A Multi-sensor Analysis of Selected Reflectance-Based Crop Coefficient Models for Daily Maize Evapotranspiration Estimation

Edson Costa-Filho¹, José L. Chávez¹ & Huihui Zhang³

¹ Colorado State University, Civil and Environmental Engineering Department, Fort Collins, CO, USA
² Water Management and Systems Research Unit, United States Department of Agriculture, Agricultural Research Service, Fort Collins, CO, USA

Correspondence: José L. Chávez, Colorado State University, Civil and Environmental Engineering Department, Fort Collins, 80523, CO, USA. Tel: (970)-491-6095. E-mail: jose.chavez@colostate.edu

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Abstract

This study evaluated three reflectance-based crop coefficient models (RBCC) for daily maize actual evapotranspiration (ETa) estimates, using multispectral data from spaceborne, airborne, and proximal platforms. The goal was to identify the optimal multispectral sensor that gives more accurate daily ETa estimates. The remote sensing (RS) multispectral platforms included Landsat-8, Sentinel-2, Planet CubeSat, handheld multispectral radiometer (MSR), and unmanned aerial system or UAS, spatial resolution from 30 m to 0.03 m. Three RBCC models that use different vegetation indices as input variables were evaluated in the study. One RBCC uses the normalized difference vegetation index (NDVI). The second model uses the soil-adjusted vegetation index (SAVI), and the third model uses canopy cover (fc). The data for this study were from two maize research sites in Greeley and Fort Collins, Colorado, USA, collected in 2020 and 2021. The Greeley site had a subsurface drip system, while the Fort Collins site had surface irrigation (furrow). Daily maize ETa predictions were compared with observed daily maize ETa data from an Eddy Covariance system installed at each research site. Results indicated that, depending on the RS of ETa algorithm and platform, the optimal input RS data was different. The MSR sensor (1 m) provided the best remote sensing data (input) for the SAVI-based RBCC ETa model, with a maize ETa error (MBE±RMSE) of -0.13 (-3%)±0.67 (16%) mm/d. Sentinel-2 was the best sensor for the remaining two RBCC daily maize ETa algorithms, since the errors for the NDVI-based and fc-based RBCC models for maize ETa were 0.21 (5%)±0.78 (18%) mm/d and 0.59 (14%)±1.07 (25%) mm/d, respectively. These results indicate the need for methods to improve the spectral quality of the remote sensing data to improve spatial ETa estimates and advance sustainable irrigation water management.

Keywords: remote sensing, evapotranspiration, crop coefficients, maize, irrigation water management.

1. Introduction

Irrigation practices in agriculture are the primary water user in the world with withdrawals of approximately 70 to 75% of the global freshwater available for human use (Wallace, 2000; Dubois, 2011; Wada et al., 2013). According to a recent FAO land use database report, cropland fields occupy 12% of the global habitable landscape (FAOSTAT, 2019). Rainfed and irrigated fields are the basis for cropland water use worldwide. Irrigated fields occupy 18% of the earth’s cultivable cropland area while responsible for about 40% of global food production (Siebert & Döll, 2010; Grassini et al., 2011; Nagaraj et al., 2021). The growing threat of climate change, alongside the urban development growth in the next 30 years, has created significant concerns about the future of water resources (Vermeulen et al., 2012; Wiebe et al., 2019a, Wiebe et al., 2019b). Extreme and prolonged drought seasons will potentially escalate yield loss due to heatwaves, soil nutrient degradation, and water access disputes (Quiring & Papakryiakou, 2003; Wang et al., 2014).

Maize is a vital agricultural product in the United States of America (USA). The impact of climate change on crop yields is observable nationwide, affecting various crops. As stated by Chung et al. (2014), there is a potential 29% reduction in maize yields across the USA by 2050 due to climate-induced extreme conditions, such as prolonged droughts. Rural regions, particularly in the Midwest of the USA, including states like Kansas, Iowa, Nebraska, and Oklahoma are expected to experience severe and prolonged droughts seasons that can contribute to a decrease in crop yields for granular commodities such as maize (Tubiello et al., 2002; Salehabadi...
et al., 2022). To mitigate the devastating effects of climate change on crop yield, precision agriculture has been promoted as a reliable approach to improve farm productivity and economics based on actual field conditions on a spatio-temporal basis (Balafoutis et al., 2017).

Pierce and Nowak (1999) defined precision agriculture as the implementation of techniques to improve irrigation water management on a spatial-temporal basis and make agriculture sustainable. When it comes to sustainable agriculture, defining the optimal time and amounts to apply water in the root zone is critical to conserving water and soil resources within an agricultural setting. Since irrigated lands are vital to improving crop yield worldwide, better irrigation scheduling has become the focus of studies to augment sustainable water management in cropland fields. Irrigation water management practices are often based on the soil water balance approach (SWB) for irrigation scheduling (Allen et al., 1998; Wery, 2005). It considers the water entering or leaving the crop root zone to monitor the changes in soil water content over time (Hoffman et al., 2007). A simplified daily SWB budget (Allen et al., 1998) is given by Equation 1 as follows:

\[ D_{r,i} = D_{r,i-1} - \{ P - RO \}_i - I_i - CR_i + ET_{c,i} + DP_i \]  

(1)

Where, \( D_{r,i} \) is the water depleted in the root zone at the end of day \( i^{th} \); \( D_{r,i-1} \) is the water in the root zone in the previous day \( (i-1)^{th} \); \( P \) is the rainfall water depth; \( RO \) is the surface water runoff; \( I \) is the net irrigation water depth; \( CR \) is the capillary rise from shallow water table (groundwater); \( ET_{c,i} \) is the daily crop evapotranspiration; \( DP \) is the deep percolation (vertical water loss beyond the root zone). All variables in Equation 1 are given as water depth units (e.g., mm or in, for instance).

Actual crop evapotranspiration (henceforth, \( ET_a \)) is a critical term for irrigation scheduling as it provides information about plant transpiration and soil water evaporation losses. At the farm scale, determining accurate \( ET_a \) rates is essential to support decision-making approaches for water allocation and optimization of irrigation water management (Anderson & French, 2019). Measurement techniques are a straightforward surrogate to determine on-site \( ET_a \) rates when instrumentation and technical expertise are available. The most commendable methods for directly or indirectly measuring \( ET_a \) are based on soil water mass balance using high-precision monolithic weighing lysimeters (Jia et al., 2006; Denich & Bradford, 2010; López-Urrea et al., 2020), turbulence measurements from high-frequency eddy covariance (henceforth, EC) heat flux or from optical large aperture scintillometer (LAS) systems (Anapalli et al., 2018; Anapalli et al., 2020), measurements of soil water content in the SWB approach (Sharma et al., 2017; Huang et al., 2021), and plant transpiration through sap flow devices (Gong et al., 2007; Zhang et al., 2014; Saitta et al., 2020).

Although \( ET_a \) measurements have become reliable for providing observed data across different methods, the spatio-temporal variability in crop water demands make measuring spatially distributed crop \( ET_a \) using the abovementioned methods unrealistic. Soil water content and sap flow sensors provide localized data (point-based), often requiring several sampling locations. Furthermore, techniques such as the EC and LAS systems, which represent the 2D heat flux source area or footprint (e.g., an upwind area from which the instruments measured most of the fluxes), have certain limitations related to the local assumptions of surface homogeneity, stationary turbulent conditions, and non-advective conditions (Arya, 2001; Foken, 2008). Thus, to circumvent the limitations of spatially measuring \( ET_a \), advances in remote sensing applications for agricultural water management have enabled the mapping of near-real-time crop water requirements for irrigation scheduling on a spatio-temporal basis. Remote sensing is the science of measuring emitted and reflected light within the visible/invisible shortwave and longwave infrared (LWIR) radiation spectrums, without having contact with the target area (Rott, 2000). The optical devices attached to airborne (e.g., small aircraft, automated aerial vehicles), spaceborne (e.g., satellites), and proximal platforms (e.g., field fixed or handheld radiometers) have provided data at different spectral and spatial resolutions for applications in irrigation water and soil nutrient management, crop growth monitoring, and yield mapping (Yang et al., 2005; Maes and Steppe, 2019; Costa-Filho et al., 2020). Regarding \( ET_a \) mapping, using multispectral data has allowed the development of algorithms to estimate spatial hourly and daily \( ET_a \) using overpass data from different platforms (Gowda et al., 2008).

Remote sensing of \( ET_a \) algorithms could be divided into two major approaches: the reflectance-based crop coefficient (RBCC) and the surface energy balance (SEB) models. The RBCC for daily \( ET_a \) mapping estimates a transpiration crop coefficient (\( K_{ct} \)) of a given vegetation type as a function of vegetation indices (VI) derived from red (RED) and near-infrared (NIR) surface reflectance (SR) within the shortwave light spectrum, such as the normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), and vegetation cover (\( f_c \)) for a variety of crop types (Bausch & Neale, 1987; Neale et al., 1990; Bausch, 1995; Jayanthi et al., 2007; Trout & DeJonge, 2018). The RBCC also relies on reference evapotranspiration (\( ET_{ref} \)) from a standardized local grass or alfalfa field to determine a given crop \( ET_a \). When the spatial \( K_{ct} \) values are multiplied by a given daily
ET$_{\text{ref}}$ (alfalfa or grass), for the day of remote sensing data overpass, spatial daily ET$_{\text{s}}$ is determined for a given sensor. The RBCC modeling approach is strictly empirical and has daily ET$_{\text{s}}$ estimation errors ranging from 15% to 40% (French et al., 2020; Pereira et al., 2020).

Given that different remote sensing sensors offer images of cropland fields with different spectral and spatial resolutions, it is imperative to investigate the performance of different remote sensing of ET$_{\text{s}}$ algorithms to identify the optimal imagery (quality) platform for a given algorithm, and to support sustainable irrigation water management. Understanding the strengths and weaknesses of a given spectral and spatial resolution in mapping ET$_{\text{s}}$ constitutes the foundation for developing enhanced calibration approaches for more accurate ET$_{\text{s}}$ mapping at the farm scale. We hypothesize that for a given crop ET$_{\text{s}}$ algorithm, there is an optimal remote sensing sensor (imagery) that provides the best multispectral data for accurately estimating daily ET$_{\text{s}}$. We also hypothesize that depending on the source of a given remote sensing image (e.g., spaceborne, airborne, proximal platforms, sensor type, imagery post-processing corrections), the accuracy of ET$_{\text{s}}$ mapping products varies for a given remote sensing of ET$_{\text{s}}$ algorithm. Finally, we envision that determining the optimal remote sensing spectral and spatial resolution is necessary to recommend further research on improving the estimation of ET$_{\text{s}}$ when sub-optimal remote sensing sensors are used with a given remote sensing of ET$_{\text{s}}$ algorithm.

Hence, we identify a relevant gap in the literature in providing answers regarding the optimal spectral and spatial resolution for mapping ET$_{\text{s}}$. Furthermore, there has not been a study that evaluates the performance of different RBCC ET$_{\text{s}}$ algorithms for estimating daily maize ET$_{\text{s}}$ when using data from common types of remote sensing sensors associated with spaceborne, airborne, and proximal devices used over irrigated fields with various irrigation systems and water management practices. Therefore, this study aimed to: a) evaluate the effect (errors) of using different spectral and spatial resolutions when estimating daily RBCC maize ET$_{\text{s}}$ from spaceborne, airborne, and proximal remote sensing platforms; b) identify the optimal remote sensing spectral and spatial data that provides the most accurate results when predicting daily maize ET$_{\text{s}}$, for a given RBCC algorithm; and c) evaluate the error analysis and optimal remote sensing sensor, for a given RBCC daily maize ET$_{\text{s}}$ algorithm, from two maize fields under different irrigation systems (surface furrow and sub-surface drip irrigation).

2. Material and Methods

2.1 Description of the Research Sites

2.1.1 Limited Irrigation Research Farm (LIRF)

One of the research sites was the Limited Irrigation research farm (LIRF) in Greeley, Colorado, USA. The United States Department of Agriculture (USDA) Agricultural Research Service (ARS) manages the LIRF site. LIRF is geographically located at latitude 40.4463°N, longitude 104.6371°W, and it is 1,432 m above sea level (ASL), as shown in Figure 1. Two adjacent rectangular-shaped maize fields (190 m × 110 m) were the ground-based plots where data were collected from July to September of 2020 and 2021 (Figure 1). For a given season, each field had different irrigation water management strategies. In 2020, The West field (henceforth Field W) was fully irrigated. In this study, the term fully irrigated indicates that frequent irrigation events were scheduled to maintain soil water content in the root zone at non-water stress levels. The East field (hereafter, Field E) was managed as a deficit irrigated field (water stress conditions). In 2021, the irrigation water management practices were interchanged between treatment plots; i.e., field W was deficit irrigated, while Field E was fully irrigated. Table 1 presents the summary data regarding the soil wetting events (irrigation and rainfall) in 2020 and 2021.
Each field had the same irrigation system (subsurface drip irrigation)—buried drip laterals at 0.23 m deep and emitters spaced every 0.30 m. Maize rows were oriented North-South and 0.76 m apart. The distance between two consecutive maize plants was 0.17 m. The maize planting density was 87,500 plants/ha during both years of data collection. In 2020, the drought-tolerant maize variety NK9227-5222A (Syngenta Inc., Basel, Switzerland) was planted on 5/6/2020 and harvested on 10/13/2020 and 10/14/2020. In 2021, drought-tolerant maize varieties P9998Q and P0157AMXT (Pioneer Hi-Bred International, Inc., Johnston, Iowa, USA) and CH 194-49 DG (Channel Bio Corporation, Saint Louis, Missouri, USA) were planted on 5/13/2021 and harvested on 10/11/2021 and 10/12/2021. Fields W and E (approximately 83% of each plot) were covered by maize variety P0157AMXT (Figure 2). In 2020, maize canopy height ($h_c$) peaked on 8/2/2020, with maximum values of 2.00 and 1.50 m in Field W (fully irrigated) and Field E (deficit irrigated), respectively. Leaf area index (LAI) around solar noon (11 am to 3 pm) peaked on 8/13/2020 with maximum values of 3.70 and 3.32 m²/m² for Fields W and E, respectively. On 8/2/2021, $h_c$ reached maximum values of 1.90 and 2.10 m for Fields W and E, respectively. No LAI measurements happened in 2021 at Fields W, and E. Figure 3 shows the experiment design and data collection points at LIRF in 2020 and 2021. The prevailing wind direction was from the Southeast (SE) to the South (S) in both years of data collection.
2.1.2 Irrigation Innovation Consortium (IIC)

The IIC Headquarters site was another location where the study collected data in 2020 and 2021. The IIC had two maize fields that provided the grounds for data collection. Located in Fort Collins, Colorado, USA, at 40.5542°N latitude, 105.0038°W longitude, and 1,486 m above sea level. The IIC site has a local climate defined as subtropical steppe with cold semiarid trends (Peel et al., 2007). Data collection happened on two surface-irrigated maize fields (furrow), in 2020 and 2021, from July to September (Figure 4a). In Figure 4a, Fields F and D depict a surface area of 64,750 m² and 74,867 m², respectively. The row orientation was East-West for Field F and North-Southeast for Field D, with 17 cm row spacing. The fields had a uniform soil texture (sandy loam) with VWC₉ₑₑ, VWC₉ₑₚₑ, VWC₉ₑₑₑ equal to 0.189, 0.069, and 0.410 m³/m³, respectively. The surface irrigation system (furrow) had aluminum 4 cm-diameter siphon tubes providing water to the fields.

The maize varieties were different in 2020 and 2021. The G02K39-3120 (Golden Harvest, Minnetonka, Minnesota, USA) was planted on 05/13/2020 with approximately 8 seeds/m². In 2021, the NK0243-3120 and NK0314-5122 (Syngenta AG, Basel, Switzerland) varieties were planted in both fields (Figure 4b). The seeding
date was on 5/13/2020 at an 8 seeds/m² rate. All maize varieties in this study were drought tolerant. On 7/28/2020, $h_c$ and LAI reached peak values of 2.20 m and 3.80 m²/m², respectively. In 2021, maximum $h_c$ and LAI occurred on 8/2/2021 at 2.45 m and 3.80 m²/m² values, respectively.

![Figure 4](image1.png)

**Figure 4.** RGB (Red-Green-Blue) map of the IIC research fields (Figure 4a) and the maize varieties planted in 2021 (Figure 4b). The study maize fields were Fields F and D. Areas in green are vegetation surfaces.

The irrigation waterfront moved from East (central channel) to West on Field F and North to Southwest on Field D, respectively. The irrigation events occurred two to three days after water request/acquisition from the Sand Dike Lateral Company (Fort Collins, CO, USA). Each irrigation event lasted from 6 to 12 hours. The prevailing wind direction was from the Southeast (SE) to the South (S) in both years of data collection. Table 2 presents the summary data regarding the soil wetting events (irrigation and rainfall) in 2020 and 2021.

<table>
<thead>
<tr>
<th>Season</th>
<th>Field</th>
<th>Number of Irrigation Events</th>
<th>Cumulative Gross Irrigation (mm)</th>
<th>Cumulative Rainfall (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>F</td>
<td>7</td>
<td>1620</td>
<td>34</td>
</tr>
<tr>
<td>2020</td>
<td>D</td>
<td>5</td>
<td>870</td>
<td>34</td>
</tr>
<tr>
<td>2021</td>
<td>F</td>
<td>8</td>
<td>1081</td>
<td>104</td>
</tr>
<tr>
<td>2021</td>
<td>D</td>
<td>4</td>
<td>1064</td>
<td>104</td>
</tr>
</tbody>
</table>

**2.2 Crop Evapotranspiration Algorithms**

**2.2.1 Reflectance-based Crop Coefficient (RBCC)**

In this study, three published RBCC models for maize were used in the multi-scale analysis of remote sensing of ET$_a$ algorithms. The three RBCC approaches use different VIs to predict maize $K_{sa}$. Neale et al. (1990) use NDVI as the predictor. Bausch (1995) considers SAVI, while Trout and DeJonge (2018) use $f_c$ as a predictor. Neale et al. (1990) RBCC ET$_a$ model was calibrated using daily maize ET$_a$ from weighing lysimeters and multispectral data from a handheld EXOTECH radiometer with a 1 m footprint and similar spectral data to Landsat-5. Bausch (1995) model developed a crop coefficient curve using SAVI from the same EXOTECH handheld radiometer mounted on a boom (5-m footprint), with a similar Landsat-5 spectral response, by linearly interpolating alfalfa-based basal crop coefficient or $K_{sa}$ values from bare soil (0.15) to effective maize canopy
cover (0.93). Trout and DeJonge (2018) model derived their $K_{cr}$ model using $f_c$ values calculated from a digital multispectral camera, 6 m above the ground surface (AGS), in which the camera had a field-of-view (FOV) consisting of 4 rows $\times$ 4 m. Trout and DeJonge (2018) model was calibrated using measured ET$_a$ from an SWB approach (Equation 1) during a six-year data collection period. All three models were calibrated data from Colorado maize fields under different irrigation systems. Neale et al. (1990) calibrated their $K_{cr}$ model using data from a maize field using surface irrigation (furrow). The RBCC ET$_a$ model from Bausch (1995) was developed using data from maize fields under center-pivot sprinkler irrigation. Trout and DeJonge (2018) developed their calibrated $K_{cr}$ model in a surface drip irrigated field. The three RBCC models are indicated by Equations 2 to 7 below:

$$ET_{ad}^{[N]} = K_{cr}^{[N]} \times ET_{rd}$$  
$$K_{cr}^{[N]} = 1.181 \times NDVI - 0.026$$  
$$ET_{ad}^{[B]} = K_{cr}^{[B]} \times ET_{rd}$$  
$$K_{cr}^{[B]} = 1.416 \times SAVI + 0.017$$  
$$ET_{ad}^{[TJ]} = K_{cr}^{[TJ]} \times ET_{rd}$$  
$$K_{cr}^{[TJ]} = 1.10 \times f_c + 0.17$$  

where, $ET_{ad}$ is the estimated actual daily maize evapotranspiration (mm/d); $ET_{rd}$ is the daily alfalfa reference evapotranspiration (mm/d); the superscripts [N], [B], and [TJ] indicate the Neale et al. (1990), Bausch (1995), and Trout and DeJonge (2018) models, respectively.

2.3 Vegetation Indices (VI) Calculation

The NDVI, SAVI (Huete, 1988), and OSAVI (Rondeaux et al., 1996) indices are calculated by Equations 8 to 10, respectively:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$  
$$SAVI = \frac{NIR - RED}{NIR + RED + L} \times (1 + L)$$  
$$OSAVI = \frac{NIR - RED}{NIR + RED + 0.16} \times 1.16$$  

where, NIR and RED are the surface reflectance data of a given remote sensing platform (dimensionless); L is the SAVI soil adjustment factor set to 0.50 (Huete, 1988).

The $f_c$ model used in the RBCC approach from Trout and DeJonge (2018) was from Johnson and Trout (2012) vegetation that developed their $f_c$ model for several crops (e.g., maize, wheat, cotton, alfalfa, barley, onions, and others) in a semiarid climate region in San Juan Valley, California, USA. Equation 11 shows the $f_c$ model from Johnson and Trout (2012) as follows:

$$f_c = \begin{cases} 
0, & \text{NDVI} < 0.15 \\
1.26 \times \text{NDVI} - 0.18, & \text{otherwise}
\end{cases}$$  

2.4 Remote Sensing Platforms

2.4.1 Spaceborne

2.4.1.1 Landsat-8

Landsat-8 is a spaceborne remote sensing platform managed by the United States Geological Service (USGS) and National Aeronautics and Space Administration (NASA). A Landsat-8 satellite has an Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) that take images of the earth’s landscape at a 30-m and 100-m spatial resolution every sixteen days, respectively. The OLI sensor provides short-wave multispectral data, and the TIRS camera measures LWIR thermal radiation images. The LIRF and IIC sites are located within the overlap region of 33/32 and 34/32 (path/row) Landsat-8 scenes, so the temporal resolution is weekly. A cubic convolution resampling approach downscales the TIRS image to the OLI imagery spatial resolution (Roy et al., 2014).

Landsat-8 has a sun-synchronous orbit around Earth at 705 km altitude, with Equator time around 11:30 am local time. The original radiometric resolution Landsat-8 imagery is 12 bits, converted to 16 bits after USGS/NASA post-processed data. The radiometric resolution of a remote sensing image indicates the capacity to record a wide
range of brightness levels. The metadata imagery file provides linear calibration coefficients to convert a digital number (DN) to surface reflectance (Landsat-8 Level-2 imagery). The Level-2 images undergo rigorous calibration procedures and do not require further post-processing after the final surface reflectance and temperature images are appropriately converted from the original DN values (Roy et al., 2014). More details about atmospheric corrections applied to Landsat-8 imagery are found in Vermote et al. (2016). Table 3 presents the spectral characteristics of the Landsat-8 bands that have been considered in the research.

Table 3. List of Landsat-8 multispectral bands used in this study.

<table>
<thead>
<tr>
<th>Bands</th>
<th>Central Wavelength (nm)</th>
<th>Bandwidth (nm)</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUE</td>
<td>480</td>
<td>60</td>
<td>30</td>
</tr>
<tr>
<td>GREEN</td>
<td>560</td>
<td>60</td>
<td>30</td>
</tr>
<tr>
<td>RED</td>
<td>655</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>NIR</td>
<td>870</td>
<td>30</td>
<td>30</td>
</tr>
</tbody>
</table>

2.4.1.2 Sentinel-2

Sentinel-2 satellites are maintained and operated by the European Space Agency (ESA), an intergovernmental entity of twenty-two European countries. The Copernicus Programme is responsible for managing the Sentinel satellite missions. There are two Sentinel-2 satellites (S2A and S2B) that each provide multispectral image scenes (290 km x 290 km, each) of the earth every ten days for one satellite device around the Equator, five days when the two satellites are combined, and two to three days revisiting time for landscape areas located at mid-latitudes. The satellite design, operation, and components can be found in Drusch et al. (2012).

The S2A and S2B satellites have a sun-synchronous orbit at an average altitude of 786 km and an Equator time around noon local time. Thermal images are not provided by Sentinel-2 satellites. The spatial resolution of Sentinel-2 images depends on the type of multispectral bands and varies from 10 m to 60 m. Only Sentinel-2 bands 2, 3, 4, and 8 (10 m pixel size) have been considered in the project since they are provided at their original spatial resolution (Table 4). The original radiometric resolution of Sentinel-2 images is 12 bits. However, when ESA post-processes images, they are converted to 16 bits. The Sentinel-2 Level-2 images are calibrated and pre-processed to provide surface reflectance through a calibration factor of 10,000. The atmospheric corrections involve using a radiative transfer algorithm developed by the ESA (Sen2Cor). More details about the use of Sen2Cor to atmospherically correct S2A and S2B satellite images are found in Main-Knorn et al. (2017) and Wei et al. (2018).

Table 4. List of Sentinel-2 multispectral bands used in this study

<table>
<thead>
<tr>
<th>Bands</th>
<th>Central Wavelength (nm)</th>
<th>Bandwidth (nm)</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUE</td>
<td>492</td>
<td>66</td>
<td>10</td>
</tr>
<tr>
<td>GREEN</td>
<td>560</td>
<td>36</td>
<td>10</td>
</tr>
<tr>
<td>RED</td>
<td>665</td>
<td>31</td>
<td>10</td>
</tr>
<tr>
<td>NIR</td>
<td>833</td>
<td>106</td>
<td>10</td>
</tr>
</tbody>
</table>

2.4.1.3 Planet CubeSat

Planet CubeSat is a low-cost and privately-owned constellation of satellites operated and maintained by Planet Labs (Planet Labs, Inc., San Francisco, CA, USA). More than 130 CubeSats units survey Earth’s landscape (24 km x 16 km scene) on high temporal (daily) and spatial (3 m) spatial resolutions providing multispectral imagery in the visible and NIR wavelengths of the light spectrum (Planet Team, 2017). The radiometric resolution of Planet CubeSat is 12-bit when the image is acquired and converted to 16-bit after post-processing steps before imagery is made available. Planet CubeSat satellites are smaller and lighter than Landsat-8 and Sentinel-2 (0.10 m x 0.10 m x 0.30 m; 4 kg weight). The satellites have a sun-synchronous orbit, with an altitude range from 450 km to 580 km and an Equator crossing time from 9:30 to 11:30 am local time (Planet Team, 2017). The CubeSat platform only provides multispectral images (Table 5).

The current Planet Satellite platforms provide no thermal images. The Planet CubeSat surface reflectance images are calibrated and pre-processed with a calibration factor of 10,000. Prior atmospheric corrections accounted for
the gases and aerosol concentration and their changes with an altitude between the landscape and the at-sensor camera in space. MODIS water vapor, ozone, and aerosol quality control products serve as complementary data to improve the calibration of Planet CubeSat imagery using the 6SV2.1 radiative transfer model (Planet Team, 2017). However, the atmospheric corrections are still a work in progress since the approach by Planet Labs does not include stray light, haze, and thin cirrus clouds effects; it assumes Earth's landscape to behave as a Lambertian surface (homogeneous light scattering in all directions) and that all scenes to be at sea level (Planet Team, 2017). During imagery post-processing, geometric corrections are done using sensor telemetry, ground control points (GCP), and fine digital elevation models (DEM). Planet Team (2017) released a harmonized version of Planet imagery (including CubeSat data) that adjusts the quality of the multispectral data to Sentinel-2 standards. More information about the imagery harmonization processes is found in Csillik et al. (2019) and Kington IV et al. (2019). The CubeSat harmonized images have been considered in this study as the primary data.

Table 5. List of Planet CubeSat multispectral bands used in this study

<table>
<thead>
<tr>
<th>Bands</th>
<th>Central Wavelength (nm)</th>
<th>Bandwidth (nm)</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUE</td>
<td>491</td>
<td>60</td>
<td>3</td>
</tr>
<tr>
<td>GREEN</td>
<td>566</td>
<td>90</td>
<td>3</td>
</tr>
<tr>
<td>RED</td>
<td>666</td>
<td>80</td>
<td>3</td>
</tr>
<tr>
<td>NIR</td>
<td>867</td>
<td>80</td>
<td>3</td>
</tr>
</tbody>
</table>

Only clear-sky images collected at LIRF and IIC sites were considered for all three spaceborne remote sensing platforms for the multi-year datasets. That is to avoid clouds affecting the research fields' surface reflectance and temperature values.

2.4.2 Proximal

Proximal surface reflectance data have been measured with a portable Cropscan multispectral (MSR5) radiometer (CropScan Inc., Rochester, MN) at all research sites during the years of data collection. An MSR5 radiometer is a lightweight handheld device that includes a quasi-cubic radiometer (8 × 8 × 10 cm), and an attached IRT (Exergen Corporation, Watertown, MA) mounted on a pole to allow readings at the nadir-looking position above the canopy. The MSR radiometer has a FOV of 28°, and it took readings at 2.2 m AGS, which provided a ground sampling area equivalent to a 1-m diameter circle (2V:1H aspect ratio). An MSR5 is a passive sensor that relies on natural incoming light from the sun and emulates Landsat-5 spectral bandwidths in the visible and invisible light spectrum. In this study, MSR5 units were deployed at the LIRF and IIC sites. Multispectral data from the MSR5 have been sampled two times at the row and inter-row (total of four readings) and averaged at each measurement location at all research sites.

Table 6. List of MSR5 multispectral bands used in this study

<table>
<thead>
<tr>
<th>Bands</th>
<th>Central Wavelength (nm)</th>
<th>Bandwidth (nm)</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUE</td>
<td>485</td>
<td>70</td>
<td>1</td>
</tr>
<tr>
<td>GREEN</td>
<td>560</td>
<td>80</td>
<td>1</td>
</tr>
<tr>
<td>RED</td>
<td>660</td>
<td>60</td>
<td>1</td>
</tr>
<tr>
<td>NIR</td>
<td>830</td>
<td>140</td>
<td>1</td>
</tr>
</tbody>
</table>

2.4.3 Airborne

The Unmanned Aerial Systems (UAS) missions have been scheduled at all two sites during the growing seasons by the USDA-ARS Water Management division and the Colorado State University (CSU) Drone Center. The USDA-ARS team was responsible for UAS images at the LIRF, while the CSU Drone Center provided imagery files at the IIC site. The UAS images were obtained from a MicaSense RedEdge-MX multispectral camera attached to a flying unit (MicaSense Inc., Seattle, Washington, USA). The RedEdge-MX detector has a five-band composition in the visible and invisible light spectrum: BLUE (475 nm, 32 nm bandwidth), GREEN (560 nm, 27 nm bandwidth), RED (668 nm, 14 nm bandwidth), and NIR (842 nm, 57 nm bandwidth). The UAS surface reflectance data will be combined with nadir-looking T\textsubscript{s} data from point-based measurements at each
research site to serve as input data to estimate ET\textsubscript{a} using the SEB approaches in this study. UAS imagery pre-processing has been done using ArcGIS 10.8 (ESRI, Redlands, CA). Table 7 summarizes the UAS missions at LIRF and IIC in 2020 and 2021.

Table 7. The UAS mission summary for the USDA-ARS and CSU Drone Center at all sites.

<table>
<thead>
<tr>
<th>UAS Unit</th>
<th>USDA-ARS</th>
<th>CSU Drone Center</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flight Altitude (m)</td>
<td>DJI S900</td>
<td>DJI M600</td>
</tr>
<tr>
<td>UAS Speed (m/s)</td>
<td>120</td>
<td>100</td>
</tr>
<tr>
<td>Imagery Pixel Size (m)</td>
<td>0.03</td>
<td>0.08</td>
</tr>
<tr>
<td>Overlap/Sidelap Percentage (%)</td>
<td>88/70</td>
<td>80/70</td>
</tr>
<tr>
<td>Temporal Resolution</td>
<td>Weekly</td>
<td>Weekly</td>
</tr>
<tr>
<td>Calibrated Reflectance Panel</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Orthorectified Coordinate System</td>
<td>WGS84 UTM</td>
<td>WGS84 UTM</td>
</tr>
<tr>
<td>Post-processing Imagery Software</td>
<td>Agisoft Metashape</td>
<td>Pix4D v4.5.6</td>
</tr>
</tbody>
</table>

2.5 Data Collection

The experiment was replicated in both LIRF and IIC sites to obtain the same datasets to evaluate the airborne, spaceborne, and proximal platforms when predicting ET\textsubscript{a} using remote sensing algorithms. A total of three ground-based measurement stations provided the ground-based input data to estimate and evaluate maize ET\textsubscript{a}. The following data were measured at each station: Net radiation (R\textsubscript{n}), soil heat flux (G), incoming short-wave solar radiation (R\textsubscript{s}), shallow soil temperature, and volumetric water content. A heat flux EC tower provided measurements of H and LE in each research site. The selection of the locations of each measurement station was done considering local soil texture conditions, field accessibility to monitoring data, and irrigation water application logistics. Each measurement station was equipped with a Campbell Scientific Datalogger (Campbell Scientific Inc., Logan, UT, USA). Data were recorded every minute and averaged every fifteen minutes. The averaged fifteen-minute time interval was chosen to better characterize the local temporal variations in the measured data, at each station, with respect to each variable measured at those locations in both research sites.

2.5.1 Surface Heat Fluxes

At the IIC site, a two-way NR-Lite and two four-way CNR1 net radiometers (Kipp and Zonen, Delft, The Netherlands) measured R\textsubscript{n} at the height of 3.3 m AGS. At the LIRF site, all three net radiometers were a two-way NR-Lite in 2020 and 2021. The CNR1 radiometer was installed on Field F (West station). NR-Lite radiometers measure net short-wave and long-wave radiation within a spectral range from 0.2 to 100 \( \mu \text{m} \), temperature dependency of 0.12 %/\( ^\circ \text{C} \), and a directional error of less than 30 \( \text{W/m}^2 \) (Campbell Scientific, 2001). The CNR1 radiometer provides data regarding all terms of the net radiation budget, it has a data uncertainty within 10 to 35 \( \mu \text{V/W/m}^2 \), and has a directional error of 25 \( \text{W/m}^2 \) at 1000 \( \text{W/m}^2 \) (Kipp & Zonen, 2002).

Surface G data were determined using the soil heat flux plate method (as described by Oschner et al., 2006). At LIRF, two HFT3-L soil heat flux plates (Radiation and Energy Balance Inc., Bellevue, Washington, USA) were buried at 0.08 m between and below maize rows at each measurement station. At the IIC site, the HFT3-L plates were placed between two consecutive maize rows due to the flooded furrow during irrigation events. One 5TE soil water content sensor (Decagon Devices Inc., Pullman, Washington, USA) was buried at 0.04 m. Two T107 temperature probes (Campbell Scientific Inc., Logan, Utah, USA) were installed at 0.02 and 0.06 m below ground surface (BGS) to determine heat storage above the 0.08 m soil layer from the HFT3-L plates. The HFT3-L sensors have thickness and diameter equal to 3.91 and 38.2 mm, respectively. The measurement uncertainty of soil heat flux from the plates is 5% (Campbell Scientific, 2003).

Measured LE and H data were acquired using an Eddy Covariance system (EC) system at each research site. At the IIC (Figure 5a), the EC system consisted of an LI-7500A open-path \( \text{CO}_2/\text{H}_2\text{O} \) gas analyzer (LI-COR Biosciences, Lincoln, Nebraska, USA) and a CSAT three-dimensional (3D) sonic anemometer (Campbell Scientific Inc., Logan, Utah, USA). At LIRF (Figure 5b), an LI-7500DS open-path gas analyzer (LI-COR Biosciences, Lincoln, Nebraska, USA) and a Gill WindMaster three-dimensional (3D) sonic anemometer (Gill Instruments, Lymington, Hampshire, UK) provided measurements of LE and H, respectively. Both EC systems at LIRF and IIC were installed at 3.5 m AGS, positioned facing the prevailing wind direction at each site (135°.
 azimuth angle), and set to a sampling frequency equal to 10 Hz (e.g., 10 measurements per second). The EC turbulent heat fluxes and respective ancillary data were recorded as 15-minute and half-hour averages at the IIC and LIRF sites, respectively. The EC system often provides imbalanced turbulent heat fluxes regarding SEB closure (Foken, 2008; Liu et al., 2021), with closure SEB ratio (H + LE)/(R_n - G) ranging from 70% to 90% (Goulden et al., 1997; Oneclay et al., 2007; Liu et al., 2011). Thus, to improve the representativeness of H, LE, and ETa measurements from the EC system, the residual-LE closure approach was chosen in this study to ensure the closure of the SEB. Twine et al. (2000) indicated that the residual-LE method calculates measured LE as the difference among measured R_n, G, and H (from the EC system). Twine et al. (2000) indicated that most of the unresolved EC system closure issue is due to LE rather than H. Table 8 shows the corrections performed in the high-frequency EC data at LIRF and IIC in 2020 and 2021. To evaluate the accuracy of RBCC ETa predictions, the EC LE data from SEB closure was extrapolated to daily values using Equation 12 below:

\[
ETa^{[EC]}_{ad} \approx \left( \frac{c \times 86,400}{\rho_a L_v} \right) \left( \frac{LE^{[EC]}_{inst}}{R_n - G} \right)_{daily} \]

(12)

where, ETa^{[EC]}_{ad} is the extrapolated daily maize ETa (mm/d) from the EC data; c is a unit conversion factor (1000 mm/m); 86,400 is the number of seconds in a day (s/d). The subscript ‘inst’ is “instantaneous” fluxes for a given timestamp (e.g., 15 min or 30 min). Only surface heat flux values coinciding with the remote sensing platform overpass times were considered to represent the daily extrapolated maize ETa from the EC station. The extrapolation of EC data from instantaneous to daily ETa was necessary because, due to the field geometry, canopy roughness, and technical aspects of the EC instrumentation, the system could not record complete 24-hour datasets of heat fluxes with the upward source always within the maize field boundaries.

Figure 5. EC systems were installed at LIRF (Figure 5a) and IIC (Figure 5b) sites in 2020 and 2021 at 3.5 m AGS. Jon Altenhofen (Northern Water) provided Figure 5a

Table 8. Summary of the correction methods applied to the EC data at LIRF and IIC.

<table>
<thead>
<tr>
<th>Correction Method</th>
<th>Source</th>
<th>Research Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind coordinate or tilt correction</td>
<td>Tanner and Thurtell (1969), and Kaimal and Finnigan (1994)</td>
<td>LIRF and IIC</td>
</tr>
<tr>
<td>Air density fluctuation—The Webb-Pearman-Leuning (WPL) correction</td>
<td>Webb et al. (1980)</td>
<td>LIRF and IIC</td>
</tr>
<tr>
<td>Humidity correction of sonic temperature</td>
<td>Schotanus et al. (1983), and van Dijk et al. (2004)</td>
<td>LIRF and IIC</td>
</tr>
<tr>
<td>Statistical analysis of data screening</td>
<td>Vickers and Mahrt (1997)</td>
<td>LIRF</td>
</tr>
<tr>
<td>The angle of attack correction for 3D wind components</td>
<td>Nakai and Shimoyama (2012)</td>
<td>LIRF</td>
</tr>
</tbody>
</table>
A two-dimensional (2D) EC H and LE footprint analysis were performed to filter the EC data to consider only areas contributing to H and LE fluxes coming strictly from the maize fields at both LIRF and IIC sites. The 2D flux footprint model chosen in this study was developed by Kljun et al. (2015), which is an analytical flux-source approach that provides 2D footprint extents based on turbulence characteristics of the air flow and surface such as the Monin-Obukhov length (LMO), shear velocity (u*), the standard deviation of lateral velocity (σv), height of wind speed measurement (Zu), roughness length for momentum flux transfer (Zom), and the atmospheric boundary layer height (Hb). Thus, to compare the predictions of remotely sensed maize ETa at each station of measurement with the hourly and daily EC ETa data, it was assumed that the area at the measuring stations, which were within the 2D EC footprint, were representative of observed ETa data from the EC system during the remote sensing platform overpass date and time. At the IIC site, the heat flux tower was located at the Northwest corner of the field in 2020. Since the West and East measurement stations (Field F on Figure 4a) were further from the footprint area for H and LE fluxes, the data from the West station was assumed to represent a maize ETa comparison between the EC data and remote sensing of ETa predictions since it was the closest station to the flux tower. Figures 6 and 7 show the 2D EC footprints that served as a reference to filter the EC data at the LIRF and IIC sites, respectively.

**Figure 6.** 2D EC footprint (yellow areas) at LIRF maize fields in 2020 (Figure 6a) and 2021 (Figure 6b)
2.5.2 Hourly and Daily Reference Evapotranspiration

A standardized agricultural weather station provided weather data to calculate reference evapotranspiration (ET$_{ref}$) to serve as input to estimate maize ET$_a$ from RBCC daily maize ET$_a$ algorithms. Hourly and daily Alfalfa-based (ET$_a$) ET$_{ref}$ were calculated using data from the station Greeley 04 (GLY04), which is part of the Colorado Agricultural Mesonet (CoAgMet) network of weather stations. The GLY04 station (40.4487°N, 104.6380°W, and 1,427 m) is located within the LIRF site, 125 m Northwest of Fields W and E, and 56 km Southeast of the IIC site. GLY04 sensors are installed over a 12-cm pristine clipped grass area of 2,148 m$^2$. The hourly weather data from GLY04 in this study consist of air temperature (T$_a$) and relative humidity (RH) from an HMP45C humidity and temperature probe (Vaisala, Helsinki, Finland); Rs data from an LI-200X pyranometer (LI-COR, Lincoln, Nebraska, USA); mean horizontal wind speed measured by an 03101-L wind santry anemometer (R.M. Young Company, Traverse City, Michigan, USA). The HMP45C probe and LI-200X pyranometer were installed at 1.5 m AGS, while the 03101-L cup anemometer was at 2 m AGS. The calculations of ET$_a$ were done considering hourly data, following the ASCE-EWRI (2005) approach. The REF-ET 4.1.4.22 software (Allen, 1992) was used to run the ET$_{d}$ calculations. Daily ET$_a$ or ET$_r$ was calculated as the sum of its respective hourly ET$_{r}$ over 24 hours within the same day (e.g., 0:00 am to 11:00 pm).

2.5.3 Canopy Architecture Data

Indirect measurements of f$_c$ happened at LIRF and IIC to assess the vegetation conditions and to evaluate the errors associated with predicting f$_c$. An LI-190R and LI-191R line quantum sensor (LI-COR Biosciences, Lincoln, Nebraska, USA), connected to a CR3000 datalogger (Campbell Scientific Inc., Logan, UT, USA), measured the above and below canopy photosynthetically active radiation (PAR), respectively. The instruments were placed in the frequently irrigated field at LIRF (Field W in 2020 and Field E in 2021) and IIC (Field F). The PAR data were recorded at a 1-minute frequency and values were averaged over a 15-minute period. The LI-190R sensor was mounted on a 4-m tall vertical post at 3.5 m AGS. The locations of the LI-190R and LI-191R at LIRF and IIC were the centered and the East station, respectively.

2.6 Statistical Data Analysis

The following statistical variables have been considered to compare the performance of the different ET$_a$ models across the spaceborne and airborne remote sensing platforms: mean bias error (MBE), root mean square error (RMSE), normalized MBE (NMBE), normalized RMSE (NRMSE), refined index of agreement (di), mean absolute error (MAE), normalized MAE (NMAE) and the coefficient of determination ($R^2$). Equations 13 to 16 indicate MBE, NMBE, RMSE, and NRMSE, respectively.
MBE = \left( \frac{1}{n} \sum_{i=1}^{n} (E_i - O_i) \right) (13)

MBE = \left( \frac{\text{MBE}}{\text{O}} \right) \times 100\% (14)

\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (E_i - O_i)^2} (15)

\text{NRMSE} = \left( \frac{\text{RMSE}}{\text{O}} \right) \times 100\% (16)

where, \( \bar{O} \) is the mean of the observed data; \( n \) is the sample size; \( E_i \) and \( O_i \) are the estimated and observed values, respectively. NMBE and NRMSE are given in percentage while Equations 13 and 15 provide statistical indicators with the same units of the primary variables. Based on Jamieson et al. (1991) guidelines, the performance of the ET\( _a \) models has been classified into one of the following categories: excellent (NRMSE \( \leq \) 10\%), good (10\% < NRMSE \( \leq \) 20\%), fair (20\% < NRMSE \( \leq \) 30\%), and poor (NRMSE > 30\%).

The \( d_r \) index (Willmott et al., 2012) is indicated by Equation 17:

\[
d_r = \begin{cases} 
1 - \frac{\sum |E_i - O_i|}{2 \sum |O_i - \bar{O}|} & \Sigma |E_i - O_i| \leq 2 \Sigma |O_i - \bar{O}| \\
1 + \frac{2 \sum |O_i - \bar{O}|}{\sum |E_i - O_i|} - \frac{\sum |E_i - O_i|}{2 \sum |O_i - \bar{O}|} & \Sigma |E_i - O_i| > 2 \sum |O_i - \bar{O}| 
\end{cases}
\]

(17)

The \( R^2 \), in the context of model performance assessment, informs about the degree of variability in the observed data explained by the modeling approach. Equation 18 gives the mathematical expression for \( R^2 \):

\[
R^2 = \frac{\sum (E_i - \bar{E})(O_i - \bar{O})}{\sqrt{\sum (E_i - \bar{E})^2 \sum (O_i - \bar{O})^2}}
\]

(18)

where, \( \bar{E} \) is the mean value of the predictions. This study defines the optimal remote sensing platform as the source of multispectral data with the smallest NRMSE. In case two or more platforms have identical NRMSE, the highest \( d_r \) index between the two platforms is considered the optimal data for a given remote sensing of ET\( _a \) algorithm.

The non-parametric Kruskal-Wallis (KW) test for differences in population means (Kruskal and Wallis, 1952) was used to identify overall differences among multispectral data from the different remote sensing sensors. The test-statistic is calculated as indicated by Equation 19 (Kruskal and Wallis, 1952):

\[
\text{TS} = \frac{12}{N_T(N_T+1)} \sum \left[ \frac{T_i^2}{N_i} - 3(N_T + 1) \right]
\]

(19)

where, \( \text{TS} \) denotes the test statistic (dimensionless); \( N_i \) is the number of observations in each sample size for variable “i”; \( N_T \) is the total sample size that is the sum of all observations across variables; \( T_i \) is the sum of the ranks for the data from a given sample size for variable “i” after combining the datasets.

The null and alternative hypotheses (\( i.e. \), \( H_0 \) and \( H_A \)) for the KW test in this study are the following, respectively:

\( H_0 \): The mean value of each remote sensing platform data is the same.

\( H_A \): At least one population mean is different from all the remaining platforms.

Multiple pairwise comparisons between groups were also performed to identify differences within the remote sensing platforms (multispectral data). The pairwise multiple comparison test developed by Dunn (1964) was used in this study. All statistical analyses were done assuming a level of confidence equals to 0.05. The p-values were corrected for multiple pairwise comparisons using the approach developed by Sidák (1967). The comparison with p-values was less than 0.025, indicating that the \( H_0 \) hypothesis needs to be rejected (Dunn, 1964). The pairwise comparison analysis was performed using the stats package in RStudio (R Core Team, 2020).

Outliers have been excluded from the analysis based on the Median Absolute Deviation Approach (MADA). The MADA method for filtering extreme values in a dataset uses the median instead of the mean as a central tendency measure. The median allows for flagging points that do not conform with the sampled data’s trends.
(Leys et al., 2013). The MADA index is defined by Equation 20 when a Gaussian distribution assumption is considered for the data without the influence of extreme values (Rousseeuw & Croux, 1993).

\[
MADA = 1.4826 \times \text{Median}\left[|x_i - \text{Median}(x)|\right]
\]

where, \(x_i\) is the value of a given variable at a specified timestep; \(\text{Median}(x)\) is the median of the variable’s sample size; In this study, the criteria for filtering the data for potential outliers was the recommendation by Leys et al. (2013). The median±2.5 times the MADA index is the cutoff value expected in each sampled dataset.

3. Results and Discussion

3.1 Statistical Analysis of the Multispectral Data from Remote Sensing Platforms

The KW analysis of the NDVI, OSAVI, and SAVI calculated from RED and NIR surface reflectance indicates significant differences among at least two or more remote sensing platforms. The respective p-values from the KW test for the NDVI, OSAVI, and SAVI were all less than \(2.2 \times 10^{-16}\). More specifically, when interpreting Dunn’s pairwise comparison test, results indicate no statistical significance in differences among the multispectral VIs from spaceborne platforms (e.g., Landsat-8 at 30 m, Sentinel-2 at 10 m, and Planet CubeSat at 3 m). However, when comparing the spaceborne platforms with both the MSR5 at 1 m (proximal) and airborne at 0.03 m (UAS) counterparts, Dunn’s test indicates that VIs were statistically different (Tables 9, 10, and 11).

The fact that spaceborne platforms would have similar spectral indices is supported in the literature. Multispectral data from Landsat-8 and Sentinel-2 are consistent within ±2.5 to 6% difference (Barsi et al., 2018; Pahlevan et al., 2019). Given that Planet CubeSat data in this study were harmonized based on Sentinel-2 bands, the consistency between Landsat-8 and harmonized CubeSat data is justified. Regarding MSR5 and UAS platforms, the VIs differed statistically from each spaceborne data. Proximal and airborne platforms do not have atmospheric corrections associated with the data processing since their readings and imagery are obtained close to the ground (< 120 m AGS). In the case of spaceborne imagery, the main difference between the data from each platform (e.g., Landsat-8, Sentinel-2, and harmonized Planet CubeSat) is mainly due to spatial scale. When comparing proximal and airborne platforms, the main difference in the data is also associated with the spatial scale since Dunn’s test indicated no statistical evidence that NDVI, OSAVI, and SAVI indices were different between MSR5 and UAS data. When comparing any spaceborne with the airborne or proximal platform, the data quality differences were the radiometric and spatial resolutions.

<table>
<thead>
<tr>
<th>Platforms</th>
<th>Landsat-8 (30 m)</th>
<th>MSR5 (1 m)</th>
<th>Planet CubeSat (3 m)</th>
<th>Sentinel-2 (10 m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSR5 (1 m)</td>
<td>-5.890025</td>
<td>&lt;- 0.025*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Planet CubeSat (3 m)</td>
<td>-1.014809</td>
<td>7.257633</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sentinel-2 (10 m)</td>
<td>-0.448217</td>
<td>7.317764</td>
<td>0.827999</td>
<td></td>
</tr>
<tr>
<td>UAS (0.03 m)</td>
<td>-4.435438</td>
<td>0.436641</td>
<td>-4.60599</td>
<td>-4.879571</td>
</tr>
</tbody>
</table>

Table 9. Summary of Dunn’s test results to analyze the NDVI spectral index from all remote sensing platforms in this study. The ** symbol indicates the pairwise comparisons that are statistically different

<table>
<thead>
<tr>
<th>Platforms</th>
<th>Landsat-8 (30 m)</th>
<th>MSR5 (1 m)</th>
<th>Planet CubeSat (3 m)</th>
<th>Sentinel-2 (10 m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSR5 (1 m)</td>
<td>-5.18065</td>
<td>&lt;- 0.025*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Planet CubeSat (3 m)</td>
<td>-1.292253</td>
<td>5.87401</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sentinel-2 (10 m)</td>
<td>-0.557653</td>
<td>6.2343</td>
<td>1.075451</td>
<td></td>
</tr>
<tr>
<td>UAS (0.03 m)</td>
<td>-4.374749</td>
<td>-0.145071</td>
<td>-4.282392</td>
<td>-4.708389</td>
</tr>
</tbody>
</table>

Table 10. Summary of Dunn’s test results to analyze the OSAVI spectral index from all remote sensing platforms in this study. The ** symbol indicates the pairwise comparisons that are statistically different
Table 11. Summary of Dunn’s test results to analyze the SAVI spectral index from all remote sensing platforms in this study. The ‘*’ symbol indicates the pairwise comparisons that are statistically different

<table>
<thead>
<tr>
<th>Platforms</th>
<th>Landsat-8 (30 m)</th>
<th>MSR5 (1 m)</th>
<th>Planet CubeSat (3 m)</th>
<th>Sentinel-2 (10 m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSR5 (1 m)</td>
<td>-4.505481</td>
<td>&lt;= 0.025*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Planet CubeSat (3 m)</td>
<td>-1.410682</td>
<td>4.808113</td>
<td>0.5617</td>
<td>&lt;&lt; 0.025*</td>
</tr>
<tr>
<td>Sentinel-2 (10 m)</td>
<td>-0.611728</td>
<td>5.325175</td>
<td>1.169234</td>
<td>0.7251</td>
</tr>
<tr>
<td>UAS (0.03 m)</td>
<td>-4.271086</td>
<td>-0.606238</td>
<td>-4.047601</td>
<td>-4.536025</td>
</tr>
</tbody>
</table>

### 3.2 Error Analysis from the RBCC Daily Maize ET$_a$ Algorithms

Sentinel-2 multispectral data provided the best results when estimating daily maize ET$_a$ using the Neale et al. (1990) and Trout and DeJonge (2018) RBCC models, while the MSR5 proximal platform gave the best results when Bausch (1995) RBCC model was evaluated with LIRF and IIC 2020/2021 data combined (Figure 9). The daily maize ET$_a$ errors (MBE±RMSE) associated with the Sentinel-2 platform were 0.21 (5%)±0.78 (18%) mm/d and 0.59 (14%)±1.07 (25%) mm/d for the Neale et al. (1990) and Trout and DeJonge (2018) models, respectively. Overestimation of daily maize ET$_a$ ranging from 5% to 24% was observed in the error analysis from all platforms when NDVI and $f_c$ were the predictors of $K_{\text{et}}$ and maize ET$_a$. For the SAVI RBCC model (Bausch, 1995), the predictions of daily maize ET$_a$ had a -0.13 (-3%)±0.67 (16%) mm/d error for the proximal MSR5 platform. There was an underestimation of maize ET$_a$ observed in the Landsat-8 (-3%), Sentinel-2 (-6%), and MSR5 (-3%) platforms, while overestimation of maize ET$_a$ occurred when using Planet CubeSat (8%) and UAS (0.10%) multispectral data. The overestimation of daily maize ET$_a$ from the Trout and DeJonge (2018) RBCC is directly associated with the trend of overestimation of $f_c$ from the Johnson and Trout (2012) $f_c$ model. When evaluating $f_c$, the model had better performance using the UAS data since the NRMSE had the lowest value among the remote sensing sensors (Figure 8). Although the UAS performed slightly better than the other platforms, it is evident that the NRMSE values from Planet CubeSat and Sentinel-2 were quite like the UAS results for the $f_c$ model. Johnson and Trout (2012) $f_c$ predictions in all remote sensing platforms were overestimated, with the highest overestimation being observed when using the Landsat-8 (30 m) and MSR5 (1 m) platforms (11%) and the lowest overestimation presented in the UAS (0.03 m) platform (5%). Since Equation 7 provides the linear $K_{\text{et}}$ model for Trout and DeJonge (2018) RBCC as a function of $f_c$, an overestimated $f_c$ value leads to a subsequent overestimation of $K_{\text{et}}$, due to a linear propagation of error. Also, since Equation 7 has $f_c$ as a linear function of NDVI, the overestimation of $f_c$ is due to NDVI values being affected by soil background effects since 90% of the $f_c$ data around solar noon was less than 0.86 for the frequently irrigated fields at both research sites.

Figure 8. Error Analysis regarding the $f_c$ modeling results for LIRF and IIC 2020-2021 data combined
The NDVI sensitivity to soil (and other materials) background reflectance in the RED and NIR bands may be another explanation why Neale et al. (1990) RBCC approach also overestimated daily maize ETₐ values. Bausch (1993), Jones et al. (2015), and Duan et al. (2017) indicated that NDVI data for row crops such as maize and wheat are subject to soil background effects and other ground-based material that mask the signals (sunlight radiation) from plant leaves alone. When SAVI was used in the Bausch (1995) RBCC model, the trend of overestimation did not appear in the data from all platforms, apart from Planet CubeSat (3 m). The underestimation of daily maize ETₐ from Bausch (1995) is due to the soil background adjustment factor (L) prescription. Most studies that use SAVI assume L to be 0.50 for most environmental and field conditions (e.g., Huete, 1988; Xue & Su, 2017). However, Huete (1988) highlighted that different ranges of LAI might influence the adjustment factor L, even though Qi et al. (1994) indicated that L = 0.50 would buffer most of the variations in the canopy signal due to soil and other element background effects, which seems acceptable in this study given that the underestimation of daily maize ETₐ from Bausch (1995) RBCC model ranged from -3% to -6%.

![Figure 9: Error analysis of the three RBCC models for daily maize ETₐ estimation using LIRF and IIC 2020-2021 data combined. The sample size (n) of each platform is indicated in the legend of the figure](image)

When independently evaluating the LIRF 2020/2021 data, the results were similar to the previous analysis with both fields’ data combined (Table 12). At the LIRF site, Planet CubeSat and Sentinel-2 had the same NRMSE (21%) for the Neale et al. (1990) and Trout and DeJonge (2018) RBCC models. The CubeSat platform had slightly better R² (0.83) and dᵣ (0.75) values than the Sentinel-2 platform (R² and dᵣ equal to 0.82 and 0.73, respectively). For the Bausch (1995) model, the MSRS5 proximal platform provided the best results, with an error of 0.15 (4%)±0.53 (14%) mm/d and 84% of explained variability in daily maize ETₐ observed data from the EC system. Trout and DeJonge (2018) and Neale et al. (1990) RBCC models continued the trend of maize ETₐ overestimation from the LIRF and IIC data analysis. For the Trout and DeJonge (2018) RBCC model, overestimation of daily maize ETₐ ranged from 7% (Landsat-8) to 27% (MSRS5), while Neale et al. (1990) RBCC predicted ETₐ overestimation varied from 8% (Planet CubeSat) to 24% (UAS).
Table 12. Error analysis for the RBCC daily maize ETa estimation for LIRF 2020-2021 data

<table>
<thead>
<tr>
<th>RBCC Model</th>
<th>Platform</th>
<th>Spatial Resolution (m)</th>
<th>n</th>
<th>MBE (mm/d)</th>
<th>NMBE (%)</th>
<th>RMSE (mm/d)</th>
<th>NRMSE (%)</th>
<th>R²</th>
<th>d&lt;sub&gt;r&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neale et al. (1990)</td>
<td>Landsat-8</td>
<td>30</td>
<td>14</td>
<td>0.29</td>
<td>7%</td>
<td>0.89</td>
<td>23%</td>
<td>0.62</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>Sentinel-2</td>
<td>10</td>
<td>34</td>
<td>0.35</td>
<td>9%</td>
<td>0.79</td>
<td>21%</td>
<td>0.82</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>CubeSat</td>
<td>3</td>
<td>60</td>
<td>0.49</td>
<td>13%</td>
<td>0.80</td>
<td>21%</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>MSR5</td>
<td>1</td>
<td>17</td>
<td>1.00</td>
<td>27%</td>
<td>1.18</td>
<td>31%</td>
<td>0.77</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>UAS</td>
<td>0.03</td>
<td>11</td>
<td>0.70</td>
<td>18%</td>
<td>1.13</td>
<td>29%</td>
<td>0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>Bausch (1995)</td>
<td>Landsat-8</td>
<td>30</td>
<td>14</td>
<td>-0.17</td>
<td>-4%</td>
<td>0.65</td>
<td>17%</td>
<td>0.70</td>
<td>0.70</td>
</tr>
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<td>0.62</td>
<td>16%</td>
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<td>1.12</td>
<td>30%</td>
<td>0.77</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>MSR5</td>
<td>1</td>
<td>17</td>
<td>0.15</td>
<td>4%</td>
<td>0.53</td>
<td>14%</td>
<td>0.84</td>
<td>0.77</td>
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<td></td>
<td>UAS</td>
<td>0.03</td>
<td>11</td>
<td>0.09</td>
<td>2%</td>
<td>0.92</td>
<td>24%</td>
<td>0.26</td>
<td>0.61</td>
</tr>
<tr>
<td>Trout and DeJonge (2018)</td>
<td>Landsat-8</td>
<td>30</td>
<td>14</td>
<td>0.62</td>
<td>16%</td>
<td>1.05</td>
<td>27%</td>
<td>0.63</td>
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<tr>
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<td>0.57</td>
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<td>0.80</td>
<td>21%</td>
<td>0.83</td>
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<tr>
<td></td>
<td>CubeSat</td>
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<td>60</td>
<td>0.32</td>
<td>8%</td>
<td>0.80</td>
<td>21%</td>
<td>0.77</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>MSR5</td>
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<td>0.68</td>
<td>18%</td>
<td>0.90</td>
<td>24%</td>
<td>0.84</td>
<td>0.63</td>
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<tr>
<td></td>
<td>UAS</td>
<td>0.03</td>
<td>11</td>
<td>0.92</td>
<td>24%</td>
<td>1.24</td>
<td>32%</td>
<td>0.41</td>
<td>0.42</td>
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</table>

When independently evaluating the IIC 2020/2021 data, the results were similar to the previous analysis with both fields’ data combined (Table 13). At the IIC site, Sentinel-2 was the optimal remote sensing platform when considering the Neale et al. (1990) and Trout and DeJonge (2018) RBCC models. The error for the Neale et al. (1990) RBCC model was 0.06 (1%)±0.79 (21%) mm/d, while the associated error when predicting daily maize ETa for Trout and DeJonge (2018) RBCC model was 0.61 (13%)±1.20 (25%) mm/d. For the Bausch (1995) model, the MSR5 proximal platform provided the best results, with an error of -0.30 (-7%)±0.75 (17%) mm/d and 81% of explained variability in daily maize ETa observed data from the EC system. Similar to the LIRF data analysis, Trout and DeJonge (2018) and Neale et al. (1990) RBCC models continued the trend of maize ETa overestimation from the LIRF and IIC data analysis combined. For the Neale et al. (1990) model, the overestimation of daily maize ETa ranged from 1% (Sentinel-2) to 14% (UAS), while Trout and DeJonge (2018) RBCC predicted ETa overestimation varied from 13% (Sentinel-2) to 30% (MSR5).

Table 13. Error analysis results from the RBCC daily maize ETa evaluation for IIC 2020-2021 data

<table>
<thead>
<tr>
<th>RBCC Model</th>
<th>Platform</th>
<th>Spatial Resolution (m)</th>
<th>n</th>
<th>MBE (mm/d)</th>
<th>NMBE (%)</th>
<th>RMSE (mm/d)</th>
<th>NRMSE (%)</th>
<th>R²</th>
<th>d&lt;sub&gt;r&lt;/sub&gt;</th>
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<td>0.44</td>
<td>12%</td>
<td>0.89</td>
<td>23%</td>
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<td>0.59</td>
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<td>32</td>
<td>0.06</td>
<td>1%</td>
<td>0.79</td>
<td>21%</td>
<td>0.82</td>
<td>0.73</td>
</tr>
<tr>
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<td>59</td>
<td>0.31</td>
<td>8%</td>
<td>0.80</td>
<td>21%</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
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<td>27</td>
<td>0.49</td>
<td>11%</td>
<td>1.18</td>
<td>31%</td>
<td>0.77</td>
<td>0.48</td>
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<tr>
<td></td>
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<td>0.03</td>
<td>13</td>
<td>0.63</td>
<td>14%</td>
<td>1.13</td>
<td>29%</td>
<td>0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>Bausch (1995)</td>
<td>Landsat-8</td>
<td>30</td>
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<td>-0.07</td>
<td>-2%</td>
<td>1.04</td>
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<tr>
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<td>-5%</td>
<td>0.73</td>
<td>19%</td>
<td>0.69</td>
<td>0.71</td>
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<tr>
<td></td>
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<td>-7%</td>
<td>0.75</td>
<td>17%</td>
<td>0.81</td>
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<td>0.92</td>
<td>20%</td>
<td>0.57</td>
<td>0.66</td>
</tr>
<tr>
<td>Trout and DeJonge (2018)</td>
<td>Landsat-8</td>
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<td>12</td>
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<td>1.35</td>
<td>37%</td>
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<td>25%</td>
<td>0.54</td>
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</tbody>
</table>
4. Conclusions

This study evaluated different remote sensing platforms when predicting daily maize ETa in a semi-arid climate area in research sites with varying irrigation systems. The study hypothesized that the ability to characterize crop ETa from different remote sensing of ETa algorithms depended on the spatial and spectral resolution of the multispectral input data and intrinsic modeling parametrization. The main research finding was that the multispectral surface reflectance values from the different platforms, for the most part, are statistically different and that different remote sensing of ETa models perform better with RED and NIR surface reflectance data for specific remote sensing platforms. For the RBCC models from Neale et al. (1990) and Trout and DeJonge (2018), the best remote sensing sensor (optimal spatial and spectral resolutions) was that from the Sentinel-2 (10 m) platform, while the RBCC from Bausch (1995) had the proximal platform MSR5 (1 m) as the optimal remote sensing data.

Even though estimating crop ETa can be achieved using multispectral data from different remote sensing sensors, considering the use of optimal sensors/data for a given remote sensing of ETa algorithm has the potential to improve crop ETa and therefore optimize irrigation water. It is essential to mention that, depending on the location of cropland fields and farming management practices, the suggested optimal remote sensing sensors in this study might not be practical. For instance, larger fields might offer challenges to use handheld (proximal) devices to measure surface reflectance and temperature; spaceborne platforms might not offer high-quality data due to sensor issues (missing or uncorrected pixel data), cloudiness conditions, and other environmental factors. Thus, this study recognizes the need for further investigation on improving the data quality of sub-optimal remote sensing platforms to enable the use of a desirable remote sensing platform at the best data accuracy possible for irrigation water management purposes.

Furthermore, a thorough investigation needs to be done to evaluate the performance of different remote sensing of ETa algorithms that are used in large-scale modeling of ETa. When moving from a farm to a large-scale area (e.g., irrigation districts, watersheds), the spatial scale of a given remote sensing imagery may contain more than just vegetation and include other surface elements (mixed pixel scenario). In that case, more research needs to be done to accommodate modeling strategies that are able to extract the vegetation features in a given pixel and provide reliable data for modeling ETa without having contaminated pixels hindering prediction accuracy. Nonetheless, our research findings support the idea that, when estimating daily maize ETa, it is important to focus on using the best multispectral data from a variety of remote sensing sensors to ensure more accurate predictions of ETa that can serve as input for irrigation water management decision-making processes.

References


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Authors Contributions
Edson Costa-Filho processed the data, conducted the statistical analysis, and wrote the bulk of the manuscript. José L. Chávez obtained financial and logistic support and guided the research efforts, and Huihui Zhang was involved in fieldwork planning, manuscript formatting, and writing adjustments.

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Competing Interests
The authors declare that they do not have any conflict of interest, as well as no competing financial interests or personal relationships that could have appeared to influence the contents of this study.

Informed Consent
Obtained.

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Data Availability Statement
The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data Sharing Statement
No additional data are available.

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