Remote Sensing and Aerodynamic Temperature-Based Energy Balance Models to Estimate Crop Evapotranspiration Rates

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Abstract

Different methods exist to measure or estimate actual crop evapotranspiration (ETₐ). However, some methods require a large number of data input or strict field conditions. Remote sensing based ETₐ algorithms based on extreme thermal pixels (hot and cold) have limitations when required extreme pixels are not present in the acquired thermal infra-red imagery. In addition, satellite overpass frequency and spatial pixel resolution may be a limitation for some agricultural fields and micro-climates. Surface energy balance methods that use surface radiometric temperatures often fail to perform well under drought, limited irrigation, salt affected soils, or under sparse vegetation conditions. One option is to measure or estimate the crop/surface sensible heat flux through the aerodynamic temperature approach, then calculate the available energy and solve the energy balance for latent heat flux. Thus, this study presents different published algorithms that characterize the crop or field surface aerodynamic temperature and then applies them to different conditions for evaluation. Determining spatial ETₐ continuously has the potential to improve the irrigation water management decision making. The aerodynamic temperature approach was initially developed with good results as a function of surface radiometric temperature, air temperature, crop leaf area index, and wind speed or surface aerodynamic resistance. However, the inclusion of the crop fractional percent cover and of a new resistance term (turbulent-mixing row resistance) greatly improved the estimation of the sensible heat and latent heat fluxes, when evaluated with heat flux data derived from eddy covariance energy balance towers. Results also indicate that the aerodynamic method has transferability potential to different regions, crops, and irrigation methods than the conditions encountered in the method development.

Keywords: irrigation management, actual crop water use, remote sensing, evapotranspiration, energy balance

1. Introduction

Increasing world population and climate change demand a global sustainable food and fiber production under well managed irrigation practices. Thus, the need to become more efficient at managing water resources in agricultural settings and at different spatial scales. In this context, remote sensing (RS) systems along with actual crop water use or evapotranspiration (ETₐ, mm d⁻¹) algorithms can be implemented to improve irrigation management decisions (Chávez et al., 2012, Gowda et al., 2008). One such ETₐ estimation method is based on the energy balance (EB) approach that provides instantaneous estimates of latent heat flux (LE, W m⁻²), at the time of satellite platform overpass, and which is converted to hourly and daily actual evapotranspiration using different time-steps scaling methods (Chavez et al., 2008). The simplified EB approach is defined by the equation “Rₜ = G + H + LE,” where Rₜ is net radiation, G is the soil heat flux, and H is sensible heat flux. All EB terms are expressed in W m⁻² units in this study. Appendix A lists the calculations needed to estimate Rₜ, G and H for the typical EB approach used in this study. The estimation of LE is performed by solving the EB equation for LE after estimating Rₜ, G, and H. Rₜ and G are estimated with acceptable accuracy (~95% and 85%, respectively). There are several RS algorithms available (Gowda et al., 2008) to estimate these variables. However, most RS and EB based ETₐ algorithms differ in the way the sensible heat flux is estimated. In most of these models, H is estimated using the radiometric surface temperature (Tₛ), derived from satellites’ thermal bands or ground-based
radiometry. Sensible heat fluxes are in general over estimated when $T_s$ is used in Equation 1 rather than the appropriate surface aerodynamic temperature ($T_o$). Equation 1 below describes the bulk surface resistance-based $H$ calculation. The over estimation of $H$ often occurs because $T_s$ is typically larger than $T_o$.

$$H = \rho_a \cdot C_{pa} \cdot \frac{(T_o - T_a)}{r_{sb}}$$

where, $\rho_a$ is air density, (kg m$^{-3}$), $C_{pa}$ is specific heat of dry air 1005 (J kg$^{-1}$ K$^{-1}$), $T_a$ is air temperature (K) at screen height (2-3 m). The surface aerodynamic temperature ($T_o$, K) is defined as the within and between canopy temperature that produces the necessary temperature gradient for the generation of sensible heat fluxes. For homogeneous canopies $T_o$ can be said to originate at the height equal to the zero plane displacement ($d$, m) plus the roughness length for heat transfer ($Z_{oh}$, m). In Equation 1, $r_{sb}$ is the surface aerodynamic resistance, (sec m$^{-1}$) to heat transfer from a height equal to “$d+Z_{oh}$” to $Z_m$. Where $Z_m$ is the wind speed measurement height, m.

Wenbin et al. (2004) indicated that for homogeneous and isothermal surfaces the definition of aerodynamic and thermodynamic (canopy or surface radiometric) temperatures are equivalent, but over heterogeneous (and/or sparse, or stressed) surfaces there are important differences between $T_o$ and $T_s$. This difference leads to errors in the estimation of $H$ which in turn leads to errors in the calculation of LE and therefore in mapping ETa. In order to account for the differences between $T_o$ and $T_s$, studies have been carried out to parameterize $H$. For instance, earlier studies by Kustas et al. (1989), and Kustas and Norman (1996) increased the surface aerodynamic resistance by adding an extra term that adjusts the surface roughness length for heat transfer. This term expresses the extra resistance that the heat flow encounters above the vegetation canopy in relation to the momentum flux. Chehbouni et al. (1996), introduced a $\beta$ parameter as function of leaf area index (LAI, m$^2$ m$^{-2}$) in an exponential relationship, in the $H$ equation, to adjust for the differences between $T_o$ and $T_s$.

Since those early studies, further research has been carried out to model and apply the surface aerodynamic temperature approach; in particular, using input data from different RS platforms. Therefore, this article summarizes different surface aerodynamic temperature modeling studies and applies selected $T_o$ models to different crops, regions, and irrigation conditions to assess their transferability.

2. Method

This section introduces several surface aerodynamic temperature models that used different remote sensing platforms (sensors and spatial scales). Then, selected $T_o$ models are applied to: a) a cotton field near Bushland, Texas; b) a maize field located near Rocky Ford, Colorado; and to c) a maize field in Fort Collins, Colorado.

2.1 Maize and Soybean $T_o$ Modeling—Rainfed Agriculture Case

Mahrt and Vickers (2004), for grass, modeled $T_o$ in terms of $T_s$, incoming shortwave solar radiation ($R_n$, W m$^{-2}$), a vegetation index (or leaf area index, LAI), horizontal wind speed (U, m s$^{-1}$) and soil water content. Similarly, Chávez et al. (2005) modelled $T_o$ (°C) as a multi-linear regression function of $T_s$, $T_a$, LAI, and $U$, for dryland maize and soybean crops located near Ames, Iowa, USA. Equation 2 below shows the resulting multiple linear regression $T_o$ model, where surface reflectance and temperature images were obtained using multispectral/thermal cameras mounted on an aircraft (1-3 m pixel spatial resolutions). These images were used to determine LAI and $T_s$, respectively. The validity of Equation 2 is for a range of LAI between 0.3 and 5.0 m$^2$ m$^{-2}$.

$$T_o = 0.534 \cdot T_s + 0.39 \cdot T_a + 0.224 \cdot \text{LAI} - 0.192 \cdot U + 1.67$$

Equation 2 above resulted with the following mean bias error (MBE) and root mean square error (RMSE) of 0.2 and 0.9 °C, respectively, when evaluated with $T_o$ derived from inverting Equation 1 and using sensible heat fluxes measured with a network of Eddy Covariance (EC) EB systems. Further, when using $T_o$ from Equation 2 in Equation 1 and solving the EB equation for $H$ as a residual and by inverting Equation 1 and solving it for $T_o$, the form of the resulting $T_o$ equation is shown below as Equation 3, with variables and corresponding units as previously defined. In Texas, the rainfed cotton was water stressed and LAI only varied from 0.2 to 1.3 m$^2$ m$^{-2}$. In this study, $T_s$ was measured with a fixed Exergen infra-red thermometer, and crop height and LAI were

2.2 Cotton $T_o$ Modelling—Dryland Agriculture Case

In a study over rainfed cotton subjected to a highly advective environment, in the Texas High Plains, near Bushland, Texas, USA, Chávez et al. (2010) modelled $T_o$ (°C) using “inverted” $T_s$ from 15-minute measured ETa, $R_n$, and G data. These variables were measured at a precision monolithic weighing lysimeter field (210 m long × 200 m wide), and by solving the EB equation for $H$ as a residual and by inverting Equation 1 and solving it for $T_o$. The form of the resulting $T_o$ equation is shown below as Equation 3, with variables and corresponding units as previously defined. In Texas, the rainfed cotton was water stressed and LAI only varied from 0.2 to 1.3 m$^2$ m$^{-2}$. In this study, $T_s$ was measured with a fixed Exergen infra-red thermometer, and crop height and LAI were
estimated using surface/vegetation reflectance data collected with an EXOTECH hand-held multispectral radiometer. Further details regarding the experiment setup can be found in Chávez et al. (2010).

\[ T_o = 0.5 \cdot T_a + 0.5 \cdot T_{rh} + 0.15 \cdot r_{ab} - 1.4 \]  \hspace{1cm} (3)

The evaluation of \( T_o \) from Equation 3 was performed with \( T_o \) data from an aerodynamic profile tower (APT) and an EC EB system. The evaluation yielded the following errors, MBE±RMSE of 0.16±1.02 °C or 0.13±3.77% and 0.67±2.14 °C (2.24±6.53%), for the APT and EC reference systems, respectively. This small error in the estimation of \( T_o \) (Equation 3) contributed to a better estimation of dryland cotton \( E_{Ta} \) rates, with an error reduction from 23.6 to 3% when \( T_o \) was used in Equation 1 instead of \( T_v \).

2.3 Merlot Vineyard \( T_o \) Modelling—Irrigated Agriculture Case

Another study was carried out to calibrate and validate the surface aerodynamic temperature method for the estimation of the spatial variability of the sensible and latent heat fluxes over a drip-irrigated merlot vineyard located in the Maule Region, in Chile, South America. Figure 1 shows the merlot vineyard site that was instrumented with an EC EB system along with ancillary sensors.

Figure 1. Merlot vineyard located in the Maule Region of Chile (35°25′ South and 71°32′ West, 125 m above mean sea level)

Source: Carrasco-Benavides et al. (2017).

The \( T_o \) calibration study was carried out by Carrasco-Benavides et al. (2017). For this study, measurements of EB components and meteorological data were collected during the 2006-2010 crop growing seasons. The experimental plot was composed of a 4.25 ha Merlot vineyard, which was equipped with an EC EB system and an automatic weather station. In this study, \( T_o \) was modelled in a similar fashion as indicated in Chávez et al. (2005), resulting in Equation 4 below. However, the RS data used were from satellite Landsat 7 optical/NIR and thermal images; which pixel spatial resolutions were 30 and 100 m for the multispectral and thermal images, respectively. The validity of Equation 4 is for a range of LAI and fractional vegetation cover values falling between 0.8-1.2 m² m⁻² and 28-31%, respectively.

\[ T_o = 0.2 \cdot T_a + 0.75 \cdot T_{rh} + 24.46 \cdot LAI - 0.95 \cdot U + 22.77 \]  \hspace{1cm} (4)

The evaluation of Equation 4 was performed with EC-derived (inverted) \( T_o \) values not used in the development of the vineyard \( T_o \) model. The evaluation indicated that Equation 4 estimated \( T_o \) with the following errors, MBE±RMSE of 0.56±0.66 °C or 2.3±2.7%. Further, the resulting sensible heat flux estimation error was 28.3±33.6 W m⁻² or 10.5±12.4%; while satellite data-based computations of LE were somewhat higher than those EC-based measured at the time of satellite overpass (53±63 W m⁻² or 28.3±33.6%), presumably due to the biases embedded in the net radiation and soil heat flux computations, according to Carrasco-Benavides et al. (2017). However, the proposed RS-based EB method to estimate \( E_{Ta} \) based on \( T_o \) is very simple to implement, presenting similar accuracies on \( E_{Ta} \) mapping than those computed by complex satellite-based EB models.

2.4 Maize \( T_a \) Modelling—Irrigated Agriculture Case

A recent study, by Costa-Filho et al. (2021), modelled \( T_o \) over maize fields (fully and deficit sub-surface drip irrigated) near Greeley, Colorado, USA, using proximal RS data collected with handheld and fixed ground-based
radiometers, and with sensible heat fluxes measured with two sets of Large Aperture Scintillometers (LAS) that provided $T_o$ values (from inverted measured $H$ values). Rambikur and Chávez (2014) presented a LAS evaluation study in which it was shown that sensible heat fluxes derived from LAS systems were comparable to $H$ values obtained with EC systems. In the Costa-Filho et al. (2021) study, $T_o$ was modelled for different ranges of maize LAI values including the following variables: fractional vegetation cover ($f_v$), $T_a$, $T_s$, and considering the wind direction (angle) interaction with the crop rows’ orientation (angle) through the so-called ‘turbulence mixing-row resistance’ ($r_p$, s m$^{-1}$). Wind direction has a significant effect on determining the wind profile within and above canopy relative to air flow direction and the crop row layout. As wind speed interacts with the crop row orientation (wind from different directions), there will be different angles of attack that will result in different aerodynamic resistances and wind penetration within the crop (i.e., variable zero-plane displacement height and roughness length); which results in different turbulent mixing of heat and vapor transport from the surface to the atmosphere above affecting $H$ and LE fluxes. Below, Equations 5-8 present Costa-Filho et al. (2021) modelled $T_o$ equations for maize grown in a high plain and semi-arid region.

$T_o = -8.742 \cdot f_v + 0.571 \cdot T_a + 0.529 \cdot T_s + 0.806 \cdot r_p + 3.295$ for $0.85 \leq \text{LAI} \leq 1.50$  
$T_o = -9.168 \cdot f_v + 0.485 \cdot T_a + 0.575 \cdot T_s - 0.160 \cdot r_p + 6.491$ for $1.5 < \text{LAI} \leq 2.50$  
$T_o = 4.708 \cdot f_v + 0.350 \cdot T_a + 0.580 \cdot T_s + 0.086 \cdot r_p$ for $2.50 < \text{LAI} \leq 3.50$  
$T_o = -1.912 \cdot f_v + 0.443 \cdot T_a + 0.509 \cdot T_s + 0.115 \cdot r_p + 5.014$ for $3.50 < \text{LAI} \leq 5.00$

The Costa-Filho et al. (2021) $T_o$ resulting modelling errors (MBE±RMSE) were -0.14±0.50 °C for the optimized models (Equations 5-8). Overall, results seemed to indicate that the optimized $T_o$ model improved the estimation of maize $H$ fluxes (error -6±19 W m$^{-2}$, or -4.9±16.3%); which resulted in an improvement of the estimation of latent heat fluxes (error -6±35 W m$^{-2}$, or -1.8±9.7%). It seems that incorporating the interactions between the crop row layout and wind direction, in the modelling of $T_o$, better describes the dynamic turbulent mixing for the generation of $H$.

2.5 Application of $T_o$ Models

Selected $T_o$ models were applied to crops and conditions different from those used in their development. The $T_o$ application was performed to assess the transferability of the models to different settings.

2.5.1 Applying the Chávez et al. (2005) Rainfed Maize $T_o$ Model to Sprinkler Irrigated Cotton

Field data were collected in 2008 at the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) Conservation and Production Research Laboratory (CPRL), located near Bushland, Texas, USA. The geographic coordinates of the USDA ARS CPRL are 35°11′ North and 102°6′ West, with an elevation of 1,170 m above mean sea level (amsl). The study area is subject to very dry air and strong winds (advection). Annual averages for air temperature, air water vapor pressure deficit, and horizontal wind speed are 14 °C, 0.3 kPa, and 4.9 m s$^{-1}$, respectively, according to Chávez et al. (2009).

Cotton was grown in a 4.7 ha research field (southeast lysimeter field) 210 m wide (East–West) and 225 m long (North–South). The field contained a precision weighing lysimeter in the center (Figure 2). The lysimeter measurements are 3.9 m wide × 3.9 m long × 2.3 m deep and it was used to directly measure cotton ET$_a$ for the evaluation of the ET$_c$ estimated with the $T_o$ approach. The lysimeter contained a monolithic Pullman clay loam soil core and it was sprinkler irrigated by a Linear Move sprinkler irrigation system.
Figure 2. Cotton field with instrumentation installed above the lysimeter box, at the USDA ARS CPRL, Bushland, Texas, USA

For the application of Equation 2, $T_s$ was obtained from infrared thermometers (model IRT/c, Exergen Corp., Watertown, Massachusetts, USA), which were mounted to view approximately at a 60° zenith angle and an azimuth toward the Southwest at 45° from due South. $T_s$ was obtained from a temperature/relative humidity sensor (model HMP45C, manufactured by Vaisala, Inc.) mounted in a Gill shield (model 41003-5 10-Plate Gill radiation shield manufactured by R.M. Young, Traverse City, Michigan, USA) at 2 m above the ground. Wind speed (U) was measured by an anemometer (model 03101-L R.M. Young wind entry anemometer, manufactured by R.M. Young, Traverse City, Michigan, USA) at 2 m above the ground. And LAI was estimated as published in Chávez et al. (2010). The normalized difference vegetation index (NDVI) was calculated using surface reflectance data obtained with an EXOTECH handheld radiometer.

2.5.2 Applying the Chávez et al. (2005) Rainfed Maize $T_s$ Model to Furrow Irrigated Maize

The study was conducted at the Colorado State University (CSU) Arkansas Valley Research Center (AVRC) near Rocky Ford, Colorado, USA. The geographic coordinates of the site are 38°2’ North and 103°41’ West, and the elevation is 1,274 m amsl. Maize was grown in the large lysimeter field (Figure 3) in 2013. The dimension of the large lysimeter field are 160 m by 250 m (4 ha). A large monolithic weighing lysimeter (3 m long × 3 m wide × 2.4 m deep) was located in the middle of the field. As part of the instrumentation in the field, there was a net radiometer (Q7.1, REBS, Seattle, Washington, USA), two infra-red thermometers (IRT Apogee model SI-111, CSI, Logan, Utah, USA) to measure crop radiometric surface temperature, soil heat flux plates (REBS model HFT3, CSI, Logan, Utah, USA) buried in the ground in the lysimeter box, 10 cm deep, along with soil temperature and soil water content sensors, for the estimation of stored soil heat and G at the ground surface. The field was furrow irrigated using siphons and a head ditch. The average annual maximum temperature is 21.1 °C. The average annual minimum temperature is 2.4°C. The long-term average annual precipitation at the site is 301 mm with approximately two-thirds of the annual total occurring from May through September. The total average annual snowfall is 589 mm.

Figure 3 shows a grid (light green dots) where ground-based multispectral/thermal radiometric data were collected over a span of 9 weeks (once a week).
These radiometric data were used to obtain surface reflectance and temperature, respectively. A weather station was installed at the middle of the field, from where air temperature, relative humidity, and wind speed data, at 3 m above ground, were obtained.

Maize Fontanelle 8A818RBC was planted on May 7th with a density of 81,382 plants/ha. Emergence took place on May 17th, while the harvest occurred on October 15th.

The EB method based on $T_o$ from Equation 2 was applied to the maize data collected at the lysimeter field.

2.5.3 Applying the Costa-Filho et al. (2021) Drip Irrigated Maize $T_o$ Model to Furrow Irrigated Maize

The new $T_o$ model was applied to furrow irrigated maize grown at the Irrigation Innovation Consortium (IIC) Head Quarters (HQ). The IIC-HQ was located at the intersection of Prospect Road and Interstate-25 highway on the outskirts of Fort Collins, Colorado, USA. The site elevation is 1,525 m amsl, Lat. 40.557270 North and Long. -105.004932 West. The research field used was approximately 6.9 ha (348 m long × 200 m wide) located at the south-west (SW) corner of the site (Figure 4). Maize (Syngenta G02K39-3120) was planted on May 13, 2020, with a density of 81,500 plants/ha. Soil texture is Otero sandy loam. The climate is cold and temperate according to the Köppen-Geiger climate classification. The irrigation system was furrows, supplied of water by siphons (every other furrow) from a head ditch. An EC tower (CSI, Logan, Utah, USA) was installed at the northwest corner of the field in order to evaluate the $T_o$-based $ET_o$ estimates. A net radiometer, soil heat flux plates, and IRTs were installed in the upper one-third of the field to assess available energy and the EC EB closure.

PlanetScope high spatial resolution surface reflectance images, from microsatellites PanetDove (PD), were used (Planet Team, 2017). PD constellation of microsatellites provide a daily overpass coverage. Only cloud free images were used. PD is a CubeSat 3U form factor (10 cm × 10 cm × 30 cm) microsatellite constellation operated by Planet, Inc. The PD constellation consists of about 130+ satellites, with the capability to image the entire Earth’s land surface on a daily basis. The PD satellites have four spectral bands; Blue (B, 455-515 nm), Green (G, 500-590 nm), Red (R, 590-670 nm), and Near Infra-Red (NIR, 780-860 nm). These have a nominal Ground Sampling Distance (GSD) of 3 m at nadir and positional accuracy of < 10 m RMSE (Planet Team, 2019). These images are atmospherically corrected to ‘Below of the Atmosphere’ (BOA) or surface reflectance, which provides more consistency across time and location localized atmospheric conditions while minimizing uncertainty in the spectral response (Planet Team, 2020). Nineteen (19) PlanetScope images were used (July-September, 2020) to obtain surface reflectance, vegetation indices, and other derived variables. However, PD microsatellites do not carry a thermal camera to characterize the maize canopy surface temperature. For this reason, $T_o$ data from fixed (ground-based) IRTs installed in the field were used. Further details can be found in Chávez (2021).
3. Results

3.1 Sprinkler Irrigated Cotton Case

During the Cotton growth period, lysimeter measured ET$_a$ varied from approximately 1.6 to 12 mm d$^{-1}$ (Figure 5). This high-end cotton evapotranspiration rate was due to the highly advective conditions of the site. The evaluation of ET$_a$ estimates, derived from the EB and T$_a$ from Equation 2, was performed with lysimeter-based ET$_a$ daily rates (Figure 5).

![Figure 5. Cotton 2008 campaign daily ET$_a$ measured (full line) and estimated (dashed line) from the USDA ARS CPRL, Bushland, Texas, USA](image)

The evaluation indicated that the cotton ET$_a$ estimation errors (MBE±RMSE) were 0.67±1.07 mm d$^{-1}$ or 9.8±15.7% of normalized error (using mean measured ET values). This result is considered good given the full irrigation conditions and the environment (highly advective semi-arid region) in Texas that were very different from the conditions (humid, rainfed agriculture) encountered in Iowa where Equation 2 was developed.

3.2 Furrow Irrigated Maize Case—Rocky Ford, Colorado, USA

Resulting estimated maize ET$_a$ values were evaluated with ET$_a$ data from the large weighing lysimeter. Results indicate that the ET$_a$ estimation errors (MBE±RMSE) were 0.28±0.52 mm d$^{-1}$ or 3.9±7.5%. This result shows a small estimation errors, which is exceptional considering that the T$_a$ model from Equation 2 was develop using data from a rainfed maize grown in a semi-humid climate, much different from the somewhat advective conditions encountered at the AVRC in Rocky Ford, Colorado. Figure 6 below illustrates the linear regression
curve fitted to the ETₐ data (x-axis lysimeter measured and y-axis estimated), depicting some over estimation of ETₐ in the range of 5.5-6.5 mm d⁻¹, for furrow irrigated maize.

![Figure 6](image)

Figure 6. Maize ETₐ (measured vs. estimated) evaluation. Data collected at the CSU AVRC research facility near Rocky Ford, Colorado, USA

3.3 Furrow Irrigated Maize—Fort Collins, Colorado, USA

Figure 7 below shows a true color (RGB) picture (left) of the maize grown at the IIC-HQ. The picture was taken with an unmanned aerial system (UAS), while the map shown on the ‘right’ hand side of Figure (7) depicts PlanetDove microsatellite-based NDVI values from the maize field during August 4th, 2020. NDVI is the “Normalized Difference Vegetation Index” equal to [NIR − R]/[NIR + R]; where NIR and R are surface reflectance values in the Near Infra-red and Red bands, respectively. For the most part, the maize biomass was homogeneous throughout the entire field as per the NDVI distributed values shown in Figure (7).

![Figure 7](image)

Figure 7. IIC-HQ west field depicting a maize field true color map (left), and an NDVI map (right) derived from a PlanetScope multispectral image acquired on 4 August 2020

Figure 8 below shows the linear regression between EC-based ETₐ and estimated ETₐ (through Equations 5-8 and the EB method); where some scatter is apparent at low and high ETₐ rates (1-2 and 4.2-5.4 mm d⁻¹, respectively), while there is little scatter (better agreement) for medium ETₐ rate values (~3.5-3.8 mm d⁻¹). Further, the ETₐ evaluation yielded estimation errors of 0.12±0.78 mm d⁻¹ or 3.2±20.7%. This result shows rather
a larger than expected ETa overestimation for the surface irrigated maize case. One plausible reason may be the mismatch of footprints between the PlanetScope multispectral image pixel size (3 m) and the IRT readings footprint (~1m), the furrow irrigation sets (number of furrows per set and number of irrigation sets per day), and calibration of the Planet multispectral images.

![Figure 8. Linear regression plot between EC-based ETa and Tc-based estimated maize ETa for a research field near Fort Collins, Colorado, USA](image)

### 4. Discussion

Actual crop evapotranspiration estimated for the fully irrigated cotton (in Texas) field resulted with relative errors of 9.8±15.7%. This error is considered acceptable given the fact that most daily ETa models present an accuracy of about 15-20% of RMSE and that the aerodynamic temperature approach used in the estimation of ETa was developed under different surface and environmental conditions. Equation 2 was developed to estimate Tc for rainfed maize subject to a semi-humid climate with relative errors of -2.7±11.7%. Further, the maize fields displayed periods of water stressed during the field data collection in Iowa, while the cotton field in Texas was not water stressed. Moreover, the irrigated cotton was subject to very advective conditions that added energy (horizontally) to the local vertical exchange of energy fluxes increasing the cotton ETa rate higher than the values encountered in Iowa for the maize crop. Therefore, using Equation 2 to estimate Tc for cotton seems feasible although a local calibration of the Tc model may improve EB-based ETa estimates. For this application case, the remote sensing data used as input in the simplified energy balance originated from a fixed stationary infrared thermometer and a roaming handheld multispectral radiometer EXOTECH.

In the case of the fully (furrow) irrigated maize field from Rocky Ford, Colorado, ETa was estimated with relative errors of 3.9±7.5%. This is considered an excellent result when compared to rainfed maize ETa estimate errors of -2.7±11.7%, and considering the fact that the maize field in southeastern Colorado was also subject to advective conditions that promoted larger ETa rates than in Iowa. This result may be evidence of the regional transferability, of the Tc model presented in Equation 2, from a semi-humid to a semi-arid region. In the case of the irrigated maize in southeastern Colorado, remote sensing data were also collected using a fixed IRT and a roaming multispectral radiometer (MSR5, CropScan, Rochester, Minnesota, USA); while Equation 2 was developed using RS data from an airborne system.

Finally, for the fully (furrow) irrigated maize grown near Fort Collins, Colorado, errors in the estimation of ETa, using updated Tc models (Equations 5-8), were larger than errors obtained for rainfed maize in central Iowa and in southeastern Colorado for fully irrigated maize; and larger than ETa errors obtained for drip irrigated (fully and deficit) maize near Greeley, Colorado. In this case, multispectral remote sensing inputs (surface reflectance in the R and NIR bands) were from a microsatellite and not from handheld radiometers. Both the footprints and radiometry of these sensors/platforms (i.e., handheld and spaceborne) are different and seem to affect the accuracy of ETa estimates. For instance, when the size of the microsatellite imagery pixel size does not much that of the IRT footprint, and there is local heterogeneity on crop stands (different crop height, fractional cover,
LAI), then the estimation of ETa may not be that accurate. Further, the radiometric calibration of the PlanetScope reflectance images may not have been accurate and consistent. On this topic, regarding the quality of the Planet microsatellite images, Frazier and Hemingway (2021) stated the following “...the variation in radiometric and geometric quality compared to traditional platforms (i.e., Landsat, MODIS, etc.) means the images are not always ‘analysis ready’ upon download...,” Meaning that further calibration is needed due to the lack of consistent good radiometric/geometric calibration. Earlier Latte and Lejeune (2020) highlighted the need of PlanetScope imagery normalization (calibration) to Sentinel-2 high quality imagery radiometric level due to frequent inconsistencies of PlanetScope microsatellites’ radiometric quality. In fact, Planet Inc., started offering harmonized or normalized (to Sentinel2) images in March of 2022.

Thus, this study assessed the accuracy in the estimation of daily actual crop evapotranspiration rates through the use of the surface aerodynamic temperature approach in the energy balance method. Several aerodynamic temperature models have been calibrated for specific crops and environmental conditions. Those calibrated Ta models have resulted in accurate ETa estimates for the locations where the models were developed for. Nevertheless, there seems that the surface aerodynamic temperature approach may be transferable to different climatic regions and crop types resulting in acceptable ETa estimates. However, local calibration may be required to improve ETa estimation results. Further, the aerodynamic temperature model is more accurate when applied using remote sensing input data collected with similar sensors/instruments as those used in the development of the Ta model. In the application cases presented in this study, the aerodynamic temperature model applied using multispectral and thermal data from proximal remote sensing devices (handheld and fixed sensors) produced more accurate ETa rates than when using input data from microsatellites that may have experienced inconsistent imagery pixel radiometric calibration. This result highlights the need to evaluate the quality of satellite images using properly calibrated ground-based radiometers, and if needed develop local calibrations for each satellite overpass/scene. Still, the combination of daily microsatellite multispectral images and ground-based thermal data is promising for daily mapping of ETa.

Even though the use of Ta models is promising, for the easier mapping of ETa, further studies are needed to turn the approach operational and applicable at larger spatial (regional) scales on a daily basis. For instance, determining the effects of RS input data of different pixel sizes and radiometry (e.g., Landsat 8 and 9, Sentinel2, MODIS, PlanetDove harmonized) on ETa is needed, as well as incorporating the different crop structures and their interaction with wind directional angle of attack, for a wide range of crop types and plating densities and spacing.

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References


Appendix A

Net Radiation and Soil Heat Flux Modeling

Net radiation (W/m²) is modeled based on Equation A1 below.
\[
R_n = (1 - \alpha) R_s + \varepsilon_a \sigma T_a^4 - \varepsilon_s \sigma T_s^4
\]  
(A1)

where, \(\alpha\) is surface albedo, \(R_s\) is incoming shortwave radiation (W/m²), \(\varepsilon_a\) is atmospheric thermal emissivity, \(\varepsilon_s\) is surface thermal emissivity, \(T_a\) is air temperature (K) and \(T_s\) is radiometric surface temperatures (K), while \(\sigma\) is the Stefan-Boltzmann constant \((5.67 \times 10^{-8} \text{ W/m}^2\text{K}^4)\).

Surface albedo is estimated using the Brest and Goward (1987) approach.
\[
\alpha = 0.512 \text{RED} + 0.418 \text{NIR}
\]  
(A2)

where, RED and NIR are surface reflectance values in the Red and Near Infra-Red bands of the electromagnetic spectrum.

Air or atmospheric emissivity is calculated using the Brutsaert (1975) approach.
\[
\varepsilon_a = 1.24 \left(\frac{e_a}{T_a}\right)^{1/7}
\]  
(A3)

where, \(e_a\) is the actual vapor pressure (mb) and \(T_a\) is air temperature in K.

Surface thermal emissivity is calculated using Brunsell and Gillies (2002).
\[
\varepsilon_s = 0.98 f_c + 0.92(1 - f_c)
\]  
(A4)

where, \(f_c\) is the fractional vegetation cover.

Soil heat flux (W/m²) is estimated using Bastiaanssen et al. (1998) approach.
\[
G/R_n = \left(\frac{T_s}{\alpha}\right)(0.0038 \alpha + 0.0074 \alpha^2)(1 - 0.98 \text{NDVI}^4)
\]  
(A5)

where, NDVI is the Normalized Difference Vegetation Index.

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