COMPARISON OF CROP WATER USE ESTIMATION METHODOLOGIES IN IRRIGATED CROPS

by

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ABSTRACT

Comparison of Crop Water Use Estimation Methodologies in Irrigated Crops

by

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Accurate estimation and continuous monitoring of evapotranspiration (ET) is an increasingly important question in water resource management as increasing drought events threaten water resources. Despite technological advancements in water use estimates, variations in results from the different methods poses the question of which one best balances accuracy, efficiency, and accessibility. This research aims to evaluate and recommend methods for estimating crop water use in sprinkler-irrigated corn and alfalfa fields based on results from soil moisture data, satellite imagery, state recommended consumptive use, and eddy covariance measurements for the 2021 growing season in Modena, UT. Daily ET estimates from soil moisture data and ET_r were estimated using two versions of a newly developed empirical Soil Moisture based ET (SMET) method. Daily and monthly ET estimates from satellite imagery were retrieved from the OpenET web platform [www.openetdata.org] and its Application Programming Interface (API). Monthly consumptive water use estimates were retrieved from a Utah Department of Natural Resources (DNR) report. ET estimates at daily, monthly, and seasonal time scales were assessed for accuracy against eddy covariance (EC) ET estimates. Overall, the results of this study indicate different levels of agreement between the evaluated methods and the EC method. Results indicate that the SMET method agrees more to EC estimates than other methods. The OpenET methods consistently slightly underestimate ET, and agreement of the Utah DNR estimates varies based on crop type. The analysis also highlights the effort necessary to generate ET information with the evaluated methodologies.

(80 pages)

PUBLIC ABSTRACT

Comparison of Crop Water Use Estimation Methodologies in Irrigated Crops

Laura Christiansen

As increasing drought events limit water resources available for irrigation, farmers and other water users are looking for ways to monitor how much water crops use over a growing season. The amount of water used by crops over time is the evapotranspiration (ET) rate. This study compares different methods for ET estimation to recommend methods to water users based on their accuracy, efficiency, and accessibility. Each method was used to estimate ET for sprinkler-irrigated corn and alfalfa fields in Modena, UT over the 2021 growing season. The Soil Moisture based ET (SMET) method was used to estimate ET based on daily changes in soil water content. The OpenET web platform [www.openetdata.org] and the OpenET Application Programming Interface (API) were used to retrieve ET estimates based on imagery from the Landsat satellite. ET estimates for the area were also retrieved from a Utah Department of Natural Resources (DNR) report. The eddy covariance (EC) method is accepted as the standard for estimating ET and served as the standard for the comparison of all other methods. Results indicate that while all methods underestimate ET, the SMET method agrees most closely to the EC method. Further analysis of the OpenET and Utah DNR methods is required to fully explain the reasons for the apparent ET estimation discrepancies. This study also highlights the advantages and limitations of each method.

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Laura Christiansen

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INTRODUCTION

Increasing frequency and intensity of drought events in the western United States (U.S.) is at the forefront of water management discussions. Rising atmospheric temperatures due to climate change coupled with natural fluctuations in precipitation have been linked to decreases in soil moisture content (Williams et al. 2020). Adequate water availability is necessary for the healthy development of vegetation - including crops used to support livestock, industrial practices, and the exponentially growing human population.

Producers, water management organizations, and state and federal agencies oriented to the distribution and access of water for crop development face challenges in accurately monitoring crop water use across farms and larger geographical regions. A study of farmers in the western U.S. found that many Utah agricultural water users are limited in their irrigation scheduling due to turn-based water distribution in which water is made available for only a set amount of time (Schumacher et al. 2022). In this case, water users have limited control over application amount and frequency. Water rights limitations account for the irrigation scheduling of 19% of growers, while 12% of growers rely on soil moisture monitors and 35% rely on previous experience (Sullivan 2022).

The amount of water used by a crop over time is the evapotranspiration (ET) rate. Accurate estimation of crop ET allows for calculation of irrigation efficiency and water budgets, which is useful in water management strategy development. While numerous methods for ET estimation are available, each varies in accessibility, time efficiency, and accuracy. Currently, the non-uniformity of the available methods means that none are implemented and accepted universally (Allen, L. et al. 2019).

A comparison of methods for ET estimation is necessary to identify which methods water users should rely on for their water management needs. The Utah Division of Water Resources (UDWRe) formed the Agricultural Water Optimization Task Force (Task Force) to complete such a comparison (Allen, L. et al. 2019). The work of the Task Force includes various projects for assessment of agricultural water depletion accounting.

As part of the Task Force, this study is focused on providing a comparison and recommendation of ET estimation methods from three sources – soil moisture data, OpenET, and the Utah Department of Natural Resources. This study aims to:

(i) assess the performance of the available ET estimation methods at different time scales (daily, monthly, seasonal),

(ii) validate each method's accuracy against eddy covariance measurements,

(iii) identify advantages and limitations of each method, and

(iv) recommend methods based on user needs.

Methodologies for ET Estimation

Eddy Covariance. The eddy covariance (EC) method is a leading method for ET estimation (Baldocchi 2003) and is often used to validate the results of other ET estimation methods (including those based on lysimeters and scintillometers). This study is relying on the EC ET estimates for validation of the results of the other methods rather than as a potential recommendation for widespread use due to the specialized equipment and knowledge required to implement the EC method. The EC method quantifies the latent heat flux (LE) as the covariance between vertical wind velocity and water vapor density over a footprint area (Wang et al. 2021). LE is a measurement of the energy consumed through the process of evapotranspiration; thus, the measurement of LE in units of energy can be converted to ET in inches of water per time.

The elliptical area upwind of the EC flux sensors for which measurements are collected is known as the footprint. The size and location of the footprint depends on the sensor height above the surface, wind direction, and properties of turbulence (Burba 2013). Historical wind measurements are used to determine the location of the EC flux tower to optimize the amount of time that the footprint covers the desired study area.

Instrumentation is also used to measure net radiation (R_n), ground heat flux (G), and sensible heat flux (H) for the footprint. The energy balance equation describes the relationship between the energy fluxes as:

$$R_n - G = LE + H \tag{1}$$

where R_n – G is the amount of energy available in the system.

In semi-arid and arid environments, such as that found in Modena, advection can impact the amount of water lost through ET. Under advective conditions, the influx of hot, dry air causes H to become negative and a source of available energy (Su et al. 2013), which causes the energy balance equation to become

$$R_n + H - G = LE \tag{2}$$

While the EC method automatically considers advection effect due to the direct measurement of water vapor density, some methods included in this study do not. The comparison of ET estimation methods to the EC method will include an analysis of the possible effects of advection.

Discrepancies in the available energy (R_n – G) and the sum of LE and H can create non-closure of the energy balance. The issue of energy balance closure can be addressed in a variety of ways (Bambach et al. 2022). The Bowen ratio, which forces closure based on the ratio of H and LE, is commonly used to address the closure issue in agricultural practices (Denager et al. 2020, Wang, F. et al. 2021, Burba 2013).

Soil Water Balance. Crop water use has traditionally been estimated by the soil water balance (SWB). The SWB uses measurements of water inflows and outflows of a system to estimate crop ET (Evett et al. 2012). The SWB equation for estimating ET for a certain time is given as (Allen et al. 1998):

$$ET = I + P - RO - DP + CR \pm \Delta SF \pm \Delta SWC \tag{3}$$

where ET is evapotranspiration (inches), I is the irrigation amount (inches), P is the precipitation amount (inches), RO is the surface runoff (inches), DP is deep percolation (inches), CR is the capillary rise (inches), ΔSF is the subsurface flow in or out of the root zone (inches), and ΔSWC is the change in soil water content (inches).

Irrigation flow meters and precipitation gauges are widely used to provide measurements of water inflow. In situ ground sensors, such as lysimeters and soil moisture sensors, provide measurements of changes in soil water content (SWC) that allows water users to monitor water movement through soil and the amount of water available to the crop. The estimate for DP and CR includes the measurement errors of all other SWB components as DP and CR currently cannot be measured with high accuracy (Evans 2006).

The SWB method is commonly relied on for research purposes and has been shown to be an effective method for irrigation scheduling (Niaghi & Jia 2019, Wang, Y.

et al. 2021, Yarami et al. 2011). However, the measurement of SWB components requires technological installation at a scale that few farmers in the U.S. can achieve due to economic limitations (Taghvaeian et al. 2020). Component measurements from non-local sources or estimates based on previous experience lessen the economic impact, but also reduce confidence in ET estimates.

Crop Coefficient. The crop coefficient (K_c) method has been shown to reliably estimate ET for irrigation scheduling purposes (Ertek 2011, Kang et al. 2003). The K_c method relies on the correlation between reference ET (ET_r) and actual ET (ET_a) at different stages in crop development to estimate ET_a (Allen 2000). The K_c method estimates actual ET using the following equation (Allen, R. et al. 1998):

$$ET_a = K_c ET_r \tag{4}$$

ET_r is defined as the ET rate of an idealized reference crop that is not water-stressed (Doorenbos and Kassam 1977). The Utah State University (USU) Climate Center (www.climate.usu.edu) manages a weather station network across the state, which includes a weather station located in the study area of this project. Datasets from this weather station network include hourly and daily measurements of micrometeorological components and ET_r based on the Penman-Monteith equation. This equation is recommended by the Food and Agriculture Organization (FAO) and is expressed as follows (Allen et al. 1998):

$$ET_r = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_{mean} + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{5}$$

where R_n is the net surface radiation ($MJm^{-1}d^{-1}$), G is the soil heat flux ($MJm^{-2}d^{-1}$), T_{mean} is the daily average temperature (°C), u_2 is the wind speed at 2 m height (m/s), e_s is the saturated water pressure (kPa), e_a is the actual water vapor pressure (kPa), Δ is the saturated water pressure curve slope (kPa $°C^{-1}$), and γ is the wet and dry table constant (kPa $°C^{-1}$).

The K_c method is empirical and requires efforts to relate K_c and growing cycles at the site of interest. Published K_c tables and growing cycles may not correspond to local climate, soil, crop type, water quality, irrigation technology, or crop management methods. Establishing local K_c trends requires technological and time commitments that are not economically feasible for many farmers; thus, this type of effort is rarely achieved or implemented across the U.S.

The K_c method was used in a project to estimate monthly and seasonal ET for 18 crop types at numerous locations around Utah (Hill et al. 2011). ET_r values for calculation of ET_a in the project were calculated based on local weather data collected from 1971 through 2008. The resulting ET estimates were submitted to the Utah Department of Natural Resources (DNR) Division of Water Rights and Division of Water Resources and are publicly available as a reference for Utah water users and organizations.

Remote Sensing. Advancements in remote sensing technologies have provided an avenue for ET estimation through satellite-collected data. The OpenET project (www.openetdata.org) uses publicly available data to provide users with field-scale ET estimates from multiple remote sensing-based ET models. OpenET requires that models included in the project have a history of use for water management in the western U.S. by a state or federal agency. Six methods currently meet the inclusion requirements: SSEBop, EEMETRIC, SIMS, DisALEXI, PT-JPL, and geeSEBAL (OpenET 2022). A seventh ET estimate calculated as the ensemble mean of all methods is also available on the OpenET platform. While each OpenET model uses unique datasets sourced from varying satellites and weather stations, all models rely on Landsat for the primary dataset (Melton et al. 2021).

The OpenET interface allows users to identify individual fields in the Field View and Raster View options. Individual field boundaries for the Field View are identified through publicly available state and federal datasets, as well as the 2008 USDA Common Land Unit database. Fields that are not included in these datasets are visible in Raster View, where users can draw the field boundary manually to view available ET estimates.

STUDY SITE

This study is part of the pilot program funded by the UDWRe in 2021, which seeks to validate and recommend methods for quantifying agricultural water use across Utah (Allen, L. et al. 2019). Irrigated fields included in this study are located at Holt Farms in Modena, UT (37.7753, -113.7927). Locations of the fields and installed instrumentation are depicted in Figure 1. In addition to the pivots, a 120 m x 120 m area within the footprint of the EC flux tower is also of interest in this study. A description of each center pivot and the applicable soil moisture sensors installed in each field is provided in Table 1.

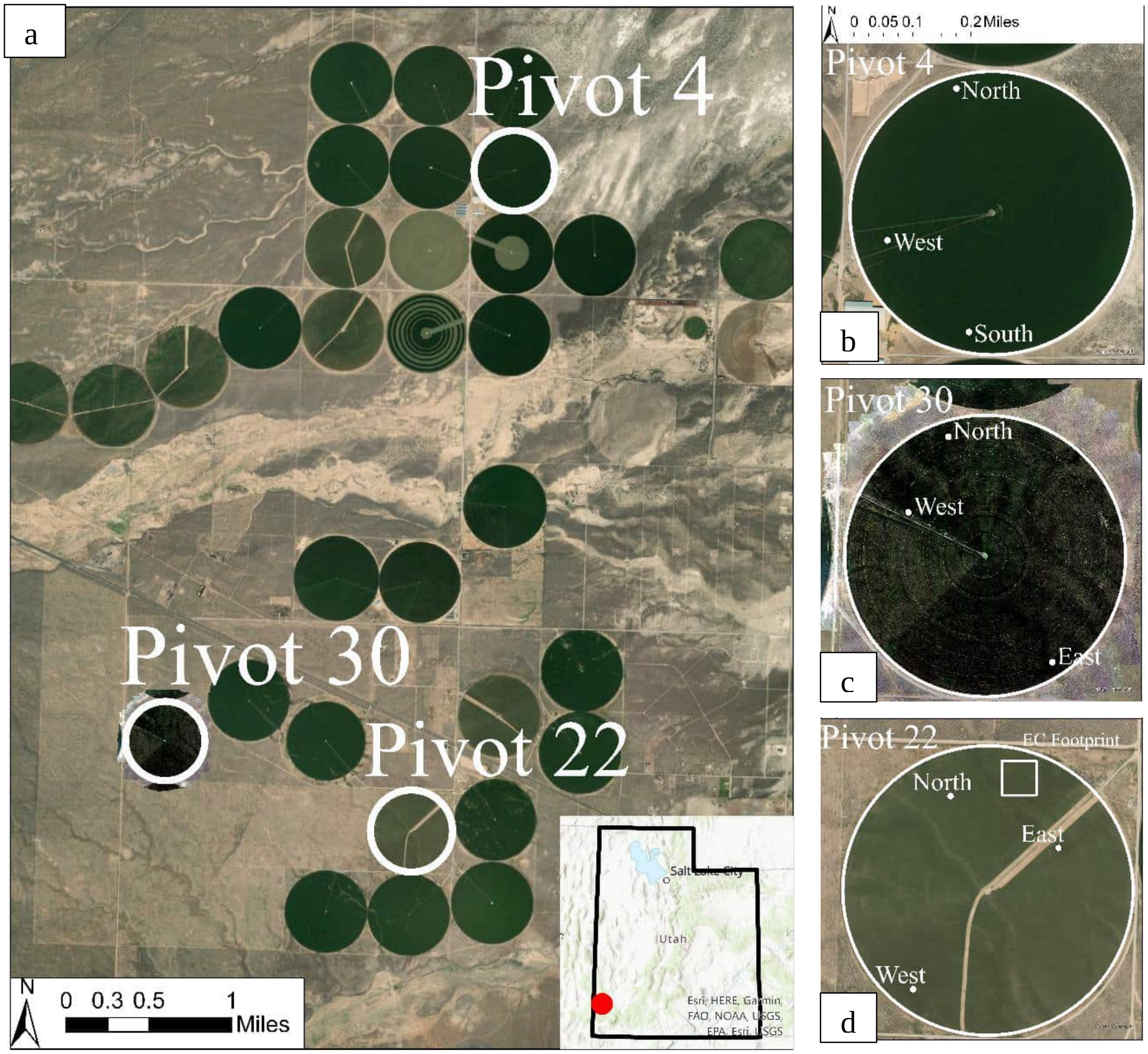

Figure 1. Irrigated fields included in this study are located in Modena, UT (a). Field views show locations of the soil sensor profiles in pivot 4 (b), pivot 30 (c), and pivot 22 (d).

Table 1. Description of pivots and soil moisture sensors used in this study. Soil characteristics prevented the installation of a sensor at 60 in. in the north profile of pivot 22.

Pivot	Crop Type	Irrigation System	Number of Soil Profiles	Sensors per Soil Profile	Sensor Depths Below the Surface (inches)
4	Corn	Sprinkler	3	8	3, 3, 6, 6, 12, 24, 36, 48
30	Corn	Sprinkler	3	8	3, 3, 6, 6, 12, 24, 36, 48
22	Alfalfa (Dairy)	Sprinkler	3	7	East & West: 3, 6, 12, 24, 36, 48, 60 North: 3, 6, 12, 24, 36, 48

DATA COLLECTION

Micrometeorological and Eddy Covariance Data

Daily and hourly measurements of precipitation and ET_r were collected by the Modena weather station and retrieved from the public datasets made available by the USU Climate Center. An EC flux measurement system was added to the weather station setup to measure energy fluxes within the footprint area (Fig. 1d). A sonic anemometer with an integrated infrared gas analyzer (IRGASON) (Campbell Scientific, Inc.) was installed on the tower at 2.78 m above ground level facing 180° due south. The IRGASON measured three-dimensional wind speed and water vapor densities at 20 Hz, which allowed for the estimation of H and LE after extensive analysis of the raw data.

Additional sensors were installed in the field approximately 36 ft away from the tower. A 4-way CNR net radiometer (Kipp & Zonen, Inc.) installed above the surface measured R_n. Two soil heat flux plates (REBS, Inc.) two soil moisture sensors (Acclima TDR10), and four soil temperature sensors (Campbell Scientific, Inc., model 109SS) installed in the upper 6 cm of the soil profile were used to estimate G.

The sensors recorded continuous measurements over the course of the growing season. The USU Biomet Lab processed and gap filled these extensive datasets as necessary to produce hourly energy flux and ET measurements. Hourly values were then aggregated to daily, monthly, and seasonal scale for the purposes of this study.

EC data collection occurs over a footprint area determined by the wind speed and direction, as well as the sensor height. Variations in wind direction at the study site caused some hourly footprints to fall outside of the field boundaries, resulting in a significant amount of necessary gap filling of sensor measurements.

Determination of the typical footprint area for each hour between 0700 and 2000 for 4 days in the 2021 growing season was completed for this study site (Kljun et al. 2015). Based on these results, the footprint area was determined to most frequently cover the area southwest of the tower (Fig. 2). A 120 m x 120 m area – the area of 4 pixels x 4 pixels of Landsat resolution – in the average direction of the footprint was used in this study to represent the footprint area to allow for method comparison at the necessary time scales.

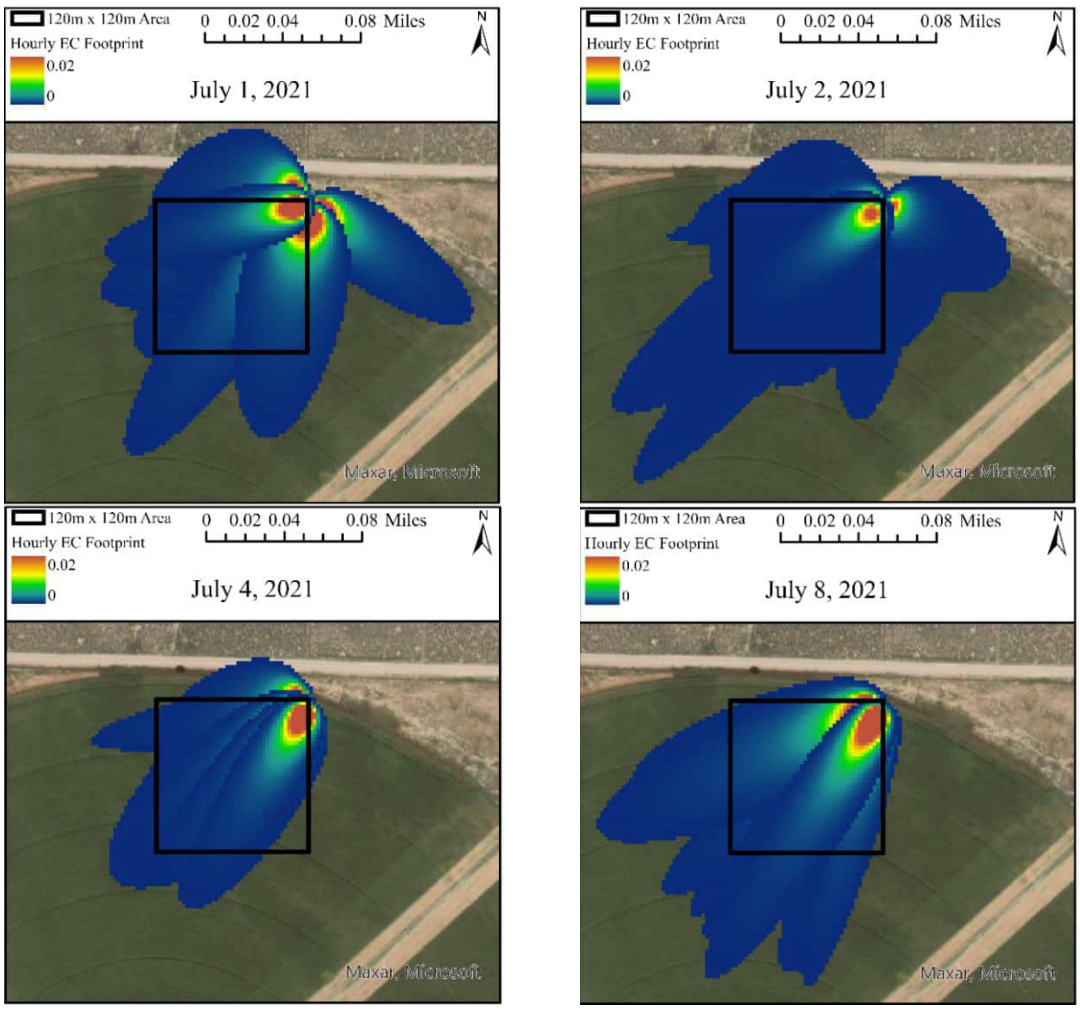

Figure 2. Hourly footprint areas between 0700 and 2000 for 4 days in the 2021 growing season. Pixel values represent the pixel contribution to the footprint. The black boundary indicates the 120 m x 120 m area used to represent the EC footprint area in this study.

Soil Water Content

Acclima 315 and 310 time domain reflectometry (TDR) soil moisture sensors were installed in three soil profiles in each pivot of interest (Fig. 1a, b, c). The TDR sensors in pivots 4 and 30 were installed in June 2021, and the sensors in pivot 22 were installed in June 2020. Sensors were installed at a 45° angle with the center of the sensor at the indicated sensor depth (Table 1). While sensors were installed to depths expected to encompass the effective root sone, soil moisture content from the topmost inches of soil where a significant portion of water is lost to ET remains unaccounted for.

Volumetric water content readings were recorded every 15 minutes over the course of the growing season. The volumetric soil moisture content readings were converted to a depth of water as soil water content (SWC) using the following formula (Wang, Y. et al. 2021):

$$SWC = C_v \times D_r \tag{6}$$

where SWC is depth of water in the soil at the sensor depth (in.), C_v is the soil volumetric water content at the sensor depth (in^3/in^3 or %), and D_r is the representative depth of the soil moisture sensor (in.). The representative depths of the sensors are shown in Figure 3.

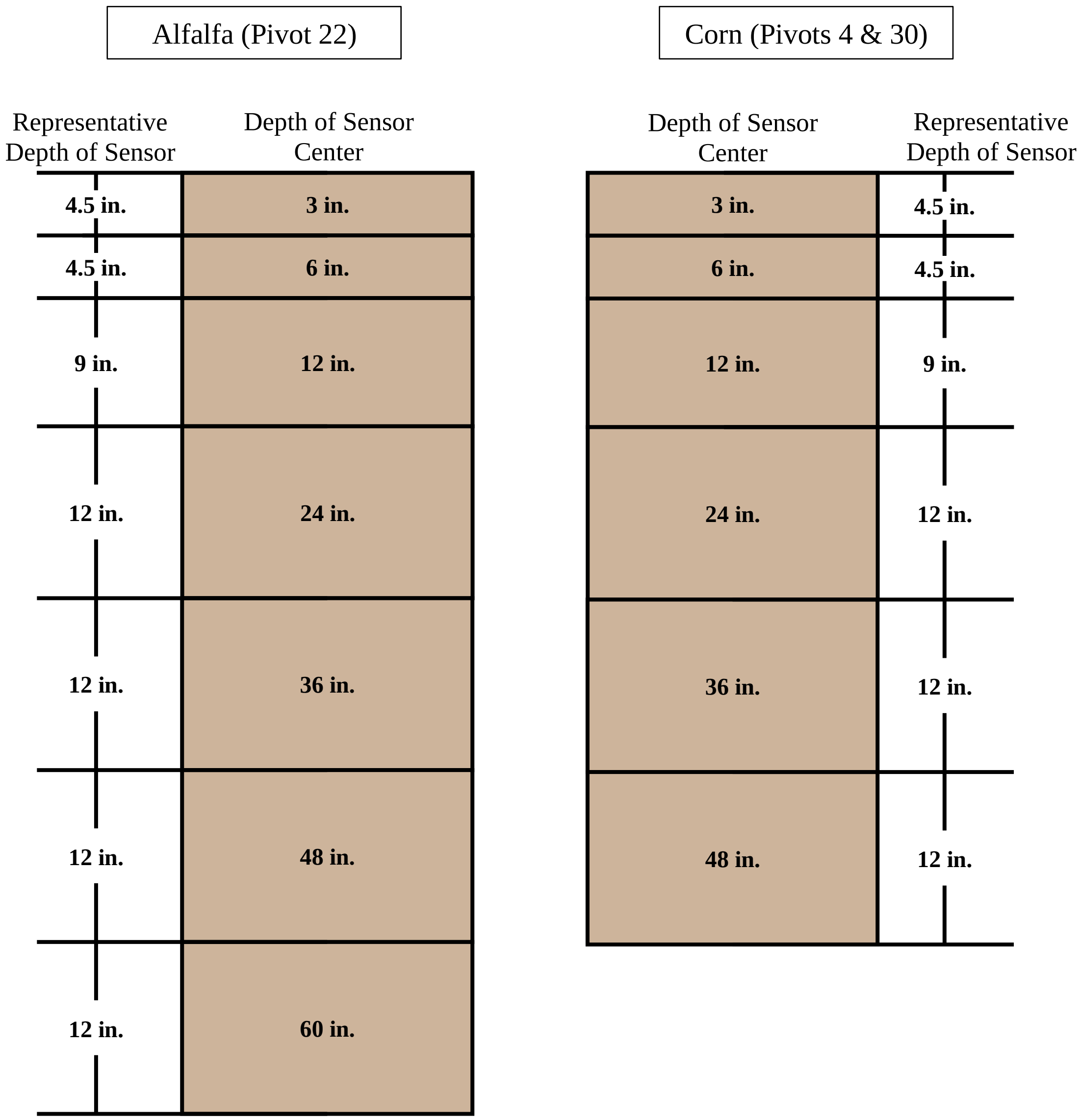

Figure 3. Installation depths and representative depths of the soil moisture sensors installed in pivots 4, 30, and 22 (not to scale). The north soil profile in pivot 22 does not include the sensor at 60 in. due to complications with the soil characteristics during installation.

The soil moisture sensors in pivots 4 and 30 were removed August 31, 2021. Harvest of pivots 4 and 30 occurred September 13-15, 2021. Alfalfa cuts occurred May 26, July 5, August 4, and September 15, 2021. The soil moisture sensors in pivot 22 were removed October 22, 2021.

Irrigation Records

Irrigation scheduling and application amounts for all fields was left entirely to the discretion of the farmer for this study. IM3000 flow meters installed within the irrigation system recorded daily measurements of water application throughout the 2021 season. The flow meter data were retrieved as a measurement of the total gallons of water applied to the field per day.

OpenET

The OpenET project provided daily and monthly estimates of ET for the different fields used in this study. OpenET provides ET estimates at 30 m x 30 m for Landsat overpass dates, which are then daily interpolated based on fractional ET values calculated as the ET divided by Penman-Monteith ET_r estimates (OpenET 2022). The daily actual ET values are aggregated to the monthly and annual estimates available on the OpenET platform.

A preliminary study suggests that the ensemble mean of the OpenET methods has reasonable agreement with the EC results for ET and has no significant difference to the estimates of the individual methods (Melton et al. 2021). This study relied on the ensemble mean ET to represent OpenET estimation.

Multispectral UAV Imagery

A DJI Matrice 600 Pro unmanned aerial vehicle (UAV) was flown over pivot 22 on May 11, 2021. The UAV payload included a MicaSense Altum camera, which captures red, green, blue, red edge, near infrared, and thermal data. The flight occurred at 400 ft above ground level (AGL), which resulted in an image resolution of 2 in. x 2 in.

METHODOLOGY

ET estimation at various time scales was completed through the application of seven methodologies included in this study. Figure 4 provides an outline of the methods with brief process descriptions. Four of the implemented methods (EC, SMET1, SMET2, and OpenET API Daily) allowed for ET estimation at daily scale. Three methods (OpenET API Raster, OpenET Platform, and Utah DNR) provided only monthly ET estimates. Seasonal ET estimates were aggregated from the monthly estimated for all methods. Comparison of the resulting ET estimates and the performance of each method was completed to address the objectives of this study.

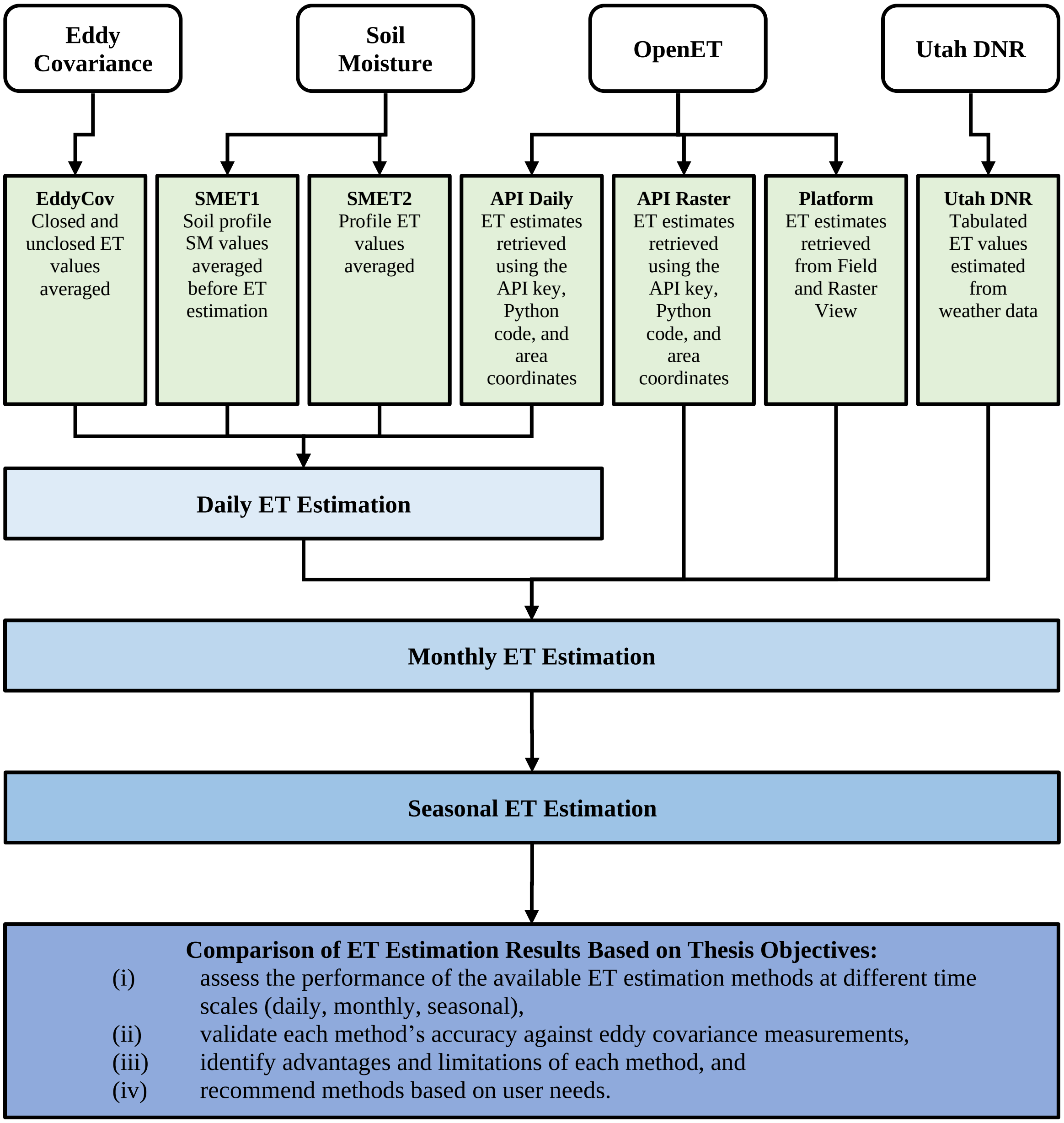

Figure 4. Flow chart of methods and work included in this study.

Eddy Covariance

Daily ET estimates from EC measurements are assumed to be underestimated due to non-closure of the energy balance. The Bowen ratio was used to force closure at hourly scale, after which the hourly estimates were aggregated to daily scale with actual ET assumed to be likely within the range of the closed and unclosed ET values. The closed and unclosed ET values were further averaged to produce a single daily ET measurement from the EC method with the closed and unclosed values taken as the maximum and minimum range for the method. Daily ET estimates were then aggregated to monthly and seasonal scale for the purposes of this study.

Advection of heat from arid surfaces upwind causes H to flow downward and becomes a source of available energy, which increases ET. Therefore, this study uses H as an indicator of advective contribution. To assess the magnitude of the contribution of advection during the day ($R_n > 0$), daily H was subtracted from the daily EC ET using the equation

$$ET_{EC} - |H| = ET_{na} \tag{7}$$

where ET_{EC} is the ET value from the EC method, H is the sum of negative sensible heat, and ET_{na} is the ET without the influence of advection.

Soil Moisture Depletion ET

Although soil moisture monitoring is not common in Utah due to economic limitations (Taghvaeian et al. 2020), this method is recognized as a suitable way to monitor water availability in the root zone and support irrigation scheduling. While soil moisture fluctuations have been shown to be correlated to actual ET and ET_r under certain conditions, this relationship may not hold for short time periods, such as daily and hourly, due to the added influence of soil and crop characteristics (Wang, Y. et al. 2021). A previously proposed method for estimating ET from SM relates soil water content and ET (Scott et al. 2003); however, this methodology does not address typical conditions on farms. Irrigation, precipitation, and rapid drainage through rocky soils alters the relationship between ET and soil moisture, causing the existing methodology to be unreliable (Kisekka et al. 2022).

Hargreaves (2022) proposed a new hybrid empirical model for seasonal ET estimation based on the relationship between ET and the change in soil water content as established by the soil water balance (equation 3), as well as the relationship between ET and the alfalfa-based ET_r as established by the crop coefficient method (equation 4). Using these relationships, the Soil Moisture based EvapoTranspiration (SMET) method poses that ET can be estimated as a function of ET_r and daily changes in soil water content:

$$ET = f(\Delta SWC, ET_r) \tag{8}$$

In development of the SMET method, the Eureqa software was used to produce empirical equations relating ET with ET_r and ΔSWC based on data collected in Vernal, UT. The resulting empirical equations included a constant α, which was found to be approximately 0.43 following the optimization process described in Hargreaves (2022). Results from Eureqa were modified to account for irrigation events. The resulting SMET model is able to estimate seasonal ET regardless of irrigation or precipitation frequency, soil characteristics, or irrigation technology and assures that the soil water content describes the entirety of the root zone.

When the daily change in SWC is under depletion conditions (ΔSWC < 0), the SMET method estimates actual ET as:

$$ET = a(ET_r + |\Delta SWC|) \tag{9}$$

For days with an increase in SWC due to irrigation or precipitation (ΔSWC > 0), actual ET is assumed to be more limited by available energy than available water and is thus more closely related to ET_r than changes in SWC. Under non-water limited conditions (irrigation and precipitation events), the SMET method estimates actual ET as:

$$ET = 2aET_r \tag{10}$$

To mitigate the effects of spikes in the soil moisture data, the SMET method includes a condition that replaces ET estimates determined to be unacceptably high:

$$If\ ET > 1.25 * ET_r, then\ ET = 1.25 * ET_r \tag{11}$$

The SMET method is recommended for seasonal and potentially monthly estimation of ET rather than daily or weekly. Two variations of this method were used to estimate daily ET for pivots 4, 30, and 22. The SMET method was applied to the EC footprint area without either variation for averaging since only a single soil profile was available.

For the first SMET variation (SMET1), the daily SWC readings in inches for each soil profile were averaged to get mean daily SWC values representative of the field. The mean SWC values for each day were then used in the equation for the calculation of the daily change in SWC, and the subsequent estimation of daily ET. The second SMET variation (SMET2) estimated daily ET for each soil profile individually, then averaged the daily profile ET values to get the representative daily ET values for the fields. To mitigate the effect of diurnal temperature changes on the evaporation and transpiration fluxes (Verhoef et al. 2006), this study used the midnight SWC readings to represent the daily SWC (Niaghi & Jia 2019).

A field uniformity assessment through UAV and OpenET imagery was performed to assess the representativeness of the three soil moisture profiles in each center pivot. A coefficient of variation (CV) was used to identify potential areas of concern in the soil moisture data. A field with CV less than 15% is considered acceptably uniform (Allen, R. et al. 2013).

Results from the UAV flight were used to estimate the CV for pivot 22 and the EC flux tower footprint using the Normalized Difference Vegetation Index (NDVI). The NDVI uses the relationship between the near-infrared (NIR) and red (R) bands to assess the greenness of vegetation, which is usually related to the health and stress of the plant. The NDVI equation is given as (Tucker 1979):

$$NDVI = \frac{NIR - R}{NIR + R} \tag{12}$$

While NDVI can be an indicator of crop uniformity, there is uncertainty in its use for estimating the uniformity of soil moisture since available water is not the only factor contributing to crop health. In areas where irrigation is frequent and heavy enough that the crop is not water stressed, the analysis of NDVI would indicate a uniform field even if one area of the field had more or less water than another area.

Due to the uncertainty of the NDVI analysis and the unavailability of UAV imagery for pivots 4 and 30, CV for all study areas was estimated using raster images retrieved through the OpenET API method. Upon confirmation of field uniformity, soil moisture data were used to estimate daily, monthly, and seasonal ET for all study areas.

OpenET

OpenET (www.openetdata.org) provides two avenues for users to extract ET values. Individual fields of interest can be selected on the OpenET platform, which then provides a selection of monthly ET estimates for download based on available ET estimation methods. Users can also access daily or monthly ET estimates for a coordinate-defined area through the use of an Application Programming Interface (API) key and Python code. Currently, the API method does not provide an ensemble mean estimate of daily ET. The ET information from OpenET was extracted on May 31, 2022.

Monthly mean ensemble ET values were retrieved from the OpenET web platform for the respective 2021 growing seasons of each pivot. Pivots 4 and 22 were identifiable and selected in Field View, which then allowed for the monthly ET estimates from all methods to be downloaded directly from the platform. Pivot 30 was unavailable in the Field View, so a polygon was drawn around the field in Raster View. A polygon was also drawn to approximate the EC footprint area. Monthly ET estimates from all methods were then available and retrieved for each polygon area.

An API key provided by the OpenET team was used to retrieve raster files containing monthly ensemble ET estimates for each month in the growing season for each field based on boundaries defined by coordinates (Figure 5). Pixel values in the raster images represent the ET estimate for the 30 m x 30 m area covered by the respective pixel. Field boundaries were used to estimate the average ET representative of the pivot. A boundary around the EC flux tower footprint was used to extract the monthly area average ET estimates from the pivot 22 raster images.

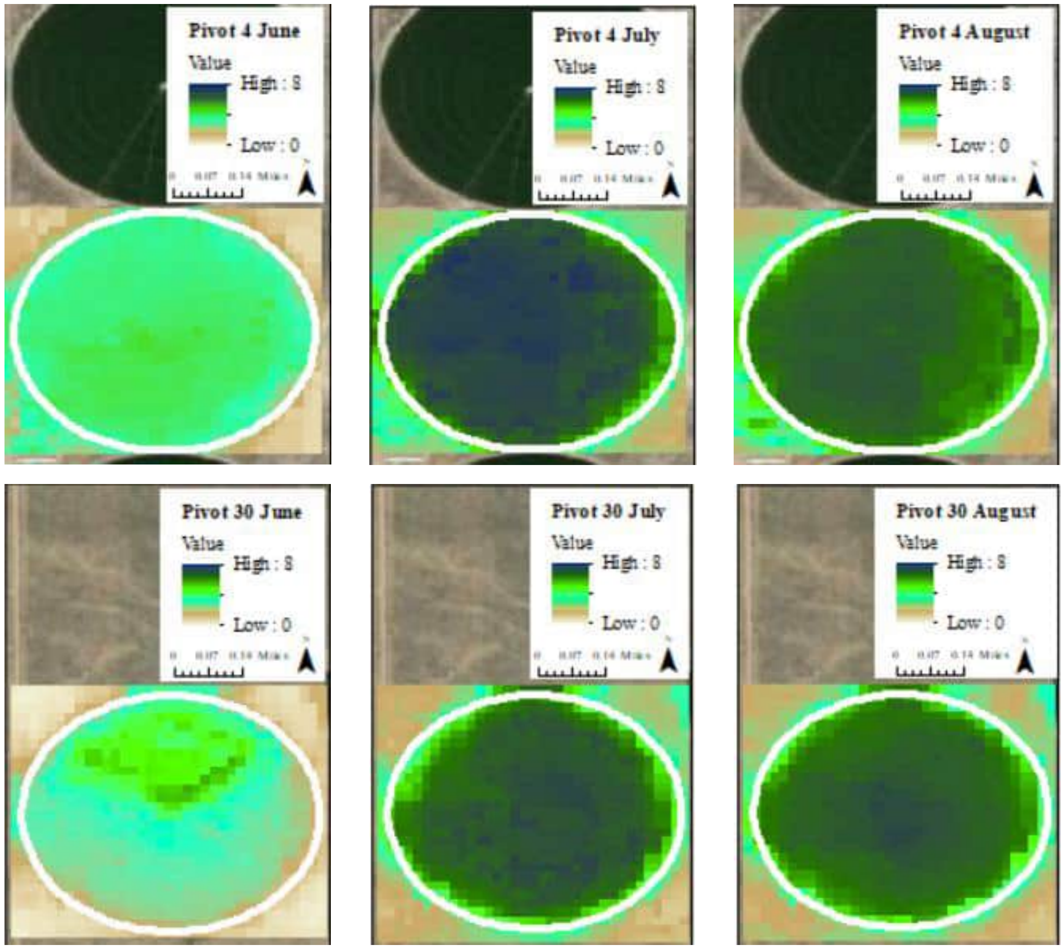

Figure 5. Example of raster images retrieved from the OpenET API method where pixel values are the respective ensemble mean ET estimates (inches/month). White area boundaries were added in ArcMap and indicate the area used for average ET estimation.
Top row: OpenET API raster images for each month in the 2021 growing season for pivot 4.
Bottom row: OpenET API raster images for each month in the 2021 growing season for pivot 30.

Daily ET estimates from each of the models, excluding the ensemble mean, were also retrieved using the API key. The daily ensemble mean was calculated following the methodology OpenET uses to estimate the monthly ensemble mean ET available through the platform and the raster extraction methods (OpenET 2022). The Median Absolute Deviation (MAD) method removes outliers from the six ET models to allow for the identification of the dataset central tendency without the influence of outliers (Leys et al. 2013). Calculation of the MAD is as follows (Huber 1981):

$$MAD = b\, M_i(|x_i - M_j(x_j)|) \tag{13}$$

where b is a constant related to the assumption of normality (1.4826), x_i represents the original observations, M_j is the median of the primary x_j series of observations, and M_i is the median of the series.

Following the calculation of the MAD, a threshold was used to determine which outliers were removed from the dataset. The threshold criteria are given as:

$$M_j - 2 * MAD < x_i < M_j + 2 * MAD \tag{14}$$

Values of x_i that fell outside of the threshold were removed from the dataset. The ensemble value was then calculated as the average of the remaining data points. Daily ensemble mean ET values were aggregated to monthly and seasonal scale for comparison to the other methods presented in this study.

Utah DNR Recommendations

A study for the Utah DNR conducted from 1971 – 2008 estimated empirical crop water use data from lysimeters and weather stations for 18 crop types at various locations around Utah (Hill et al. 2011). The monthly ET estimates published from this study are available to water users as ET recommendations by the Utah DNR to be used for water management and irrigation scheduling. Monthly ET estimates for corn and alfalfa from the Beryl Junction site were retrieved from these recommendations to be used in this comparison.

ET Estimation Influence in Soil Water Balance Calculations

The SWB method (equation 3) is unable to reliably estimate ET for days where soil water content is increasing due to irrigation or precipitation. The frequency of irrigation events at this study site would necessitate a significant amount of gap filling to estimate ET. For this reason, the SWB method was not used in this study to estimate ET. Instead, the SWB equation was used to estimate the amount of water unaccounted for in the system to identify potential sources of uncertainty in the calculation of the SWB components.

ET estimates from the methods considered in this study allowed for the implementation of the SWB at seasonal scale. From Eq. 3, CR and ΔSF are assumed to be negligible for this study site as there is no indication of a high water table influencing the root zone. Seasonal irrigation amounts were aggregated from the daily flow meter readings. Seasonal precipitation amounts were aggregated from the daily precipitation readings collected by the Modena weather station. The seasonal ΔSWC is taken as the midnight soil moisture reading of the last day of the season less the midnight soil moisture reading of the first day of the season.

The simplified SWB equation used for this study is

$$Inflow - \Delta SWC - ET = Residual \tag{15}$$

where the inflow is the sum of I and P, and the residual value is an estimation of the water unaccounted for in the system based on the seasonal ET estimate from each method. The calculated residual is the sum of the measurement errors of I, P, ΔSWC, and the estimated ET and potentially includes water lost to DP and RO.

RESULTS & DISCUSSION

Daily ET Estimation Methods

The ET estimation needs of water users may vary depending on a variety of factors, including crop type, economic and technology limits, and water availability. ET estimation at monthly scale is desirable. However, methods that allow daily ET estimation could be beneficial for water users that wish to estimate water use for a defined range of dates.

The OpenET API Daily method provides daily ET estimates for the entirety of the area of interest and can therefore be used regardless of field uniformity. The SMET methods rely on SWC measurements from three locations to represent the conditions of the field as a whole and can therefore be affected by field uniformity. For pivot 22 and the EC footprint, a CV was calculated based on available UAV imagery and NDVI. These results are available in Appendix C and support the analysis provided in Table 2.

The CV for all fields was calculated based on the raster images of spatial ET estimates retrieved through the OpenET API Raster method (Table 2). The seasonal CV is 9% for pivot 4, 16% for pivot 30, 9% for pivot 22, and 8% for the EC flux tower footprint. Under the assumption that spatial changes in NDVI and ET accurately reflect spatial changes in SWC, all study areas were considered uniform enough to continue with soil moisture ET analysis.

Table 2. Mean, standard deviation, and coefficient of variation for each area of interest over the growing season based on raster images containing ET estimates (inches) retrieved through the OpenET API Raster method.

Area	Month	Mean (inches/month)	Standard Deviation	Coefficient of Variation
Pivot 4	Jun	3.95	0.48	0.12
	Jul	6.93	0.65	0.09
	Aug	6.48	0.54	0.08
	Season	17.4	1.58	0.09
Pivot 30	Jun	3.16	1.05	0.33
	Jul	6.39	0.91	0.14
	Aug	6.29	0.88	0.14
	Season	15.8	2.54	0.16
Pivot 22	Apr	3.36	0.35	0.11
	May	6.56	0.74	0.11
	Jun	7.76	1.02	0.13
	Jul	5.83	0.65	0.11
	Aug	5.77	0.43	0.07
	Sep	4.61	0.42	0.09
	Oct	3.08	0.36	0.12
	Season	36.9	3.48	0.09
EC Flux Tower Footprint	Apr	3.42	0.18	0.05
	May	6.36	0.66	0.10
	Jun	6.85	0.87	0.13
	Jul	5.46	0.61	0.11
	Aug	5.71	0.32	0.06
	Sep	4.60	0.26	0.06
	Oct	3.22	0.18	0.06
	Season	35.6	2.94	0.08

SWC measurements from individual soil sensors and the total SWC measurements in each soil profile in pivot 30 are presented in Fig. 6. SWC measurements in the soil profiles of the other study areas are available in Appendix A.

SWC increases due to irrigation events visible in the graphs indicate a 2 – 3 day pivot rotation. Large spikes visible in Fig. 6 are attributed to sublayers with high rock content, which creates voids that allow for the rapid increase and decrease of water content. Frequent water application allows the producer to minimize crop water stress and the effects of the rocky sublayer.

The indicated presence of rocky sublayers suggests heterogeneity in the field. The CV for pivot 30 is slightly above the 15% threshold for uniformity. Since the CV is not significantly above the threshold, this study accepts that the CV analysis does not indicate significant heterogeneity. However, use of the soil moisture data to represent pivot 30 as a whole is done so with the acknowledgement of possible uncertainty that cannot currently be accounted for.

Spikes in the soil moisture data introduce uncertainty to the SMET ET estimation results. The SMET method attempts to lessen the level of uncertainty by identifying and replacing the ET estimates impacted by these spikes through equation 11. It should be noted that this process causes the SMET method results to be forced to the ET_r to some extent. This gap filling did not significantly impact the results from the SMET method at this location.

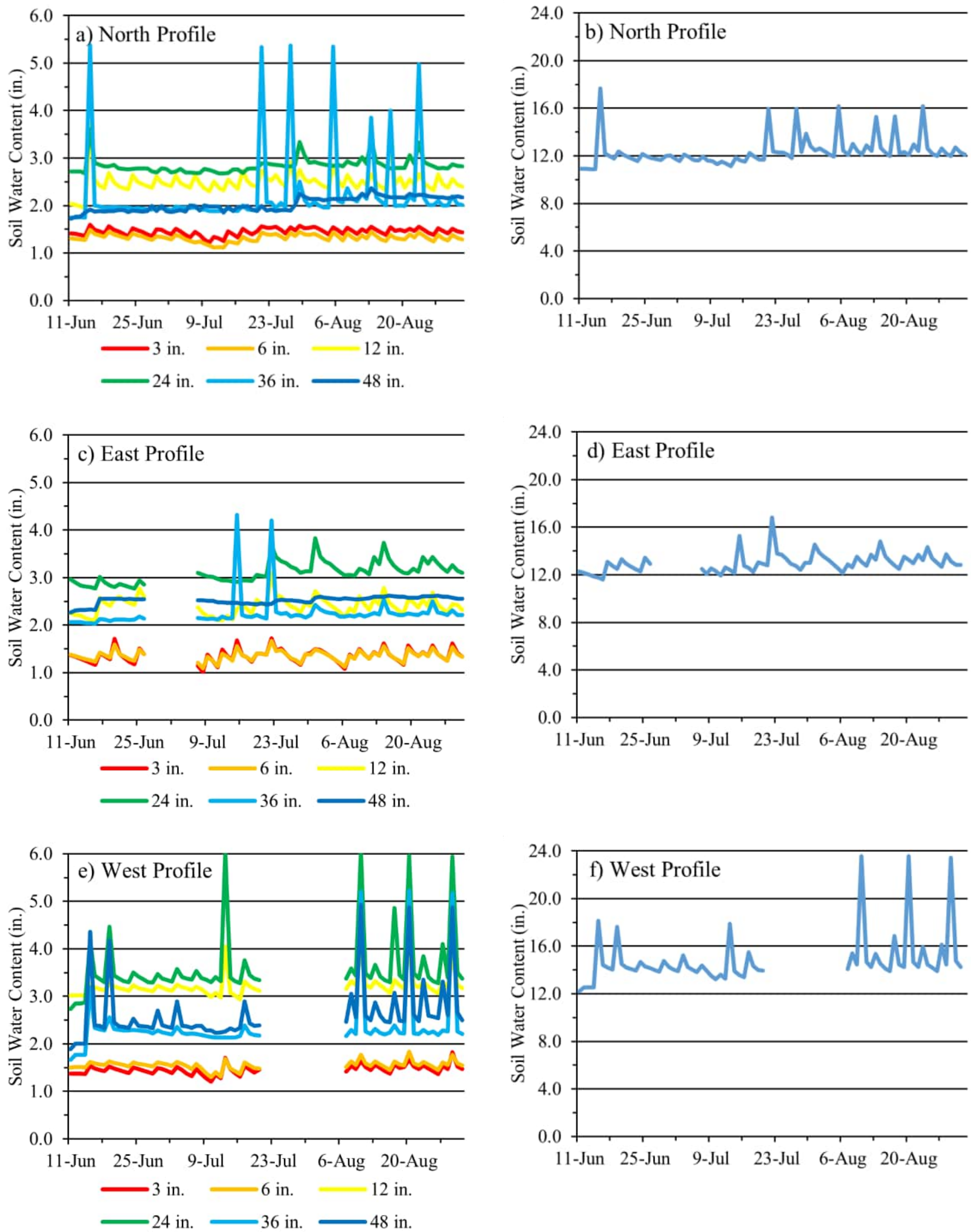

Figure 6. Example of daily midnight soil water content measurements (inches) per sensor depth (left column) and in total (right column) for all soil profiles in pivot 30.

The typical EC flux tower footprint (Fig. 2) does not encompass any of the soil profiles. However, the north soil profile in pivot 22 is within reasonable distance to the footprint such that the assumption can be made that the SWC readings of this profile are representative of the footprint area. Therefore, the SMET method was applied to the footprint area using only the north soil profile dataset. The assumption could be made that the east and west soil profiles could also be representative of the EC footprint area due to the uniformity of the field. The SMET results for the individual soil profiles in all fields are available in Appendix B.

Daily ET estimation for all study areas was possible with the SMET and OpenET API Daily methods. The EC method provided daily ET estimates for only the EC footprint. The growing season cumulative ET estimates for each of the daily methods for each study area are shown in Figure 7.

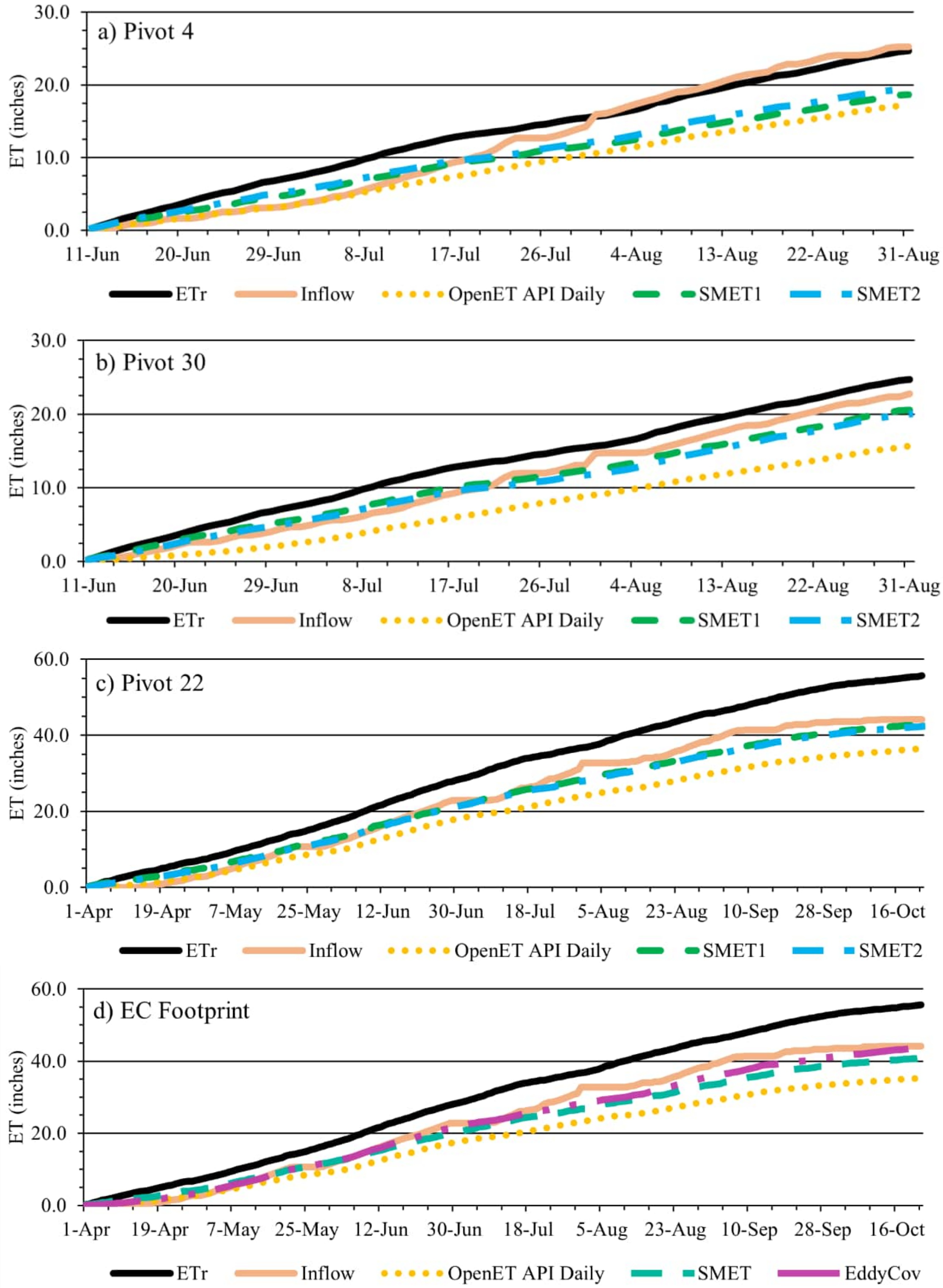

Figure 7. Cumulative ET estimates (inches) over the 2021 growing season based on daily ET estimates from all methods for each study area. ET_r and inflow (irrigation & precipitation) values are provided for reference.

The graphs presented in Fig. 8 present the relationships between the daily EC ET estimates and the ET estimates from the OpenET API Daily and SMET methods as they correspond to a one-to-one line. The OpenET API Daily plot shows less dispersion than the SMET plot, but the OpenET API Daily plot indicates that the method is underestimating ET compared to the EC method. The SMET method plot shows more dispersion, but a greater correlation between the results of the SMET and EC methods.

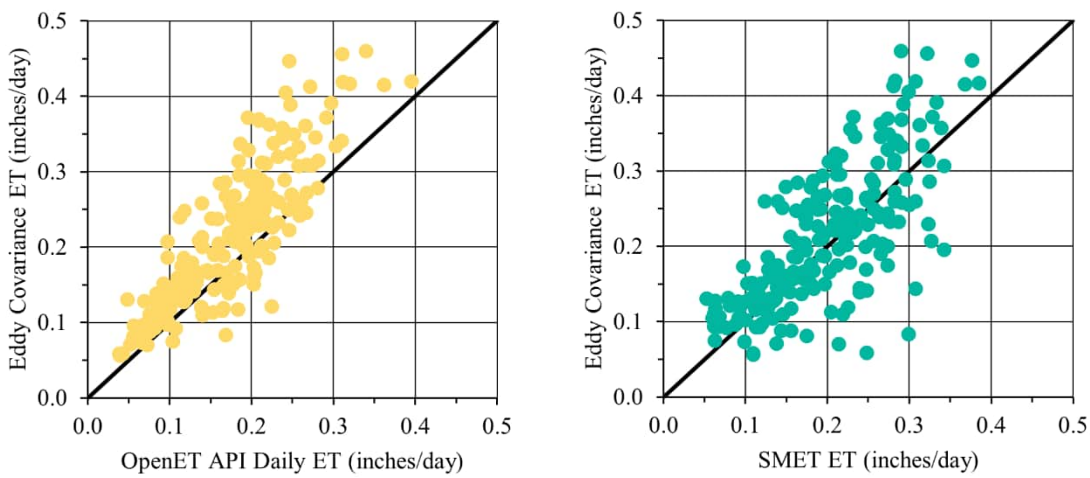

Figure 8. Comparison of daily ET estimates (inches) from the OpenET API Daily and SMET methods against daily eddy covariance ET estimates (inches) in one-to-one plots.

In the EC footprint, the OpenET API Daily and SMET cumulative trends underestimate ET compared to the EC ET. However, the SMET trend follows the EC estimates more closely than the OpenET API Daily method. A similar trend is apparent in pivots 4, 30, and 22 where the OpenET API Daily method appears to underestimate ET compared to the SMET methods. The SMET methods are consistently similar to each other over the course of the growing season in pivots 4, 30, and 22.

The tendency of the OpenET API Daily method to underestimate ET compared to the EC method could potentially be explained by the effects of advection at the site. The stacked bar portion of the graph in Figure 9 indicates the portion of the ET estimated by the EC method that is attributed to advection as H. Over the season, the OpenET API Daily method closely follows the trend of the EC ET less the advection effect. By the end of the growing season, the cumulative OpenET API Daily method is within 10% (3.8 in.) of the cumulative EC ET less the advection effect. This trend indicates that the lack of correction for advection in the OpenET API Daily method is a potential explanation for the method's underestimation of ET.

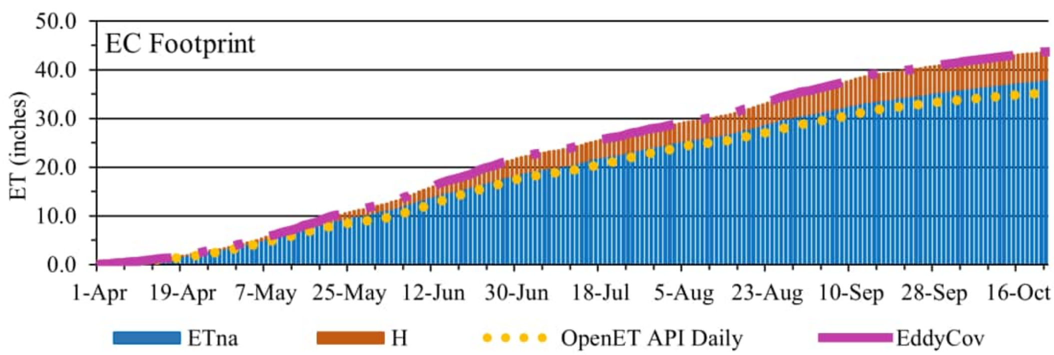

Figure 9. The stacked bars indicate the contributions of negative sensible heat (H) and other energy components (ET_{na}) to the total EC ET estimates (EddyCov) accumulated over the 2021 growing season. H is used as an indicator of the advective effect on EC ET estimates. These components are compared to the cumulative daily ET estimates (inches) from the OpenET API Daily method over the 2021 growing season.

Monthly ET Estimation Methods

Monthly ET estimates aggregated from daily scale only include dates within the growing season. Methods that only provide ET estimates at monthly scale are likely to overestimate growing season crop water use due to the extra dates beyond the defined growing season. Therefore, for this analysis, monthly-only methods include an additional

10 days of data in June for pivots 4 and 30, and an additional 9 days of data in October for pivot 22 and the EC footprint.

It should also be noted that the irrigation data for all pivots was only available through October 1, 2021, which limits the inflow levels for pivot 22 and the EC flux tower footprint. The inflow value presented is the sum of monthly irrigation and effective precipitation. Monthly ET estimates, ET_r, and inflow values for all study areas are presented in Table 3 and graphically in Figure 10.

Table 3. Monthly ET estimates (inches) per method for each area of interest. Monthly ET_r and inflow values are included for reference.

Area	Month	Method									
		OpenET Platform	**OpenET API Raster**	**OpenET API Daily**	**SMET 1**	**SMET 2**	**SMET**	**Utah DNR**	**Eddy Cov**	**ET_r**	**Inflow**
Pivot 4	Jun	3.9	3.9	3.3	4.8	5.2	-	5.7	-	7.1	3.2
	Jul	6.9	6.9	7.3	7.0	7.0	-	9.7	-	8.6	9.9
	Aug	6.5	6.5	6.7	6.9	7.3	-	7.2	-	9.0	8.9
Pivot 30	Jun	3.1	3.2	2.2	5.3	5.0	-	5.7	-	7.1	4.4
	Jul	6.4	6.4	6.9	7.2	6.8	-	9.7	-	8.6	7.4
	Aug	6.3	6.3	6.6	8.0	8.2	-	7.2	-	9.0	7.7
Pivot 22	Apr	3.3	3.4	3.1	5.0	4.8	-	2.6	-	7.5	2.4
	May	6.5	6.6	6.4	7.7	7.6	-	7.0	-	9.6	8.7
	Jun	7.6	7.8	8.4	8.5	8.8	-	8.2	-	11.0	11.2
	Jul	5.8	5.8	6.1	7.1	6.7	-	7.5	-	8.6	7.1
	Aug	5.7	5.8	5.8	6.8	6.8	-	6.9	-	9.0	5.5
	Sep	4.6	4.6	4.7	5.6	5.5	-	3.5	-	7.1	4.4
	Oct	3.1	3.1	2.0	2.1	2.1	-	0.3	-	2.8	0.1
EC Footprint	Apr	3.4	3.4	3.1	-	-	4.6	2.6	3.8	7.5	2.4
	May	6.5	6.4	6.2	-	-	7.5	7.0	8.3	9.6	8.7
	Jun	8.0	6.8	8.2	-	-	8.1	8.2	9.7	11.0	11.2
	Jul	5.7	5.5	5.8	-	-	6.5	7.5	6.3	8.6	7.1
	Aug	6.0	5.7	5.6	-	-	6.6	6.9	7.4	9.0	5.5
	Sep	4.7	4.6	4.6	-	-	5.6	3.5	5.6	7.1	4.4
	Oct	2.8	3.2	1.8	-	-	1.9	0.3	2.6	2.8	0.1

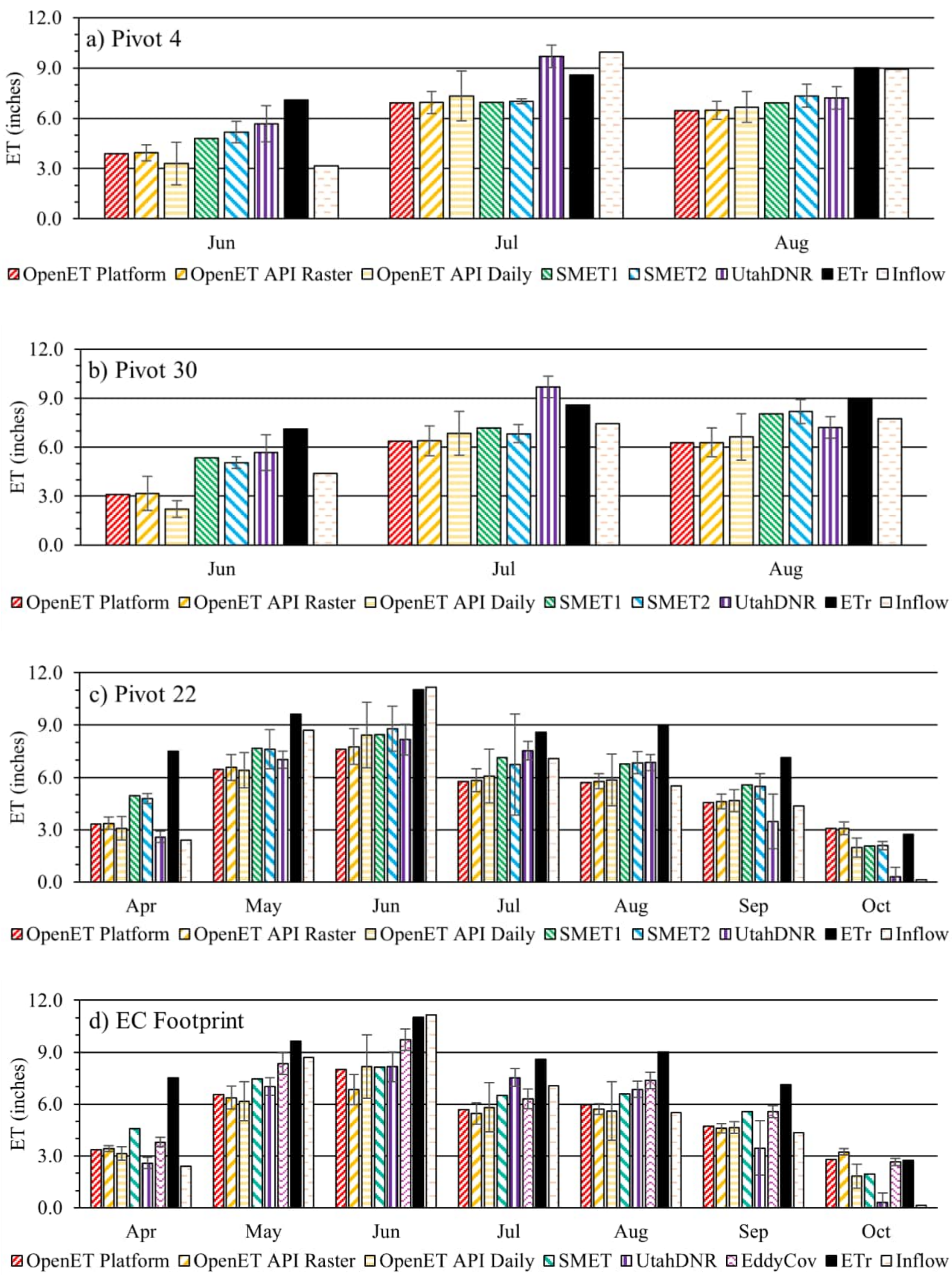

Figure 10. Monthly ET estimates (inches) for the 2021 growing season from each method for every study area are presented, along with the monthly ET_r and inflow values for reference. Error bars indicate the standard deviation of the respective method. EC method error bars indicate the maximum (closed) and minimum (unclosed) accepted ET.

The trends over the growing season for all locations follow expected trends for crop water use. A drop-off in ET can be seen in pivot 22 and the EC footprint between June and July. This is attributed to the cyclical cutting of the alfalfa. Taking into consideration allowances for periods of missing soil moisture data, the three OpenET methods produce consistently similar ET estimates to each other. The estimates extracted from the OpenET Platform are consistently within 1% (0.1 in.) of the OpenET API Raster estimates. For months with complete datasets, the OpenET API Daily estimates are on average 5% (0.4 in.) higher than the other OpenET methods in pivots 4 and 30, 1% (0.1 in.) higher than the other OpenET methods in pivot 22. In the EC footprint, the OpenET API Daily method is 3% (0.1 in.) lower than the OpenET Platform method and 1% (0.2 in.) higher than the OpenET API Raster method for months with complete datasets.

The SMET methods also perform similarly to each other and are generally slightly higher than the OpenET results, particularly in pivot 22. On average, the SMET2 method is 5% (0.3 in.) higher than the SMET1 method in pivot 4, 7% (0.4 in.) lower than the SMET1 method in pivot 30, and 1% (0.1 in.) lower than the SMET1 method in pivot 22. Compared to the OpenET Platform and OpenET API Raster methods for months with complete datasets, the SMET1 method is 4% (0.2 in) greater in pivot 4, 20% (1.3 in.) greater in pivot 30, 18% (1.1 in.) in pivot 22, and 15% (0.9 in.) greater in the EC footprint.

The Utah DNR recommendations are 24% (1.76 in.) higher than the OpenET methods and 14% (1.16 in.) higher than the SMET methods in pivot 4, and 31% (2.27 in.) higher than the OpenET methods and 9% (0.88 in.) higher than the SMET methods in pivot 30. On average, the Utah DNR recommendations are 2% (0.1 in.) lower than the

OpenET methods and 26% (0.9 in.) lower than the SMET methods in pivot 22 for months with complete datasets. In the EC footprint area, the Utah DNR recommendations are 1% (0.4 in.) lower than the OpenET methods and 11% (0.3 in.) lower than the SMET methods.

In the EC footprint, the monthly EC ET estimates are, on average, 16% (1.1 in.) greater than the OpenET Platform estimates, 19% (1.4 in.) greater than the OpenET API Raster estimates, and 18% (1.3 in.) greater than the OpenET API Daily estimates. The monthly EC ET estimates are, on average, 2% (0.5 in.) greater than the SMET method estimates and 15% (0.9 in.) greater than the Utah DNR estimates. Conclusions from the comparison to the EC method are only applicable to alfalfa since no EC information is available for the corn sites (pivots 4 and 30).

The plots in Fig. 11 show the relationship between the monthly ET estimates from each method in the EC footprint area and the ET estimates from the eddy covariance method in comparison to a one-to-one line. The OpenET methods have similar relationships to the EC method, but the discrepancies are apparent in the departure from the one-to-one line, when the ET values surpass 6 in/month. The weak relationship between the Utah DNR method and the EC method indicates that the Utah DNR method is underpredicting alfalfa ET. The SMET method shows strong correlation to the EC method, which supports the conclusion that the SMET method is the most accurate method included in this study to the EC method.

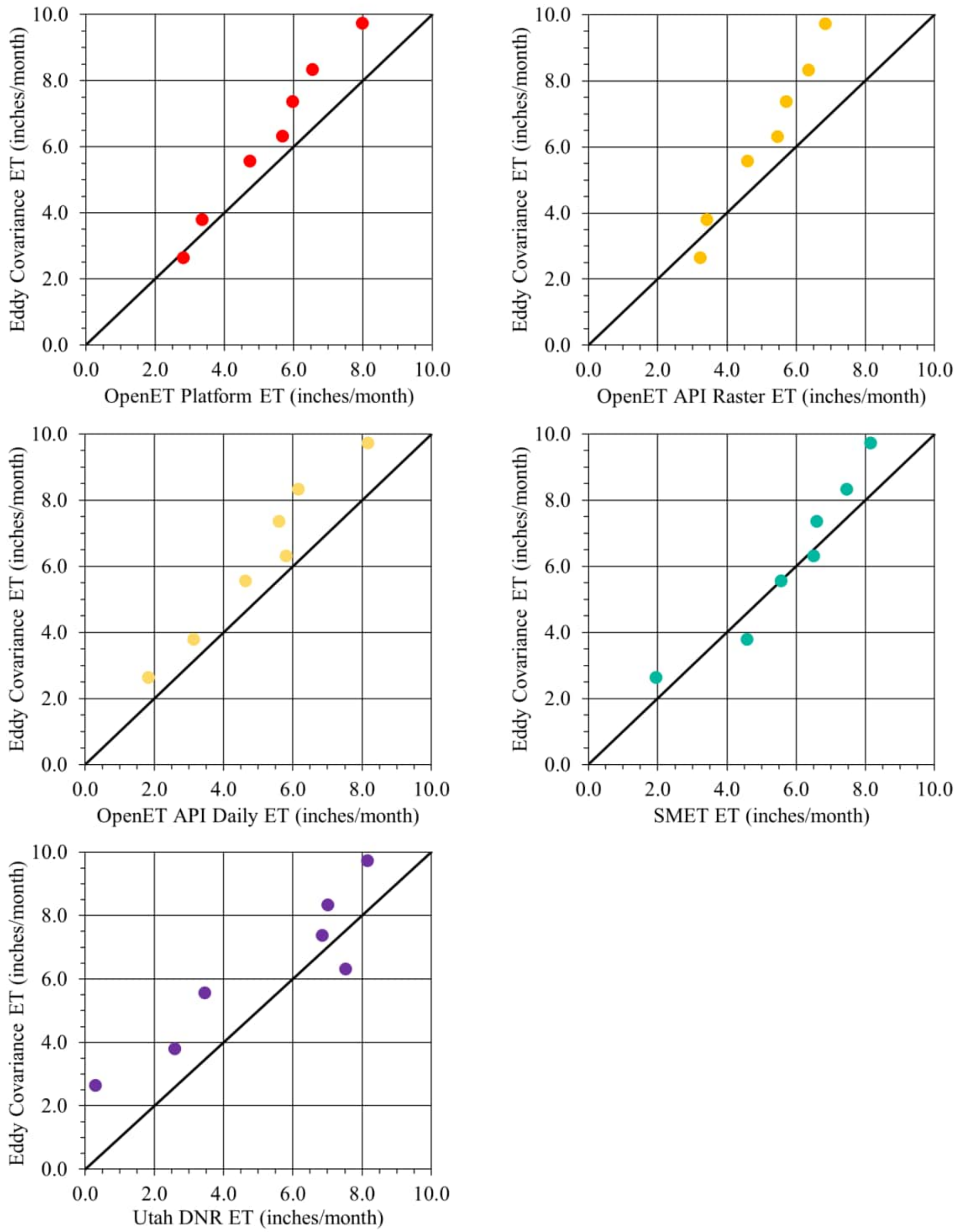

Figure 11. Comparison of monthly ET estimates (inches) from the OpenET Platform, OpenET API Raster, OpenET API Daily, SMET, and Utah DNR methods against monthly eddy covariance ET estimates (inches) in one-to-one plots.

The estimated contribution of advection to ET as indicated by H and calculated with equation 7 varies each month over the growing season (Table 4). Under the assumption that H is a reliable indicator of advection, this analysis suggests that advection contributed as much as 21% (2 in.) to the total estimate in June. A comparison of the ET estimation methods to the EC method with (Table 5) and without (Table 6) considering advection indicates that the OpenET and Utah DNR methods would more closely match the EC ET estimates if advection was considered. The SMET methods are not impacted by the presence of advection since these methods rely on direct measurements of SWC for ET estimation and are therefore not included in the assessment of advective impact.

Table 4. The monthly EC ET estimates, the monthly sum of negative sensible heat (H), and the estimated EC ET without the contribution of H (ET_{na}) are presented for comparison. The H values indicate the estimated contribution of advection to the EC ET estimates (inches and %).

Month	EddyCov (in.)	ET_{na} (in.)	H (in.)	% H Contribution to EddyCov
Apr	3.8	3.6	0.2	5%
May	8.3	7.1	1.2	14%
Jun	9.7	7.7	2.0	21%
Jul	6.3	5.9	0.4	7%
Aug	7.4	6.3	1.1	15%
Sep	5.6	4.8	0.7	13%
Oct	2.6	2.4	0.2	9%

Table 5. A comparison of the monthly ET estimates from each of the methods that do not consider advection is presented as a percent above (positive) or below (negative) the monthly EC ET estimate, along with the corresponding difference in inches.

Month	OpenET Platform		OpenET API Raster		OpenET API Daily		Utah DNR	
	%	in.	%	in.	%	in.	%	in.
Apr	-12%	0.4	-10%	0.4	-18%	0.7	-32%	1.2
May	-21%	1.8	-24%	2.0	-26%	2.2	-16%	1.3
Jun	-18%	1.7	-30%	2.9	-16%	1.6	-16%	1.6
Jul	-10%	0.6	-14%	0.9	-8%	0.5	19%	1.2
Aug	-19%	1.4	-22%	1.7	-24%	1.8	-7%	0.5
Sep	-15%	0.8	-17%	1.0	-17%	0.9	-38%	2.1
Oct	6%	0.2	22%	0.6	-31%	0.8	-89%	2.3

Table 6. A comparison of the monthly ET estimates from each of the methods that do not consider advection is presented as a percent above (positive) or below (negative) the monthly EC ET estimate less the advection effect (ET_{na}), along with the corresponding difference in inches.

Month	OpenET Platform		OpenET API Raster		OpenET API Daily		Utah DNR	
	%	in.	%	in.	%	in.	%	in.
Apr	-7%	0.3	-5%	0.2	-14%	0.5	-29%	1.0
May	-8%	0.6	-11%	0.8	-14%	1.0	-2%	0.1
Jun	3%	0.3	-11%	0.9	6%	0.5	6%	0.4
Jul	-4%	0.2	-7%	0.4	-1%	0.1	28%	1.7
Aug	-5%	0.3	-9%	0.6	-11%	0.7	9%	0.6
Sep	-3%	0.1	-5%	0.3	-4%	0.2	-29%	1.4
Oct	16%	0.4	33%	0.8	-25%	0.6	-88%	2.1

The consistent underestimation of ET by the OpenET methods and the Utah DNR method compared to the EC method is presented in Table 5. The differences become less significant when the effect of advection (H) is removed from the EC ET estimate (Table 6). While the OpenET methods continue to underestimate ET, the differences are within 1 in. of the EC ET estimates. The differences between the Utah DNR method and the EC method are also reduced when the contribution of advection is removed, with most months being within 1 in. of the EC ET estimate.

Seasonal ET Estimation Methods

Monthly ET estimates were aggregated to seasonal scale for all methods (Table 7 & Figure 12). The similarities between the OpenET methods are even more pronounced at seasonal scale, as are the similarities between the SMET methods. The Utah DNR recommendation for ET is slightly higher than the estimation from other methods in pivots 4 and 30. However, the Utah DNR recommendation is close to the OpenET estimates and lower than the soil moisture estimates in pivot 22 and the EC flux tower footprint.

Table 7. Seasonal ET totals (inches) per method for each study area. ET_r and inflow values are provided for reference.

Method	Pivot 4	Pivot 30	Pivot 22	EC Footprint
OpenET Platform	17.2	15.7	36.5	37.0
OpenET API Raster	17.4	15.8	37.0	35.6
OpenET API Daily	17.3	15.7	36.5	35.3
SMET1	18.7	20.6	42.6	-
SMET2	19.5	20.1	42.3	-
SMET	-	-	-	40.8
UtahDNR	22.6	22.6	35.9	35.9
EddyCov	-	-	-	43.7
ET_r	24.7	24.7	55.6	55.6
Inflow	22.0	19.6	39.4	39.4

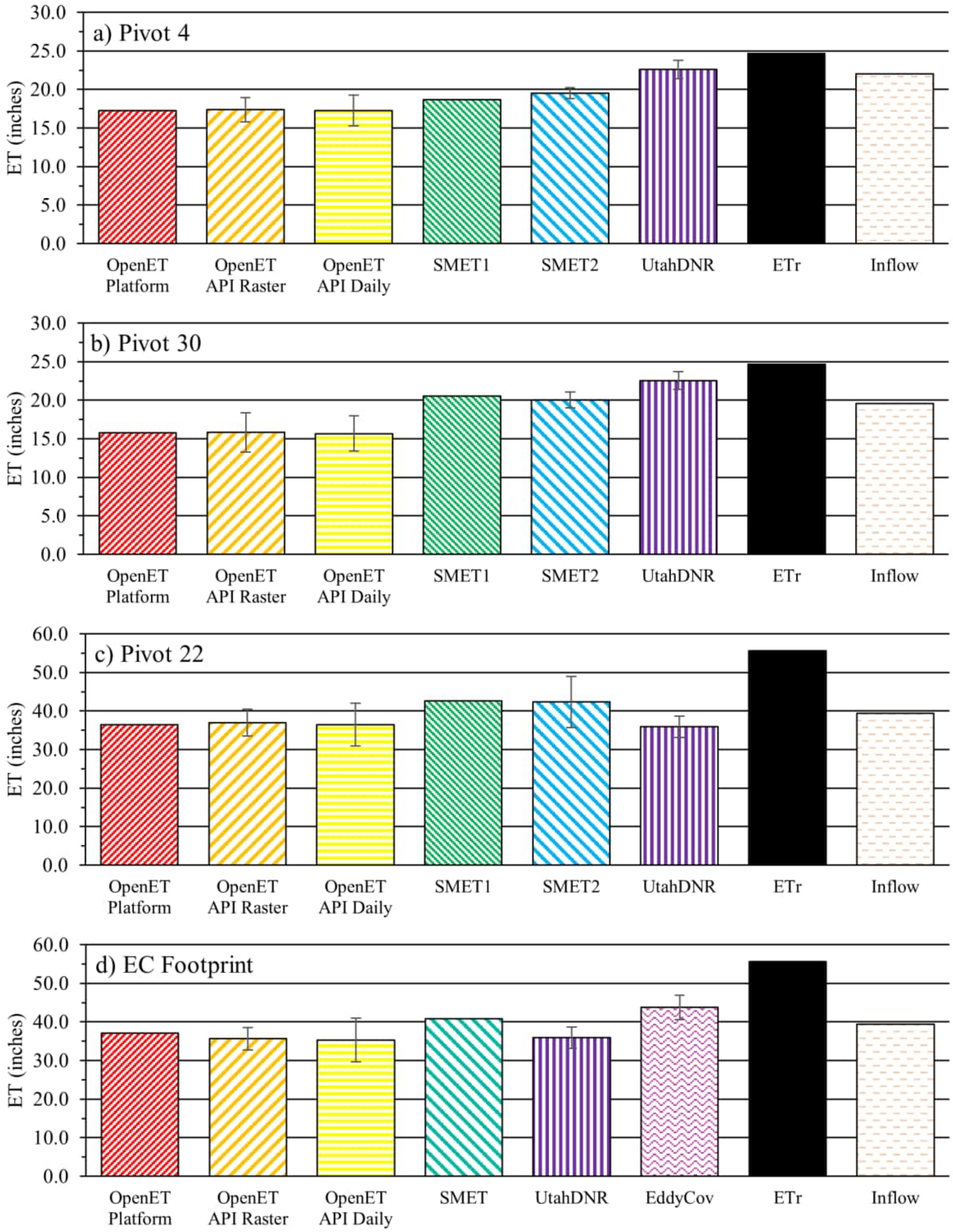

Figure 12. Seasonal ET estimates (inches) for the 2021 growing season from each estimation method are presented with ET_r and inflow for reference. Error bars indicate standard deviation.

In pivots 4, 30, and 22 the OpenET Platform method is 1% (0.2 in. in pivot 4, 0.1 in. in pivot 30, 0.5 in. in pivot 22) lower than the OpenET API Raster method and shows nearly no difference to the OpenET API Daily method. In the EC footprint area, the OpenET Platform method is 4% (1.4 in.) higher than the OpenET API Raster method, and 5% (1.7 in.) higher than the OpenET API Daily method. In all study areas, the OpenET API Raster method is 1% (0.1 in. in pivots 4 and 30, 0.5 in. in pivot 22, and 0.3 in. in the EC footprint) higher than the OpenET API Daily method.

The seasonal SMET1 estimates are 1% (0.3 in.) higher than the SMET2 estimates in pivot 22, 5% (0.8 in.) lower than the SMET2 estimate in pivot 4, and 3% (0.5 in.) higher than the SMET2 estimate in pivot 30. Compared to all OpenET methods, the SMET1 method is 7% (1.4 in.) higher in pivot 4, 23% (4.8 in.) higher in pivot 30, and 14% (6 in.) higher in pivot 22. Compared to all OpenET methods, the SMET2 method is 11% (2.2 in.) higher in pivot 4, 20% (4.3 in.) higher in pivot 30, and 13% (5.7 in.) higher in pivot 22. The SMET method is 13% (5.3 in.) higher than the OpenET API Raster and Daily methods and 9% (3.8 in.) higher than the OpenET Platform method in the EC flux tower footprint.

The seasonal Utah DNR estimate in pivot 4 is 23% (5.3 in.) higher on average than all other OpenET methods, and 15% (3.5 in.) higher than the SMET methods. In pivot 30, the Utah DNR estimate is 30% (6.8 in.) higher than the OpenET methods and 10% (2.3 in.) higher than the SMET methods. In pivot 22, the Utah DNR estimate is 2% (0.8 in.) lower on average than the OpenET methods, and 18% (6.6 in.) lower on average than the soil moisture methods. In the EC footprint, the Utah DNR estimate is 3% (1.1

in.) lower than the OpenET Platform method, 2% (0.3 in.) higher than the OpenET API Raster and OpenET API Daily methods, and 14% (4.9 in.) lower than the SMET method.

The ET_r estimate is higher than all other methods, even under advective conditions where ET > ET_r is possible. Compared to the OpenET, SMET, and Utah DNR methods, the ET_r estimate is on average 24% (5.9 in.) higher in pivot 4, 25% (6.3 in.) higher in pivot 30, 31% (16.7 in.) and 22, and 34% (18.7 in.) higher in the EC footprint.

In the EC footprint, seasonal EC ET estimates are 15% (6.7 in.) greater than the OpenET Platform estimates, and 19% (8.3 in.) greater than the OpenET API Raster and Daily estimates. Seasonal EC ET estimates are 7% (2.9 in.) greater than the SMET method and 18% (7.8 in.) greater than the Utah DNR estimate. Conclusions from the comparison to the EC method are only applicable to alfalfa since no EC information is available for the corn sites (pivots 4 and 30).

Analysis of the advective contribution was also completed at seasonal scale (Table 8). After the removal of the advective contribution from the EC ET estimate, all OpenET methods and the Utah DNR method still underestimated seasonal ET. However, the underestimation of all methods is within 10% of the EC ET estimate less advection.

Table 8. A comparison of the seasonal ET estimates from each of the methods that do not consider advection is presented as a percent above (positive) or below (negative) the seasonal EC ET estimate with and without the contribution of advection (ET_{na}), along with the corresponding difference in inches.

Method	**Difference From EddyCov**		**Difference From ET_{na}**	
	%	**in.**	**%**	**in.**
OpenET Platform	-15%	6.7	-2%	0.9
OpenET API Raster	-19%	8.1	-6%	2.3
OpenET API Daily	-19%	8.4	-7%	2.6
Utah DNR	-18%	7.8	-5%	2.0

Seasonal Soil Water Balance

The seasonal SWB (equation 15) for each area of interest was calculated using the ET estimates from every method to identify the amount of water unaccounted for in the system. The calculated residual values are presented in Table 9. A positive residual indicates water is leaving the system, likely through deep percolation or runoff. A negative residual is explained by movement of water into the system supplied by an unidentified source. There is no indication of a high water table that would be contributing water to the system at this study site; therefore, the negative residuals here are explained as a result of data collection or other errors.

Table 9. Water balance residuals (inches) for all study areas for months with complete datasets.

Method	Pivot 4	Pivot 30	Pivot 22	EC Footprint
OpenET Platform	6.1	5.5	7.0	6.4
OpenET API Raster	6.1	5.4	6.5	8.2
OpenET API Daily	5.5	4.6	5.9	7.1
SMET1	5.6	2.9	-0.2	
SMET2	5.2	3.1	0.1	
SMET				1.8
UtahDNR	2.6	1.2	4.8	5.0
EddyCov				-0.5

The ET estimate from the EC method results in a negative residual value. While the negative residual is small, the lack of complete balance of the SWB equation indicates possible uncertainty in data collection. Uncertainties are more likely found in SWC measurement since the EC method is understood to generate reliable ET estimates. The size of the negative residual indicates that any errors in estimating SWB components are not significant at this location.

The residuals of the SMET, OpenET, and Utah DNR methods in the EC footprint are positive, with the SMET residual being the closest to the EC residual. These positive residuals could indicate water lost to DP or RO over the season. However, when compared to the EC residual, this study recognizes that the positive residual could be the result of ET underestimation.

While the results from the EC footprint cannot be directly applied to pivot 22, the results do follow a similar trend. Residuals from the SMET methods are close to a complete balance of the SWB equation, indicating any uncertainties in SWB measurement are insignificant in this area. The magnitude of the positive residuals from the OpenET and Utah DNR methods indicate underestimation of ET for this site.

All residuals in pivots 4 and 30 are positive, with the Utah DNR residuals being the lowest. The size of the residuals from the SMET methods indicates uncertainty in SWC measurements. The presence of the rocky sublayer indicated by the SWC dataset analysis in both fields is the likely source of this uncertainty, causing potential overestimation of root zone SWC and necessitating gap filling procedures. The uncertainty in SWC measurement in these fields could be one component in explaining the residuals from OpenET and the Utah DNR. The more significant component is likely these methods’ apparent underestimation of ET.

Method Advantages and Limitations

The SMET and OpenET API Daily methods provide water users the flexibility to analyze ET for a time period requiring subsets of months. These methods could be useful for water users wanting to understand their water use for a defined growing season, cut cycle, or water turn.

All OpenET methods are available for public use and require little effort from the user, making these methods economically and time efficient. However, data availability currently lags and is therefore not available for real-time irrigation scheduling. The OpenET Platform method is the most accessible and efficient of the OpenET methods, only requiring users to select the field of interest before retrieving ET estimates.

The OpenET API Raster and Daily methods require users to obtain an API key and have some understanding of coding in Python for data retrieval. The OpenET API Raster method also requires users to have basic knowledge of image processing to analyze the provided raster files. The OpenET API Daily method does not currently provide the ensemble mean at daily scale. Users would need to estimate the daily ensemble mean manually using the MAD method.

The SMET model is consistent in both variations and most closely matches the EC method. While the SMET method is the most accurate method included in this study, the SMET model requires further validation in other crop types and locations before being recommended for widespread use. The greatest limitations to the SMET model are the time frame for which data collection occurs and ability of the sensors to accurately measure soil moisture content.

Soil moisture sensor accuracy can be affected based on calibration, installation, and soil characteristics. Spikes in the soil water content datasets indicate the presence of rocky sublayers. While gap filling can reduce the impact of the uncertainty introduced by the spikes, the gap filling procedure forces the ET results to ET_r to some extent.

Soil moisture sensors require proper installation and maintenance, which is not economically or time appropriate for some water users. Soil moisture readings are limited to the location of the sensors; therefore, any use of the readings to represent the entire field is done under the assumption of field uniformity. Sensor installation should aim to maximize the representation of the field without straining the user financially.

The Utah DNR report provides publicly available monthly and seasonal ET estimates, which is economically and time efficient for water users. While ET estimates are available for multiple crops in numerous locations around Utah, the differences in ET over even a short geographic area prevent the ET estimates from being fully reliable in surrounding areas. Users should be aware that the Utah DNR ET estimates are based on historical weather data and do not consider individual management practices, such as variations in growing seasons and water application.

As seen in the comparisons of the methods at daily, monthly, and seasonal time scales, the OpenET methods consistently underestimate ET compared to the SMET and EC methods. Analysis of the EC components indicates that advection contributes significantly to ET at this location. The EC method and SMET method are unaffected by the influence of advection, as these methods estimate ET directly from soil water and water vapor. The OpenET and Utah DNR methods do not account for the effect of advection, and therefore are likely missing a key component to ET estimation. While the influence of advection at the study site is one possible explanation for this trend, the influence of other unknown errors cannot be ruled out.

CONCLUSION

As technologies and methods for ET estimation are proposed, water users should be aware of the advantages and limitations of each method to inform their water management practices. This study provides such information on ET estimation methods from three sources- soil moisture data, OpenET, and the Utah DNR. The analysis was completed to:

(i) assess the performance of available ET estimation methods at different time scales (daily, monthly, seasonal),

(ii) validate each method's accuracy against eddy covariance measurements,

(iii) identify advantages and limitations of each method, and

(iv) recommend methods based on user needs.

This study showed that the SMET and OpenET API Daily methods were able to provide daily ET estimates that can be aggregated to monthly and seasonal scale. The OpenET Platform, OpenET API Raster, and Utah DNR methods were able to estimate ET at monthly and seasonal scale.

The SMET method ET estimates were most accurate to the EC ET estimates compared to the other methods included in this study. The OpenET and Utah DNR methods underestimated ET compared to the EC method.

While this study recognizes the apparent accuracy of the SMET model, the reliance on soil moisture data has been shown to introduce complications to the efficiency and accessibility of this model. Soil characteristics at this location led to spikes in the soil moisture datasets that made gap filling necessary. The gap filling forced the SMET results to ET_r to some extent. This study recommends that users be able to analyze soil moisture datasets for possible sources of uncertainty and understand the gap filling process to benefit from the SMET method. The SMET method is recommended for users willing to invest time and money into the process for increased accuracy.

The OpenET methods have been shown to consistently provide similar results to each other. However, this study has shown that the OpenET methods are potentially underestimating ET due to a lack of correction for advection. The OpenET methods require no financial investment from users and are therefore recommended for users prioritizing accessibility with the understanding that some level of accuracy may be lost.

This study has shown that the Utah DNR ET estimates vary in accuracy between crop types. As a publicly available report, this method is easily accessible and efficient for users to implement. However, this study has shown that the lack of accounting for current weather conditions and management practices, as well as the potential effects of advection, limit the accuracy of the Utah DNR method.

Further analysis of these methods should be completed at a location that does not result a significant amount of gap filling of the EC measurements to preserve the reliability of the EC ET estimates. Further validation of the SMET method in other crop types and locations should be completed before the SMET model can be recommended for widespread use. Future work should also include an in-depth analysis of advective contribution to ET estimates, as well as the development of corrections for advection for the OpenET models. The OpenET methods should also make ET estimates available without a lag so water users can use reliable ET estimates for irrigation scheduling. Regarding the EC footprint, future work should include an analysis of methods based on the elliptical footprint with considerations for the respective impact on measurements from varying locations within the footprint.

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APPENDICES

Appendix A. **Soil moisture data collected over the 2021 season in pivots 4 and 22.**

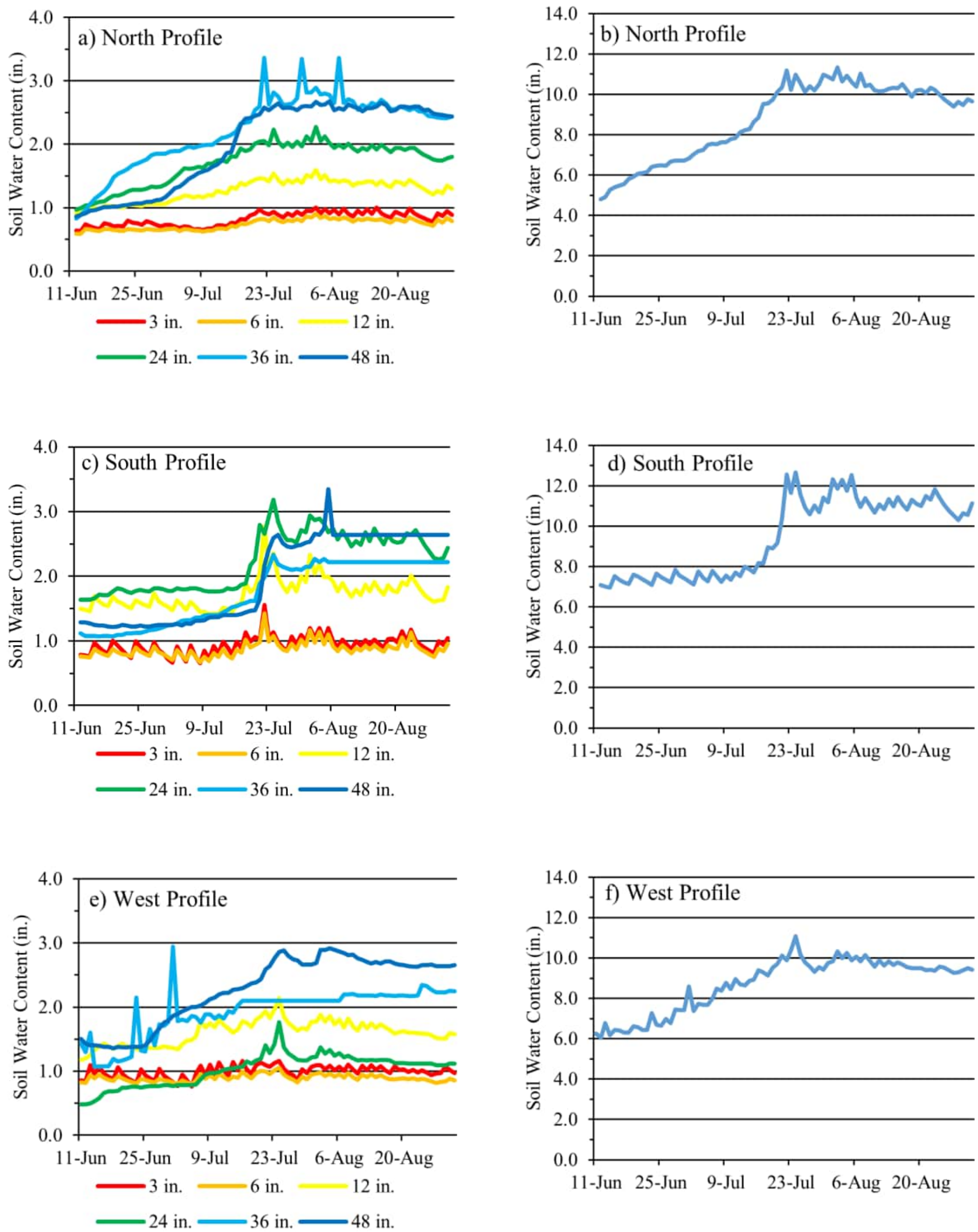

Figure 13. Daily midnight soil water content (inches) per sensor depth (left column) and total (right column) for all sensors in pivot 4 soil profiles.

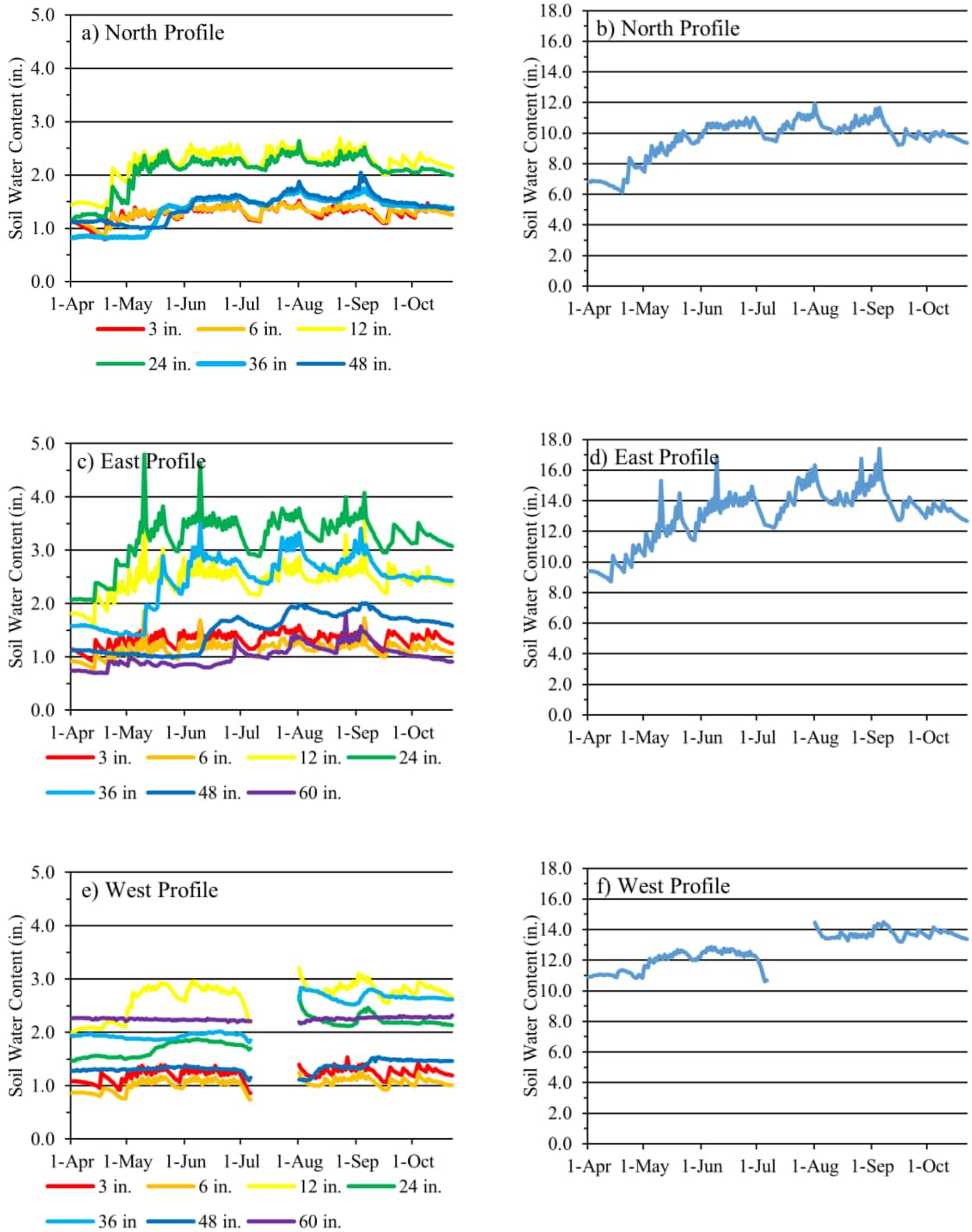

Figure 14. Daily midnight soil water content (inches) per sensor depth (left column) and total (right column) for all sensors in pivot 22 soil profiles.

Appendix B. **Daily Soil Moisture based ET (SMET) results for all soil profiles.**

Table 10. Daily ET estimates (inches) from SMET for each soil profile in pivot 4.

Date	SMET2			SMET1
	North	South	West	
6/11/2021	0.38	0.22	0.25	0.28
6/12/2021	0.38	0.22	0.25	0.28
6/13/2021	0.38	0.22	0.38	0.38
6/14/2021	0.37	0.21	0.44	0.23
6/15/2021	0.32	0.32	0.32	0.32
6/16/2021	0.28	0.22	0.15	0.16
6/17/2021	0.30	0.21	0.20	0.17
6/18/2021	0.31	0.19	0.16	0.31
6/19/2021	0.27	0.27	0.27	0.27
6/20/2021	0.34	0.22	0.19	0.18
6/21/2021	0.33	0.22	0.21	0.20
6/22/2021	0.37	0.24	0.19	0.20
6/23/2021	0.27	0.20	0.27	0.27
6/24/2021	0.27	0.27	0.38	0.27
6/25/2021	0.22	0.19	0.13	0.14
6/26/2021	0.17	0.22	0.33	0.33
6/27/2021	0.34	0.23	0.26	0.19
6/28/2021	0.34	0.34	0.34	0.34
6/29/2021	0.10	0.22	0.11	0.14
6/30/2021	0.13	0.18	0.26	0.14
7/1/2021	0.22	0.18	0.22	0.22
7/2/2021	0.24	0.18	0.35	0.29
7/3/2021	0.25	0.25	0.25	0.25
7/4/2021	0.27	0.26	0.16	0.18
7/5/2021	0.26	0.21	0.13	0.26
7/6/2021	0.34	0.34	0.34	0.34
7/7/2021	0.18	0.27	0.33	0.33
7/8/2021	0.39	0.32	0.23	0.23
7/9/2021	0.16	0.31	0.31	0.31
7/10/2021	0.37	0.27	0.32	0.23
7/11/2021	0.28	0.28	0.28	0.28
7/12/2021	0.25	0.20	0.23	0.14
7/13/2021	0.33	0.33	0.18	0.33
7/14/2021	0.27	0.19	0.27	0.27
7/15/2021	0.28	0.21	0.28	0.28
7/16/2021	0.27	0.27	0.27	0.27
7/17/2021	0.23	0.13	0.16	0.23
7/18/2021	0.17	0.17	0.16	0.17
7/19/2021	0.17	0.11	0.17	0.17
7/20/2021	0.15	0.15	0.15	0.15
7/21/2021	0.16	0.16	0.16	0.16

7/22/2021	0.11	0.11	0.16	0.11
7/23/2021	0.28	0.28	0.19	0.28
7/24/2021	0.22	0.22	0.22	0.22
7/25/2021	0.29	0.34	0.34	0.34
7/26/2021	0.18	0.18	0.18	0.18
7/27/2021	0.23	0.26	0.21	0.15
7/28/2021	0.19	0.21	0.21	0.11
7/29/2021	0.19	0.24	0.19	0.19
7/30/2021	0.15	0.15	0.13	0.15
7/31/2021	0.11	0.17	0.15	0.15
8/1/2021	0.13	0.13	0.13	0.13
8/2/2021	0.20	0.29	0.20	0.20
8/3/2021	0.34	0.23	0.25	0.20
8/4/2021	0.24	0.35	0.24	0.24
8/5/2021	0.32	0.37	0.34	0.37
8/6/2021	0.32	0.63	0.43	0.38
8/7/2021	0.21	0.30	0.21	0.11
8/8/2021	0.44	0.35	0.35	0.35
8/9/2021	0.33	0.33	0.28	0.25
8/10/2021	0.26	0.28	0.26	0.26
8/11/2021	0.13	0.23	0.23	0.23
8/12/2021	0.23	0.22	0.22	0.18
8/13/2021	0.27	0.27	0.27	0.27
8/14/2021	0.27	0.30	0.22	0.21
8/15/2021	0.13	0.24	0.24	0.24
8/16/2021	0.23	0.27	0.17	0.16
8/17/2021	0.27	0.26	0.20	0.24
8/18/2021	0.29	0.29	0.16	0.29
8/19/2021	0.12	0.15	0.07	0.12
8/20/2021	0.18	0.14	0.18	0.10
8/21/2021	0.20	0.27	0.18	0.27
8/22/2021	0.25	0.21	0.25	0.25
8/23/2021	0.19	0.28	0.17	0.28
8/24/2021	0.24	0.32	0.29	0.21
8/25/2021	0.22	0.28	0.16	0.22
8/26/2021	0.21	0.26	0.19	0.22
8/27/2021	0.21	0.22	0.18	0.20
8/28/2021	0.21	0.20	0.21	0.21
8/29/2021	0.17	0.21	0.21	0.21
8/30/2021	0.23	0.15	0.23	0.23
8/31/2021	0.10	0.10	0.09	0.10

Table 11. Daily ET estimates (inches) from SMET for each soil profile in pivot 30.

Date	SMET2			SMET1
	North	East	West	
6/11/2021	0.16	0.22	0.32	0.32
6/12/2021	0.16	0.22	0.32	0.32
6/13/2021	0.21	0.25	0.19	0.22
6/14/2021	0.19	0.25	0.19	0.21
6/15/2021	0.32	0.20	0.32	0.32
6/16/2021	0.33	0.20	0.33	0.33
6/17/2021	0.26	0.30	0.24	0.30
6/18/2021	0.24	0.31	0.24	0.26
6/19/2021	0.28	0.25	0.28	0.28
6/20/2021	0.28	0.34	0.40	0.40
6/21/2021	0.26	0.39	0.28	0.29
6/22/2021	0.25	0.30	0.25	0.26
6/23/2021	0.21	0.23	0.19	0.21
6/24/2021	0.27	0.20	0.27	0.27
6/25/2021	0.20	0.22	0.26	0.22
6/26/2021	0.22	0.38	0.22	0.28
6/27/2021	0.22		0.24	0.22
6/28/2021	0.21		0.24	0.22
6/29/2021	0.19		0.19	0.19
6/30/2021	0.26		0.30	0.24
7/1/2021	0.21		0.19	0.20
7/2/2021	0.23		0.19	0.21
7/3/2021	0.25		0.25	0.25
7/4/2021	0.22		0.32	0.32
7/5/2021	0.25		0.22	0.23
7/6/2021	0.18		0.26	0.22
7/7/2021	0.33	0.33	0.33	0.33
7/8/2021	0.34	0.38	0.38	0.37
7/9/2021	0.17	0.31	0.36	0.31
7/10/2021	0.30	0.28	0.31	0.30
7/11/2021	0.28	0.33	0.28	0.28
7/12/2021	0.21	0.25	0.29	0.25
7/13/2021	0.26	0.25	0.33	0.33
7/14/2021	0.27	0.24	0.31	0.31
7/15/2021	0.25	0.28	0.28	0.28
7/16/2021	0.18	0.32	0.22	0.32
7/17/2021	0.23	0.18	0.23	0.23
7/18/2021	0.20	0.20	0.20	0.20
7/19/2021	0.20	0.17	0.20	0.17
7/20/2021	0.08	0.13	0.09	0.10
7/21/2021	0.16	0.14		0.16

7/22/2021	0.13	0.11		0.11
7/23/2021	0.12	0.22		0.22
7/24/2021	0.12	0.14		0.13
7/25/2021	0.18	0.27		0.23
7/26/2021	0.14	0.14		0.14
7/27/2021	0.23	0.19		0.23
7/28/2021	0.25	0.25		0.25
7/29/2021	0.19	0.19		0.19
7/30/2021	0.17	0.08		0.17
7/31/2021	0.18	0.15		0.15
8/1/2021	0.13	0.15		0.15
8/2/2021	0.23	0.23		0.23
8/3/2021	0.23	0.27		0.27
8/4/2021	0.19	0.28		0.23
8/5/2021	0.37	0.34		0.37
8/6/2021	0.49	0.37		0.49
8/7/2021	0.24	0.21	0.21	0.21
8/8/2021	0.35	0.29	0.35	0.35
8/9/2021	0.38	0.33	0.38	0.26
8/10/2021	0.26	0.31	0.27	0.27
8/11/2021	0.23	0.27	0.27	0.27
8/12/2021	0.27	0.23	0.27	0.12
8/13/2021	0.27	0.31	0.27	0.27
8/14/2021	0.32	0.28	0.32	0.32
8/15/2021	0.28	0.28	0.28	0.28
8/16/2021	0.27	0.27	0.20	0.27
8/17/2021	0.29	0.34	0.29	0.29
8/18/2021	0.34	0.27	0.34	0.34
8/19/2021	0.12	0.12	0.14	0.12
8/20/2021	0.21	0.21	0.18	0.18
8/21/2021	0.28	0.27	0.32	0.32
8/22/2021	0.29	0.25	0.29	0.16
8/23/2021	0.28	0.33	0.28	0.28
8/24/2021	0.34	0.29	0.34	0.34
8/25/2021	0.30	0.30	0.24	0.30
8/26/2021	0.23	0.31	0.31	0.31
8/27/2021	0.25	0.29	0.25	0.25
8/28/2021	0.25	0.22	0.25	0.25
8/29/2021	0.19	0.24	0.21	0.21
8/30/2021	0.23	0.27	0.27	0.27
8/31/2021	0.12	0.05	0.12	0.12

Table 12. Daily ET estimates (inches) from SMET for each soil profile in pivot 22.

Date		SMET2		SMET1
	North	East	West	
4/1/2021	0.11	0.11	0.11	0.21
4/2/2021	0.11	0.11	0.11	0.21
4/3/2021	0.25	0.13	0.25	0.25
4/4/2021	0.14	0.15	0.27	0.27
4/5/2021	0.17	0.18	0.17	0.18
4/6/2021	0.10	0.11	0.18	0.10
4/7/2021	0.21	0.14	0.21	0.11
4/8/2021	0.16	0.14	0.13	0.14
4/9/2021	0.11	0.15	0.13	0.13
4/10/2021	0.14	0.14	0.24	0.13
4/11/2021	0.13	0.15	0.12	0.14
4/12/2021	0.15	0.16	0.11	0.14
4/13/2021	0.16	0.18	0.14	0.16
4/14/2021	0.12	0.21	0.11	0.21
4/15/2021	0.12	0.21	0.10	0.15
4/16/2021	0.07	0.13	0.08	0.09
4/17/2021	0.10	0.12	0.15	0.15
4/18/2021	0.14	0.16	0.23	0.12
4/19/2021	0.20	0.22	0.29	0.19
4/20/2021	0.18	0.17	0.11	0.18
4/21/2021	0.15	0.26	0.13	0.26
4/22/2021	0.15	0.24	0.12	0.17
4/23/2021	0.27	0.22	0.15	0.27
4/24/2021	0.24	0.24	0.17	0.22
4/25/2021	0.22	0.27	0.21	0.27
4/26/2021	0.06	0.06	0.06	0.06
4/27/2021	0.08	0.08	0.04	0.08
4/28/2021	0.23	0.23	0.23	0.23
4/29/2021	0.14	0.25	0.14	0.18
4/30/2021	0.17	0.18	0.16	0.18
5/1/2021	0.20	0.24	0.28	0.28
5/2/2021	0.20	0.20	0.10	0.20
5/3/2021	0.22	0.32	0.15	0.23
5/4/2021	0.21	0.27	0.24	0.24
5/5/2021	0.26	0.25	0.19	0.26
5/6/2021	0.30	0.27	0.18	0.27
5/7/2021	0.29	0.41	0.33	0.25
5/8/2021	0.26	0.26	0.18	0.26
5/9/2021	0.25	0.35	0.24	0.24
5/10/2021	0.25	0.25	0.16	0.25
5/11/2021	0.32	0.35	0.18	0.35

5/12/2021	0.19	0.28	0.25	0.15
5/13/2021	0.21	0.28	0.20	0.23
5/14/2021	0.29	0.29	0.21	0.29
5/15/2021	0.28	0.38	0.33	0.23
5/16/2021	0.26	0.26	0.19	0.26
5/17/2021	0.21	0.33	0.22	0.19
5/18/2021	0.22	0.22	0.15	0.22
5/19/2021	0.30	0.48	0.33	0.28
5/20/2021	0.38	0.38	0.25	0.38
5/21/2021	0.32	0.36	0.25	0.36
5/22/2021	0.17	0.25	0.12	0.17
5/23/2021	0.20	0.18	0.13	0.17
5/24/2021	0.16	0.19	0.15	0.17
5/25/2021	0.21	0.29	0.21	0.24
5/26/2021	0.24	0.26	0.20	0.23
5/27/2021	0.19	0.21	0.20	0.20
5/28/2021	0.17	0.17	0.33	0.33
5/29/2021	0.26	0.26	0.16	0.26
5/30/2021	0.16	0.30	0.30	0.17
5/31/2021	0.29	0.29	0.16	0.29
6/1/2021	0.17	0.40	0.27	0.20
6/2/2021	0.27	0.22	0.27	0.27
6/3/2021	0.17	0.29	0.18	0.29
6/4/2021	0.28	0.30	0.28	0.28
6/5/2021	0.18	0.34	0.23	0.34
6/6/2021	0.32	0.48	0.42	0.31
6/7/2021	0.32	0.32	0.26	0.32
6/8/2021	0.31	0.50	0.39	0.31
6/9/2021	0.39	0.39	0.29	0.39
6/10/2021	0.33	0.56	0.22	0.56
6/11/2021	0.28	0.30	0.28	0.15
6/12/2021	0.21	0.32	0.24	0.32
6/13/2021	0.28	0.38	0.38	0.23
6/14/2021	0.37	0.37	0.28	0.37
6/15/2021	0.28	0.38	0.32	0.25
6/16/2021	0.28	0.28	0.22	0.28
6/17/2021	0.23	0.39	0.30	0.22
6/18/2021	0.31	0.30	0.19	0.17
6/19/2021	0.21	0.27	0.19	0.27
6/20/2021	0.28	0.36	0.24	0.29
6/21/2021	0.33	0.32	0.33	0.33
6/22/2021	0.29	0.37	0.28	0.37
6/23/2021	0.27	0.35	0.27	0.16
6/24/2021	0.21	0.27	0.22	0.27

6/25/2021	0.22	0.28	0.22	0.22
6/26/2021	0.28	0.33	0.22	0.33
6/27/2021	0.31	0.35	0.34	0.24
6/28/2021	0.34	0.34	0.28	0.34
6/29/2021	0.19	0.28	0.19	0.15
6/30/2021	0.23	0.27	0.16	0.22
7/1/2021	0.22	0.27	0.19	0.23
7/2/2021	0.20	0.24	0.23	0.22
7/3/2021	0.21	0.26	0.27	0.25
7/4/2021	0.22	0.25	0.31	0.26
7/5/2021	0.25	0.29	0.33	0.29
7/6/2021	0.34	0.18	0.34	0.34
7/7/2021	0.17	0.18		0.33
7/8/2021	0.22	0.21		0.21
7/9/2021	0.31	0.18		0.16
7/10/2021	0.23	0.20		0.21
7/11/2021	0.16	0.28		0.28
7/12/2021	0.25	0.25		0.25
7/13/2021	0.33	0.28		0.33
7/14/2021	0.21	0.27		0.27
7/15/2021	0.28	0.24		0.28
7/16/2021	0.27	0.27		0.27
7/17/2021	0.23	0.15		0.23
7/18/2021	0.17	0.17		0.17
7/19/2021	0.16	0.25		0.22
7/20/2021	0.10	0.17		0.13
7/21/2021	0.16	0.15		0.16
7/22/2021	0.11	0.11		0.11
7/23/2021	0.19	0.19		0.19
7/24/2021	0.12	0.15		0.14
7/25/2021	0.26	0.34		0.34
7/26/2021	0.12	0.12		0.12
7/27/2021	0.25	0.33		0.28
7/28/2021	0.21	0.21		0.21
7/29/2021	0.22	0.28		0.28
7/30/2021	0.15	0.15		0.15
7/31/2021	0.16	0.23		0.23
8/1/2021	0.13	0.13	0.13	0.13
8/2/2021	0.29	0.29	0.20	0.29
8/3/2021	0.26	0.32	0.23	0.27
8/4/2021	0.25	0.28	0.21	0.25
8/5/2021	0.27	0.30	0.27	0.28
8/6/2021	0.24	0.27	0.23	0.25
8/7/2021	0.13	0.14	0.14	0.13

8/8/2021	0.18	0.22	0.35	0.19
8/9/2021	0.18	0.22	0.33	0.19
8/10/2021	0.16	0.14	0.14	0.15
8/11/2021	0.17	0.16	0.23	0.14
8/12/2021	0.13	0.23	0.12	0.23
8/13/2021	0.17	0.28	0.27	0.18
8/14/2021	0.27	0.27	0.17	0.27
8/15/2021	0.17	0.31	0.24	0.14
8/16/2021	0.19	0.22	0.17	0.19
8/17/2021	0.29	0.24	0.19	0.29
8/18/2021	0.23	0.29	0.22	0.29
8/19/2021	0.06	0.18	0.13	0.16
8/20/2021	0.14	0.12	0.18	0.18
8/21/2021	0.27	0.22	0.14	0.27
8/22/2021	0.26	0.25	0.21	0.25
8/23/2021	0.28	0.30	0.28	0.28
8/24/2021	0.34	0.29	0.24	0.29
8/25/2021	0.23	0.38	0.26	0.24
8/26/2021	0.27	0.27	0.19	0.27
8/27/2021	0.25	0.36	0.25	0.36
8/28/2021	0.21	0.28	0.15	0.11
8/29/2021	0.23	0.21	0.15	0.21
8/30/2021	0.22	0.29	0.23	0.17
8/31/2021	0.10	0.10	0.10	0.10
9/1/2021	0.11	0.11	0.05	0.11
9/2/2021	0.20	0.20	0.20	0.20
9/3/2021	0.19	0.19	0.14	0.19
9/4/2021	0.30	0.30	0.21	0.29
9/5/2021	0.20	0.20	0.13	0.20
9/6/2021	0.33	0.34	0.18	0.34
9/7/2021	0.28	0.33	0.24	0.20
9/8/2021	0.22	0.29	0.17	0.23
9/9/2021	0.15	0.20	0.15	0.17
9/10/2021	0.22	0.24	0.17	0.21
9/11/2021	0.18	0.24	0.23	0.22
9/12/2021	0.18	0.21	0.13	0.18
9/13/2021	0.19	0.24	0.18	0.21
9/14/2021	0.19	0.21	0.18	0.20
9/15/2021	0.23	0.23	0.23	0.23
9/16/2021	0.30	0.30	0.17	0.15
9/17/2021	0.13	0.24	0.13	0.24
9/18/2021	0.14	0.14	0.14	0.14
9/19/2021	0.27	0.25	0.27	0.27
9/20/2021	0.24	0.17	0.21	0.17

9/21/2021	0.12	0.17	0.10	0.17
9/22/2021	0.13	0.21	0.13	0.16
9/23/2021	0.13	0.16	0.11	0.13
9/24/2021	0.11	0.13	0.09	0.11
9/25/2021	0.11	0.14	0.12	0.12
9/26/2021	0.18	0.13	0.18	0.18
9/27/2021	0.14	0.16	0.13	0.15
9/28/2021	0.13	0.16	0.12	0.14
9/29/2021	0.13	0.15	0.13	0.14
9/30/2021	0.15	0.15	0.12	0.14
10/1/2021	0.10	0.14	0.11	0.14
10/2/2021	0.11	0.17	0.10	0.13
10/3/2021	0.15	0.15	0.15	0.15
10/4/2021	0.14	0.15	0.15	0.15
10/5/2021	0.06	0.09	0.09	0.04
10/6/2021	0.08	0.09	0.08	0.08
10/7/2021	0.09	0.11	0.08	0.09
10/8/2021	0.06	0.08	0.07	0.07
10/9/2021	0.11	0.11	0.11	0.11
10/10/2021	0.12	0.15	0.10	0.12
10/11/2021	0.11	0.14	0.10	0.12
10/12/2021	0.05	0.06	0.06	0.06
10/13/2021	0.07	0.07	0.07	0.07
10/14/2021	0.07	0.11	0.06	0.08
10/15/2021	0.09	0.11	0.09	0.09
10/16/2021	0.08	0.10	0.08	0.09
10/17/2021	0.09	0.10	0.09	0.10
10/18/2021	0.06	0.09	0.08	0.08
10/19/2021	0.09	0.08	0.07	0.08
10/20/2021	0.06	0.08	0.06	0.07
10/21/2021	0.06	0.06	0.07	0.06
10/22/2021	0.09	0.11	0.08	0.09

Appendix C. Results from the analysis of the Normalized Difference Vegetation Index (NDVI) in pivot 22 and the eddy covariance flux tower footprint area.

Table 13. NDVI mean, standard deviation, and CV based on UAV imagery of pivot 22 and the EC footprint area.

Area	Mean	Standard Deviation	Coefficient of Variation
Pivot 22	0.89	0.06	0.07
EC Flux Tower Footprint	0.89	0.05	0.06