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Development of a new UAV-thermal imaging based model for estimating pecan evapotranspiration

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A R T I C L E I N F O

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A B S T R A C T

Pecans are a specialty crop in New Mexico's Lower Rio Grande Valley (LRGV), a region that produces around 30% of pecans in USA. Pecans are also a major water consumer, requiring 1200–1300 mm depth for maximum yield in this region. The combination of prolonged drought and increasing competition for water among various water consumers has created an urgency for the efficient use of scarce water resources in the LRGV. More efficient water management through the real-time irrigation scheduling is one method to promote reduced water application in agriculture. This study was conducted to calibrate and validate a new modified model for estimating the pecan actual evapotranspiration (ET_a) based on canopy temperature using thermal images taken from an Unmanned Aerial Vehicle (UAV) during three growing seasons in a drip irrigated pecan orchard. A capacity to estimate the relation between ET_a and canopy temperature provides an important information to guide water management choices. The Simplified Surface Energy Balance (SSEBop) model was modified and used for calibration and validation. Applied irrigation water based on ET_a was used to calibrate and validate the proposed modified model. The scaling factor of K in the SSEBop model was calculated as 0.75 through the calibration process. Findings showed a good agreement between estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during calibration ($R^2 = 0.72$, RMSE = 0.6 mm/d, MAE = 0.48 mm/d) and validation period ($R^2 = 0.90$, RMSE = 0.24 mm/d, MAE = 0.22 mm/d). Also, findings confirmed the utility of modified model for estimating monthly pecan ET_a (RMSE = 8.87 mm/month, MAE = 6.55 mm/month). The proposed modified model provides pecan farmers with a simple real-time irrigation scheduling tool where they can better practice precision irrigation. Although the modified model was calibrated and validated for irrigation scheduling in the LRGV, it has potential to see application for other locations with different crops using similar calibration approach.

1. Introduction

New Mexico (NM) is the second highest pecan producer in the USA with 35.74 thousand tons of in-shell nuts production in 2020 (USDA-NASS, 2021). The value of the pecan produced in NM was 122.9 million dollars which contributed 28% of the total value of the pecan produced in the USA in 2020 (USDA-NASS, 2021). Pecan is a major crop in New Mexico's Lower Rio Grande Valley (LRGV) where the majority of NM's pecan orchards are located. Pecan is known as a major water consumer in the LRGV where the annual evapotranspiration (ET) for pecan is estimated to range from 1200 to 1300 mm (Samani et al., 2009). With limited precipitation, agriculture in the LRGV depends on irrigation both from the Rio Grande River and groundwater pumping. The flow of the Rio Grande River has reduced significantly since 2000 which was the beginning of the recent long-term drought. In addition, the average on-farm irrigation efficiency in the LRGV has been estimated as 60–65% with values as low as 20% (Ahadi et al., 2013). There is an urgent need to improve irrigation efficiency to save water. One way to improve irrigation efficiency is through real-time irrigation scheduling with the aid of technologies such as remote sensing. The recent study in the LRGV showed that the long-term drought has not only reduced the availability of water, but also has increased the pecan water consumption through

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increased temperature (Mokari et al., 2021).

Water is the most important factor in irrigated agriculture in the LRGV. A wide variety of pecans at different ages is being grown in the area. Understanding crop coefficient (K_c) and Spatiotemporal variability of ET are major factors in proper water management. There are various methods to measure K_c and crop water consumption (ET). Direct ET measurement approaches such as Flux Towers (Samani et al., 2009) can provide continuous ET measurement within a limited area, but Flux Towers are expensive to install and operate. Flux Towers are often used for research and validation of other methods such as remote sensing ones. Remote sensing technology provides an alternative and innovative approach to improve productivity, increase water use efficiency and accelerate economic return. The recent developments in remote sensing technology have provided an immense opportunity for large-scale and low-cost assessment of the pecan ET and K_c (Samani et al., 2009; Samani et al., 2011; Wang et al., 2007). Satellites based remote sensing images can also provide spatially distributed measurements. However, the spatial resolution of this multispectral satellite imagery does not provide the precision that is needed for small scale fields. In addition, the timing or frequency of satellites overpass is not always enough to meet the research or real time water management needs. More than 90% of pecan fields in the LRGV are limited to farm sizes of less than 25 acres, limiting the use of Landsat images due to low resolution (Piñón-Villarrea et al., 2020). The other problem with using satellite-based multispectral images is the complexity of data analysis and the lag-time associated with data availability and analysis, making it inaccessible to individual farmers.

On the other hand, Unmanned Aerial Vehicles (UAVs) with mounted multispectral cameras provide a low-cost alternative for real-time irrigation scheduling and precision agriculture (PA) which can lead to the improved water use efficiency, economic productivity and compatibility in irrigated agriculture. UAVs can help to solve the spatial and temporal variabilities associated with large scale remote sensing images. UAVs can be flown any time as long as the weather condition is good. Moreover, the cloud cover is less of a concern than satellite remote sensing when UAVs are employed. Over the years, UAVs have been widely employed for PA solutions (Das et al., 2021; Mogili and Deepak, 2018) and have shown great potential for reducing working hours where stability, measurement accuracy, and productivity are increasingly improved in agriculture operations (Huang et al., 2009; Huang et al., 2013; Primicerio et al., 2012; ten Harkel et al., 2020). Several models have developed for satellite-based ET measurements (Allen Richard et al., 2007; Anderson et al., 2011; Fisher et al., 2020; Fisher et al., 2008; Senay et al., 2019; Senay, 2018; Su, 2002). Although these models have different data requirements and biases, they can be modified to use UAVs mounted multispectral and thermal sensors for estimating ET. Hoffman et al. (2016) investigated a UAV based water deficit index (WDI) for producing accurate crop water stress maps for barley in different weather situations. They showed that the UAV-based WDI could produce ET estimations generally aligned with the eddy covariance tower measurements.

This study demonstrates precision irrigation (PI) with thermal imaging which is known as an effective technique for product identification and detection in agriculture (Kheiralipour et al., 2015; Kheiralipour et al., 2013; Singh et al., 2020; Vadivambal and Jayas, 2011; Zeng et al., 2020). Although there are other PI techniques such as leaf monitor system (Dhillon et al., 2019), sap flow measurements (Fernández et al., 2008), and soil moisture sensors (Sui, 2018), these methods accompany with several limitations and difficulties. As an example, Zuazo et al (2021) discussed the leaf monitor system technique as a less reliable PI method for fruit trees because of monitoring leaf water potential than stem water potential. Sap flow sensors are fragile and need frequent maintenance. Burgess and Dawson (2008) recommended caution when using sap flow measurements for estimating plant water capacitance. Therefore, the objectives of present study were (i) to evaluate the feasibility of using UAV based sensors to estimate real time pecan water consumption (ii) to validate the use of single thermal sensor combined with modified Senay's model for estimating the pecan actual ET. To achieve these objectives, the remote sensing based ET estimation model proposed by Senay (2018) and Senay et al. (2019) was modified and applied to the UAV thermal based images. The modified model was calibrated and validated using three years of field measured data. The modified model is tested for its effectiveness and utility for irrigation scheduling of pecan water management.

2. Method and materials

2.1. Experimental site

Field measurements of canopy temperature were conducted during three growing seasons of 2019, 2020 and 2021 in a drip irrigated pecan orchard located in the Leyendecker Plant Science Research Center (PSRC) of New Mexico State University (latitude 32°11′56.66″N, longitude 106°44′30.50″W). The orchard area is about 3 ha with twenty-seven rows of 10-year-old 'Pawnee' pecan trees planted in a 9 m × 9 m pattern with 475 trees in total. No tillage operations have been done since installation of drip lines in 2016. Spraying herbicide in tree rows and mowing the region between tree rows are being done on a regular basis. The surface and groundwater are the irrigation sources. Soil texture in the experimental site is clay loam (74%) and silty loam (26%). Irrigations were made according to the proposed method by Wang et al. (2007). More information on irrigation can be found in Section 2.3.

2.2. Model development and theory

The Simplified Surface Energy Balance (SSEBop) model calculates actual evapotranspiration (ET_a) for each satellite image (Senay et al., 2019; Senay, 2018). This model uses satellite-based surface temperature and reference evapotranspiration (ET_0) as the main model inputs, and it is based on an energy balance approach where the latent heat flux is only solved at the daily time scale to calculate the ET fraction (ET_f) for each satellite image pixel as follow:

$$ET_f = 1 - \gamma^s (T_s - T_c) \tag{1}$$

$$\gamma^s = \frac{1}{(T_h - T_c)} \tag{2}$$

where γ^s is the dry-bare surface psychrometric constant, T_s is obtained from the satellite image thermal band (K), T_c is the coldest surface temperature limit (K) which is a function of the near surface maximum temperature, and T_h is the hot dry surface temperature (K) (Senay et al. 2013).

Once ET_f is determined, the ET_a is calculated as follow:

$$ET_a = K \times ET_f \times ET_0 \tag{3}$$

where ET_a is the actual evapotranspiration, ET_0 is the reference evapotranspiration which can be derived from various methods proposed by FAO-56 (Allen et al., 1998), and K is the scaling coefficient of 1.25 (Senay et al., 2019). K value is variable and needs to be calibrated for new crops (Senay et al., 2013).

Although the albedo value for most agricultural fields is less than 0.25, the SSEBop model can be applied to the vegetated surfaces with albedo higher than 0.25 using the albedo correction method proposed by Senay et al. (2013). Areas such as dark lava rocks in parts of Nevada have high emissivity values and these areas can affect T_s measurement which can result in underestimating ET_f although these areas do not play a crucial role in total seasonal ET due to lack of precipitations and vegetations in these areas. However, the SSEBop model can still work well when emissivity value is less than 1 (Senay et al., 2013).

As it was mentioned above, the SSEBop model is designed for estimating ET_a using satellite images. To make the model work more accurately when a thermal image taken from UAV mounted thermal camera is used, the SSEBop model needs to be modified. Fig. 1 represents a sample image taken from a UAV in the visible and thermal ranges. Fig. 1b shows the minimum, maximum, and average temperatures measured in the sensor scene representing 12 pecan trees (Fig. 1).

Thus, the modified SSEBop model with respect to the thermal image taken from a UAV over an irrigated pecan orchard can be proposed as follow:

$$ET_a = K \times \left[1 - \frac{(T_c - T_a)}{(T_d - T_a)}\right] \times ET_0 \quad (4)$$

where ET_a is the actual pecan water consumption (mm/d), K is the scaling coefficient, T_c is the overall average temperature in the sensor scene (°C) (Fig. 1b) which includes trees canopies as well as the spacing between the trees, T_a is the air temperature which can be derived from either a nearby weather station or a handheld thermometer (°C), T_d is the dry spot surface temperature which is equal to the maximum measured temperature in the sensor scene (°C) (Fig. 1b), and ET_0 is reference evapotranspiration (mm/d) which can be obtained from various methods (Allen et al., 1998). It is important to note that the T_d is the same as T_h in the Eq. (2). However, T_h is an estimated value through several empirical equations (Senay et al., 2013) while T_d in our proposed model is an easily measured value which can contribute to more accuracy.

2.3. Data collection

In order to calibrate and validate the modified SSEBop model for the UAV based thermal images, the UAV was flown 15 times over the pecan orchard and thermal images were taken at height of 60 m above the ground at noon during three growing seasons of 2019–2021. The flight operations were done in sunny days at noon in order to minimize the effect of cloud and shade in the thermal measurements. The thermal sensor used in this study is developed by the DJI Corporation where the thermal resolution in pixels, frame rate, and temperature measurement accuracy are 640 × 512, 30 Hz, ±2 °C, respectively. Although the manufacturer has announced ±2 °C error in the sensor measurement accuracy, the accuracy of thermal sensor was tested and measured within ±1.8 °C error in the pecan orchard using a calibrated hand-held FLUKE thermometer which was within the manufacturer error range. To calculate the surface thermal emissivity (ε_o) in the pecan orchard, the Tasumi model was used (Samani et al., 2009; Tasumi, 2003). Based on this model, ε_o is a function of Leaf Area Index (LAI) as follow:

$$\varepsilon_o = 0.95 + 0.01 \ \mathrm{LAI} \quad (5)$$

where ε_o is the thermal emissivity and LAI is the leaf area index. LAI is

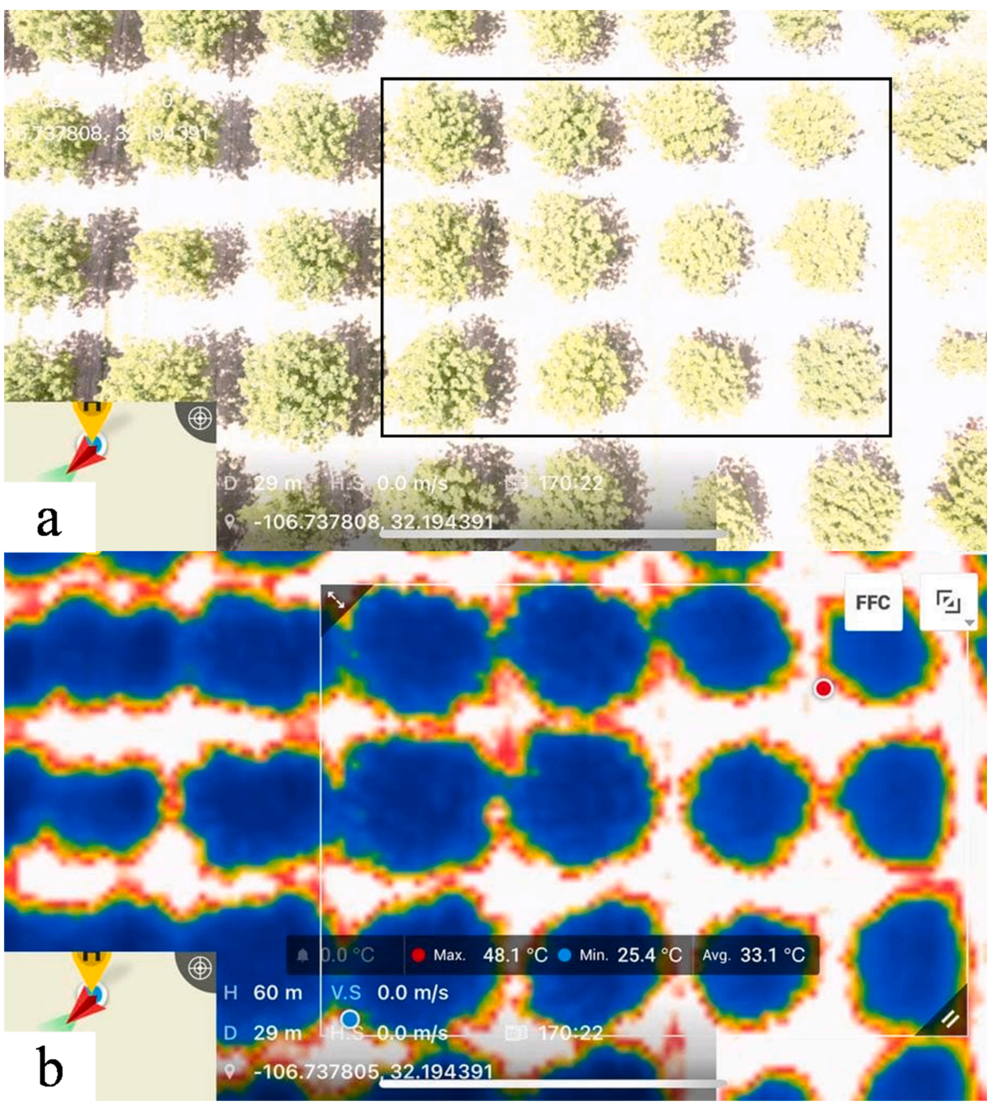

Fig. 1. A sample image taken from a UAV in the visible (a) and thermal (b) ranges.

ranging from 0 to 3 representing a bare soil to the fully covered agricultural field.

To have an estimate value of LAI for the studied pecan orchard, the results from a recent study on estimating LAI of pecan orchard was used (Othman and St Hilaire, 2021). The study was conducted on two mature (20–30 years old) pecan orchards in the Mesilla Valley where one orchard was located in PSRC of New Mexico State University. Based on this study, LAI was ranged between 1.01 and 1.60 across the two growing seasons for the pecan orchard located in PSRC. Assuming the maximum LAI value for the studied pecan orchard and Eq. (5), ε_o was found 0.966 which was within the calibration range of the thermal sensor indicating there were no significant effects on UAV temperature measurements caused by ε_o.

Irrigation scheduling of the studied orchard was based on a methodology described by Wang et al. (2007) as follow:

$$ET_a = K_c \times ET_0 \tag{6}$$

$$\frac{K_C}{K_{Cmax}} = 1.33ECC \tag{7}$$

where ET_a is consumptive water consumption, K_c is crop coefficient and ET_0 is the reference evapotranspiration, ECC is the effective canopy cover and K_{cmax} is the K_c for a closed-canopy pecan orchard which can be derived from Sammis et al. (2004).

To calculate ET_0, climatic data from the weather station located in PSRC of New Mexico State University were collected and daily ET_0 was calculated using the FAO Penman-Monteith equation (Allen et al., 1998). Effective precipitation was calculated using the methodology proposed by USDA-SCS (1967). The irrigation efficiency of 90% was used to calculate the irrigation depth. The applied irrigation water was considered as the pecan ET_a as the deep percolation was negligible in the studied pecan orchard.

2.4. Statistical measures

To evaluate the performance of modified SSEBop model for estimating pecan ET_a during calibration and validation periods, the following quantitative measures were applied (Despotovic et al., 2015).

$$R^2 = \frac{\sum_{i=1}^{n}(P_i - A_i)^2}{\sum_{i=1}^{n}(A_i - A_{ave})^2} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - A_i)^2}{N}} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - A_i| \tag{10}$$

where R^2 is the coefficient of determination, RMSE is the root mean square error, MAE is the mean absolute error, P_i is the *i*th value of predicted ET_a by the modified SSEBop model, A_i is the *i*th value of the applied water based on ET_a, A_{ave} is the average of applied water based on ET_a values, and N is the number of paired values.

Higher values of R^2 indicate more efficient model while lower values of RMSE and MAE show a better model performance.

2.5. Result and discussion

The modified SSEBop model was calibrated using the thermal images taken in the growing season of 2019 and the new optimized scaling factor of K for pecan was obtained as 0.75 which was much lower than the proposed K value for SSEBop model. To validate the modified SSEBop model using new optimized K value (K = 0.75), thermal images taken in two next growing seasons (2020 and 2021) were used. Figs. 2 and 3 show the differences between estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during the calibration and validation periods. Generally, there were good agreements between estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during both calibration and validation periods (validation period in particular) where R^2 were observed 0.72 and 0.90 for these periods, respectively (Figs. 2 and 3). During the calibration period, RMSE and MAE were found 0.6 (mm/d) and 0.48 (mm/d), respectively, while these values were observed 0.24 (mm/d) And 0.22 (mm/d) during the validation period, respectively (Figs. 2 and 3). Fig. 4 compares the estimated monthly pecan ET_a using modified SSEBop model and applied water based on ET_a during 2021 growing season. A good agreement was observed between the estimated monthly pecan ET_a and applied water based on ET_a where RMSE and MAE were 8.87 mm/month and 6.55

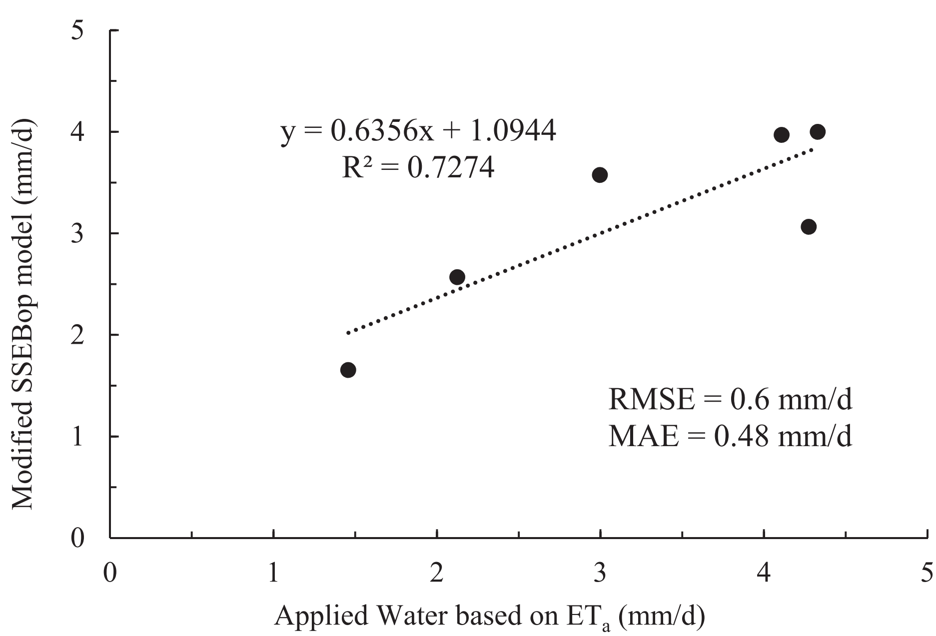

Fig. 2. Scatter plot of estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during the calibration time period (2019).

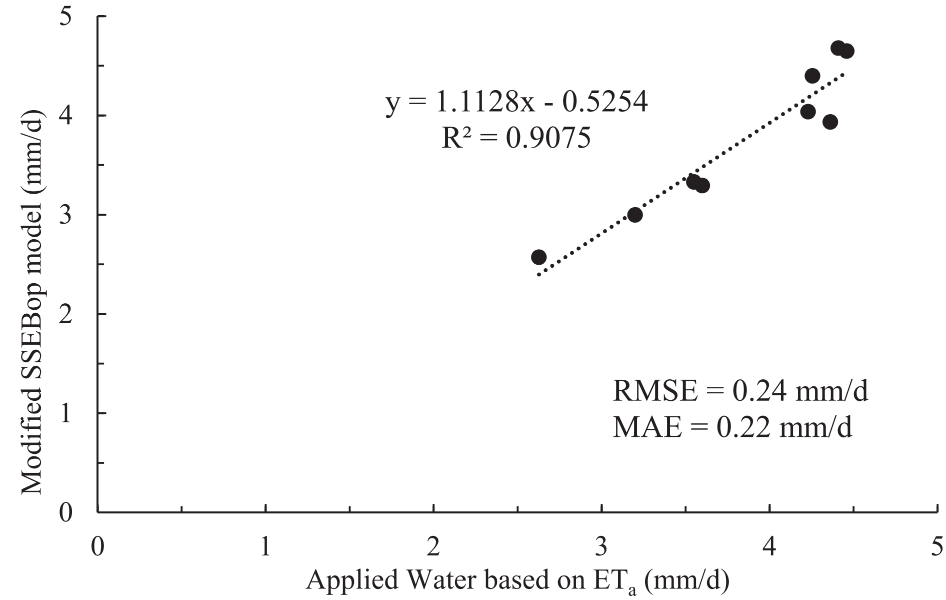

Fig. 3. Scatter plot of estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during the validation time period (2020–21).

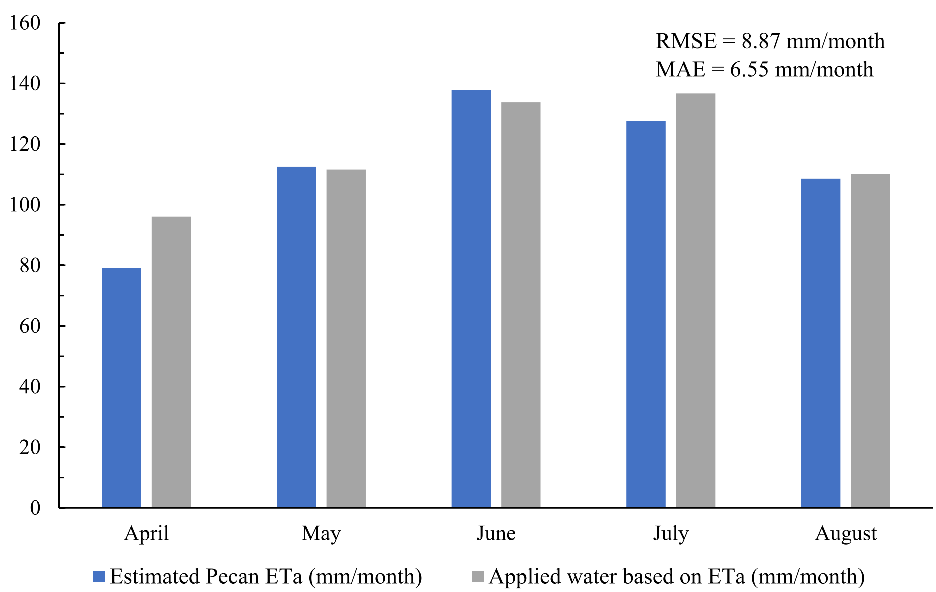

Fig. 4. Comparison between estimated monthly pecan ET_a using modified SSEBop model and applied water based on ET_a during 2021 growing season.

mm/month, respectively. Results showed that the proposed modified model can be applied to estimate the pecan ET_a with relatively high accuracy.

Other investigator (Samani et al., 2011) used multispectral images to estimate pecan ET for various field conditions in same areas. They developed a linear regression model between the ratio $K_c/K_{c\text{-}ref}$ and f_c, where $K_{c\text{-}ref}$ and f_c were the measured K_c for a mature pecan orchard and fractional cover canopy, respectively. Ibraimo et al. (2016) applied this K_c-f_c model for monthly estimation of pecan ET in South Africa and their findings proved satisfactory results although they concluded adjusting $K_{c\text{-}ref}$ for local climate conditions in order to achieve more accurate estimation of monthly ET. Even though both K_c-f_c and our proposed methods resulted in similar accuracy, our proposed model is much simpler and less time consuming. The proposed model is simplified and is capable of estimating ET_a with easily derived temperature data. It can also apply to other crops similar to the study presented by Senay et al (2019) and it is not restricted to the pecan. However, a proper calibration and validation is highly recommended. Also, it is highly recommended to operate UAV in sunny days preferably at noon to eliminate the effects caused by cloud and trees shade on thermal measurements.

The proposed model has practical application in water conservation and irrigation scheduling of pecan. A pecan farmer can easily use a small drone mounted with a single thermal sensor to capture the canopy temperature scene and use a simple model (Eq. (4)) to estimate the daily water consumption. In addition, the information can be used to calculate temporal values of pecan crop coefficients for estimating pecan ET_a between the drone flights. The application of the model is limited to the availability of cloud and wind free days. In addition, the accessibility to reliable climate date for calculating ET_0 is needed.

2.6. Conclusion

A simple procedure is presented where canopy temperature can be measured to estimate pecan ET_a. The concept was derived from the SSEBop model which was introduced for measuring ET_a using satellite images. The proposed model was modified and simplified in order to make the model work for UAVs purposes. The scaling factor of K was optimized through a proper calibration/validation process which includes data from three growing seasons. The new optimized scaling factor of K for pecan was calculated as 0.75. Good agreements were observed between the estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during both calibration and validation periods ($R^2 > 0.72$, RMSE < 0.6 mm/d, MAE < 0.5 mm/d). The comparison between the estimated pecan ET_a using modified SSEBop model and applied water based on ET_a during validation period confirmed that pecan ET_a can be estimated with accuracy where RMSE and MAE were observed 0.24 mm/d and 0.22 mm/d, respectively. Also, comparisons between the estimated monthly pecan ET_a using modified SSEBop model and applied water based on ET_a during 2021 growing season indicated that the proposed model is an accurate tool for estimating monthly pecan ET_a with RMSE and MAE of 8.87 mm/month and 6.55 mm/month, respectively. This ET_a information can be combined with soil properties for developing real-time irrigation scheduling. The proposed model is applicable for other crops although a proper calibration for scaling factor of K is recommended.

CRediT authorship contribution statement

Esmaiil Mokari: Conceptualization, Methodology, Writing – original draft. **Zohrab Samani:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Richard Heerema:** Investigation, Writing – review & editing. **Ehsan Dehghan-Niri:** Investigation, Methodology. **Dave Dubois:** Investigation. **Frank Ward:** Writing – review & editing. **Curt Pierce:** Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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