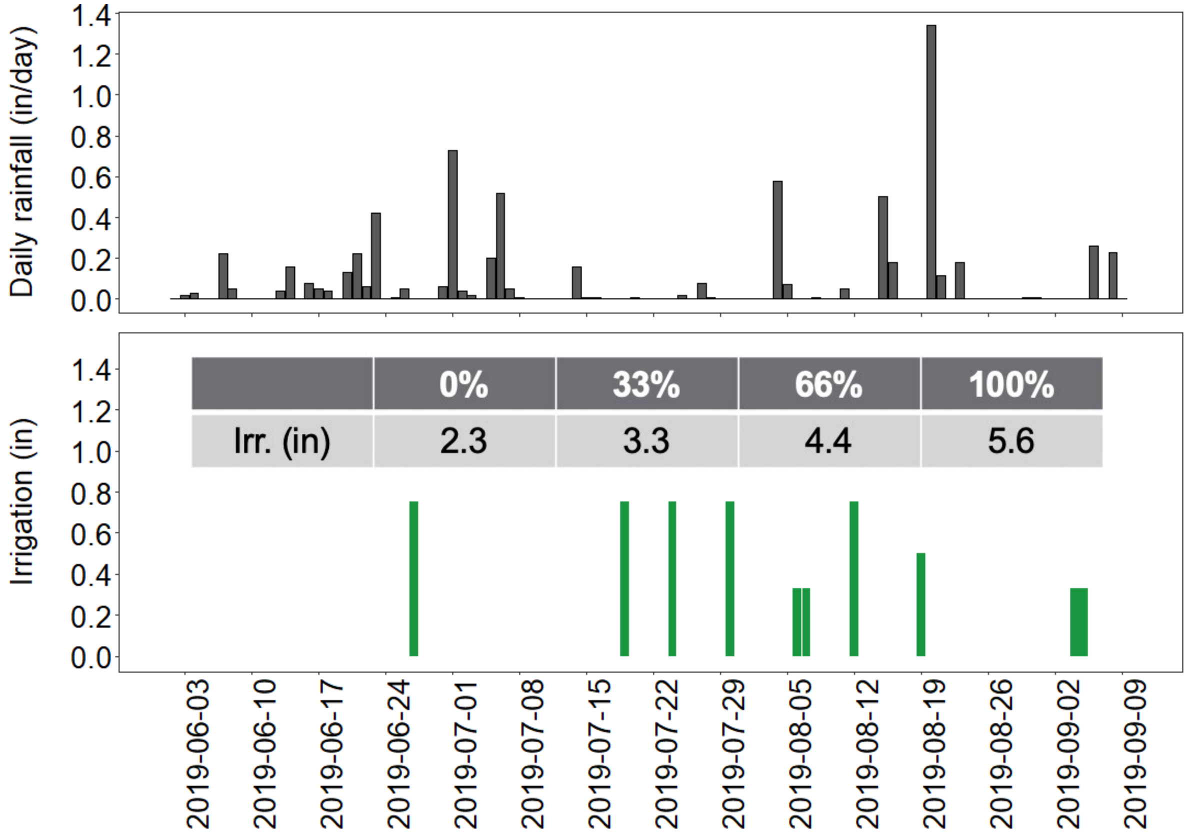

Figure 2. Rainfall and irrigation (100% or full irrigation shown here) in 2019 growing season.

Both TSEB-PM and TSEB-PT models were calculated hourly based on frequency of input data (weather, measured and interpolated field measurements). Thus actual ET_C from the two models were also in hourly frequency. For convenience of representation and comparison, modeled ET_C values were summed to daily frequency and are referred as $ET_{TSEB\text{-}PT}$ and $ET_{TSEB\text{-}PM}$ hereafter. Measured ET_C from FAO-56 and soil water balance using neutron probe are respectively referred as ET_{FAO56} and ET_{NP}. During 2019 growing season, $ET_{TSEB\text{-}PM}$ and $ET_{TSEB\text{-}PT}$ of the 100% irrigation treatment were compared with FAO-56-ET_C. In addition, $ET_{TSEB\text{-}PM}$ and $ET_{TSEB\text{-}PT}$ of all treatments were compared with ET_{NP} between July 18th and August 14th before the hail storm happened. The daily ET_C among four irrigation treatments calculated by Tukey's honest significance test showed significant differences (p=0.013) during 2019 growing season (Figure 3). The average $ET_{TSEB\text{-}PM}$ of the 0%, 33%, 66%, and 100% were 0.09 in d^{-1}, 0.13 in d^{-1}, 0.16 in d^{-1}, and 0.19 in d^{-1}, respectively. The average $ET_{TSEB\text{-}PT}$ of the 0%, 33%, 66%, and 100% were 0.09 in d^{-1}, 0.13 in d^{-1}, 0.17 in d^{-1}, and 0.20 in d^{-1}, respectively. It was observed that the $ET_{TSEB\text{-}PT}$ and $ET_{TSEB\text{-}PM}$ increased with irrigation amounts; higher irrigation rates would produce higher ET values. The R^2 of ET_{FAO56} with $ET_{TSEB\text{-}PM}$ at 100% irrigation treatment ranged from 0.73 to 0.88 whereas the R^2 with $ET_{TSEB\text{-}PT}$ ranged from only 0.60 to 0.75 (Figure 3).

Figure 3. Daily ETC of FAO-56 (100% irrigation treatment only), TSEB-PM, and TSEB-PT among 4 different irrigation treatments in 2019 growing season.

For ET_{NP}, since neutron probe readings were taken on weekly basis, ET_{NP} was also reported weekly (in week^{-1}). The RMSE of ET_{NP} with $ET_{TSEB\text{-}PM}$ model ranged between 0.07 to 0.36 in week^{-1}, whereas with $ET_{TSEB\text{-}PT}$ the RMSE ranged from 0.13 to 0.38 in week^{-1}. The overall RMSE in determination of ET_C by TSEB-PM and TSEB-PT models among the four irrigation treatments were 0.24 in week^{-1}and 0.30 in week^{-1}, respectively. Neutron probe measured ET of dry edible bean correlated with $ET_{TSEB\text{-}PT}$ and $ET_{TSEB\text{-}PM}$ well by having slope of 0.99 and 1.03 and R^2 were 0.71 and 0.82, respectively (Figure 4). The overall RMSE of $ET_{TSEB\text{-}PT}$ and ET_{NP} is 0.3 in week^{-1}, whereas the RMSE of $ET_{TSEB\text{-}PM}$ and ET_{NP} is 0.24 in week^{-1} (Table 1). Some data points were away from the dotted 1:1 line (Figure 4), and many happened during the period when large rainfall events occurred. A possible reason is each ET_{NP} data point was accumulated in weekly interval, and neutron probe would fail to tell what happened exactly during that period, especially whether runoff or deep percolation occurred. The analysis showed that the TSEB-PM model could account for less bias of ET prediction compared to TSEB-PT model in dry growing season, which indicated somewhat greater accuracy (Figure 4). The results indicated that IRT and calibrated TSEB-PM model provide reasonable estimation of ET_C of dry edible beans, which agreed that TSEB-PM is adequate to apply in strong advection (Colaizzi et al., 2012) environment such as western NE. The results also indicated that using TSEB-PM model with our software determined canopy parameters provided reasonable estimation of ET_C with different irrigation treatments for dry edible beans in western Nebraska.

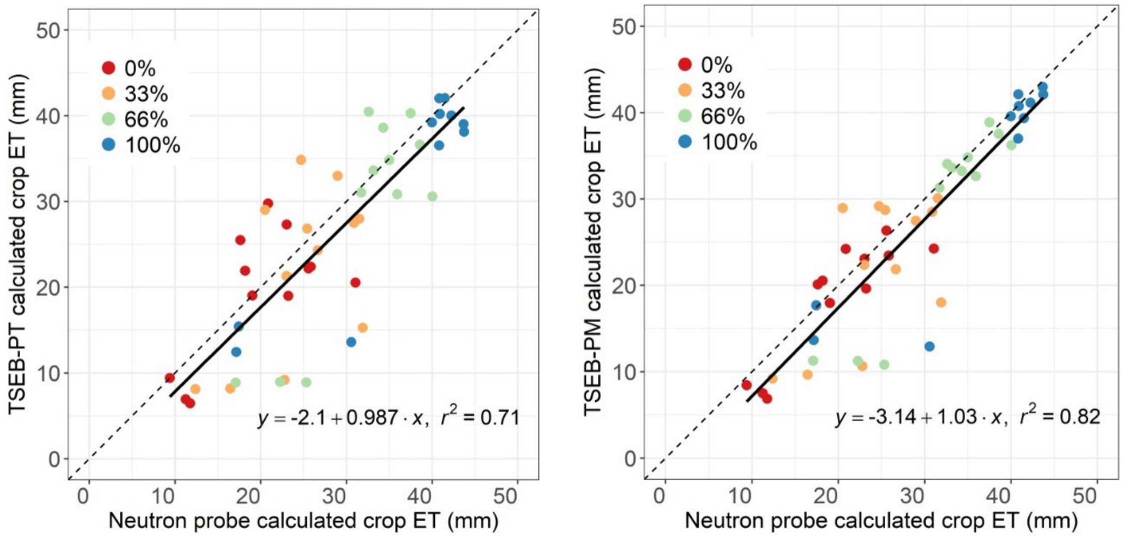

Figure 12. Comparison of the TSEB-PT calculated ET_C (left) and TSEB-PM calculated ET_C (right) with neutron probe calculated ET on an approximately weekly basis . Note: Dotted line is 1:1 line.

CONCLUSION

This study described a methodology to estimate dry edible bean ET_C that involves canopy temperature measurement using IRT, digital canopy analysis using RGB images, and computing with TSEB models in semi-arid western Nebraska. The results indicated that IRT and TSEB models provided reasonable estimation of ET_C for dry edible beans in western Nebraska. Also, by using digital images, it provides an easier and more approachable way to manage irrigation using IRT and TSEB models. Future work remains such as to quantify partition accuracy of E and T estimated by the TSEB models and they are not addressed in this study.

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