Evaluating Conserved Consumptive Use in the Upper Colorado: 2022 Annual Report

Application of an Energy Balance Method for Estimating Actual Evapotranspiration in High-Elevation Hay Pastures under Different Irrigation Regimes

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Abstract

Consumptive use (CU) and conserved CU (CCU) was evaluated under a compensated, temporary and voluntary irrigation withdrawal program on irrigated high-elevation pastures, which dominate agricultural water use in Western Colorado[1]. The thermal-based eeMETRIC model was used to perform this evaluation on 10 separate treatment (TRT) sites totaling 460.8 ha (1,138.7 ac) under two forms of irrigation withdrawal and 5 fully irrigated reference (REF) sites totaling 161.9 ha (400.0 ac) for the study period 2016-2022. A key aspect of this work involved assessing the CU under two conditions: unchanged REF irrigation practices versus TRT irrigation withdrawal conditions for one year. This assessment was done using two methods: 1) comparing the actual evapotranspiration rates (ET_a) of the TRT sites to a prior year baseline average for 2016-2019, and; 2) comparing ET_a for the TRT sites against neighboring REF sites during the same-year in 2020. Based on the prior years approach, the spatial average of May-Sept ET_a was 53.4% lower for sites where irrigation was completely withdrawn in 2020 versus the 2016-2019 baseline average for these same sites. Subsequently, May-Sept ET_a rates in 2021 and 2022 were 13.9% and 1.7% lower, respectively, than the same 2016-2019 baseline. The sites that adhered to a partial-season approach where irrigation was withdrawn after June 15, 2020, exhibited May-Sep ET_a that was 14.7% lower than the 2016-2019 baseline average for these same sites, then exhibited rates in 2021 and 2022 that were 16.1% and 6.6% lower than the baseline. In general, fields on which irrigation was fully withdrawn appeared to return more vigorously to pre-stress ET_a, compared to the fields under partial-season irrigation withdrawal. This trend continued in the second year, possibly due to more favorable soil conditions or the accumulation of fructans before dormancy, allowing stored energy reserves to aid grasses when conditions are again favorable for growth. Using the same-year reference site approach, ET_a was 57.5% lower for the TRT sites where irrigation was completely withdrawn versus their companion REF sites and only 20.9% lower for the TRT sites under partial-season irrigation withdrawal. The ET_a for TRT sites under full irrigation was then 5.2% lower and 0.6% higher compared with their respective REF sites in 2021 and 2022, indicating an overall effect of the sites returning fairly

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[1] The authors wish to note that the data used in this Technical Bulletin was supplied on November 18, 2022. The results presented here shall supersede all prior reporting documents, based on revisions to modeling approaches internal to the OpenET project. This data is available as a public record, although participant names have been coded for anonymity.

closely to expected pre-withdrawal rates of water consumption. For the partial-season withdrawal condition, the ET_a for the TRT sites was 20.9% lower than for their companion REF sites, 11.9% lower in 2021, then 0.5% higher in 2022. Another element of this work includes an intercomparison between the results of remote sensing-based modeling and field data from eddy covariance and local weather stations. Estimates of ET_a from six remote sensing-based models were compared with ET_a derived from eddy covariance instrumentation coinciding with the days of satellite passes. Among the modeled results, the determinations made by eeMETRIC agreed best with the ET_a estimates derived from the EC tower, exhibiting an average deviation from 1:1 slope = 1.00, RMSE = 1.27, and $R^2 = 0.78$, based on 50 observations. This study demonstrates that remote sensing and modeling tools are important for estimating ET_a on high elevation pastures and hay fields in Western Colorado under both irrigation withdrawal and full irrigation. As reported here, these results are based on spatial averages over the entire fields, thus representing a generalized impact of irrigation withdrawal across a diversity of field conditions. Work that will occur subsequent to this bulletin will include determinations of ET_a by different methods, which will utilize various subsets of the spatial data for these fields, in order to remove edge effects or strong outliers.

1. Introduction and Background

The Colorado Basin Roundtable (CBRT), with support from the Colorado Water Conservation Board (CWCB), initiated an evaluation of consumptive use (CU) in 2020 at a high-elevation ranching area more than 1,828 m (6,000 ft) above Mean Sea Level (MSL) near Kremmling, CO where irrigated agriculture is dominantly made up of hay fields and pastures. Remote sensing-based modeling was used to estimate CU under irrigation withdrawal (defined periods of time without irrigation) on large (200-1000 acres) high-elevation pastures characterized by various grasses, forbs, and sedges under varying soil and groundwater conditions. Irrigation withdrawal programs are a strategy used to augment flows in the Colorado River during times of natural drought and/or water sharing arrangements that compensate water rights holders for voluntarily and temporarily reducing their use of irrigation water. As such, these programs are water conservation efforts aimed at developing conserved CU (CCU), by eliminating a portion of beneficial CU inherent to a water right for an irrigated cropping system by diverting less than the right allows, presumably to convert into another beneficial use or simply to increase the supply of water within the delivery system (CAWA, 2008).

The focus of this evaluation is on the CU rates of high-elevation irrigated pastures, which comprise the majority (>80%) of Western Slope agricultural land and have not been previously well-studied. These landscapes warrant greater attention, given their heterogenous topography, micrometeorology, and underlying soil characteristics that can uniquely affect CU (Allen et al., 1998; Henning and Henning, 1981; Li et al., 2008; Goulden and Bales, 2014; Liou and Kar, 2014). Temperature and vapor pressure, for example, both decrease with increasing altitude along an atmospheric lapse rate, resulting in a decrease in CU. Conversely, lower atmospheric pressure and higher solar radiation levels at higher altitudes can contribute to an increase in CU. More accurate, scalable, and transferrable approaches to estimate CU at high-elevations are needed for agricultural water-sharing and drought resilience programs to be cost-effectively implemented, monitored, and verified across large, diverse and administratively decentralized areas (Jones and Colby, 2012).

The Landsat 8 and Landsat 9 satellites collectively capture imagery of the entire Earth every 16 days, with an 8-day offset between their passes. In this study, space-borne data from these satellites was utilized in conjunction with remote sensing-based models to assess actual evapotranspiration (ET_a) extensively agricultural field used for hay and livestock production. These models have the capability to estimate actual water consumption over substantially large geographic areas, which helps mitigate some of the limitations associated with existing methods of estimation (Burkhalter et al., 2013; Cuenca et al., 2013). For example, conventional diversion records data lacks the fine granularity necessary to estimate ET_a at the specific parcel scale where irrigation withdrawal programs are implemented (URS, 2013).

Empirical methods (Blaney-Criddle, Hargreaves, Penman-Monteith) have been used in the past to estimate water use from local weather data to calculate water balances for individual parcels but must be calibrated with local crop coefficients developed through lysimeter work, and at best provide estimates of potential[2] ET (ET_p) at high elevations (Kruse and Haise, 1974; Walter et al., 1990; Leonard Rice Consulting Engineers, 1994; Smith, 2004). For example, Pochop et al. (1984) determined that altitude-based correction factors are necessary for improving ET estimates along elevation gradients when using the Blaney-Criddle method. In some cases, the traditional methods employed by these studies have also exhibited estimation errors in semi-arid, high-elevation environments (Smith, 2008). Moreover, the use of ET_p as a basis for conservation programs can artificially inflate the quantity of CU that is presumed conserved and transferrable. Physically-based methods, on the other hand, are highly accurate for point-source measurements, but may be conducted at locations that are not reflective of the meteorological conditions for the parcels enrolled and are too costly to implement and maintain for multiple parcels across broad areas under various irrigation conditions (Walter et al., 1990; Carlson et al., 1991; Tang et al., 2009). Given the limitations of these other methods, remote sensing-based models have been adopted as a tool for large-scale CU evaluations (UCRC, 2022). Mefford et al. (2022) have also advised these models be used to improve the US Bureau of Reclamation “indicator gage method” by which seasonal CU calculations are performed to assess water supply limitations across watersheds (Bruce et al., 2018).

Certain limitations of remote sensing-based modeling should be acknowledged. To begin with, the accuracy of remote sensing models can be affected by environmental conditions, availability of local weather data, calibrations, and operator expertise. Continued ground-based monitoring, which is a specific aspect of this evaluation, is therefore critical because Landsat satellites passes (every 16 days at best for one Landsat; 8 days at best for both Landsat 8 and 7) are still infrequent enough for remotely sensed data to be limited by cloud cover, which can affect image quality, especially at higher elevation areas where cloud cover can be more frequent. This limitation can be resolved using a “time integration approach” by which the temporally irresolute ET estimates can be correlated with weekly or even daily estimates from ground-based monitoring and local reference ET using the Gridded Surface Meteorological (gridMET) dataset (Allen et al., 2007). Currently, the Landsat suite of satellites are the only space-borne units with the highest spatial resolution (100 m) for the thermal band needed for energy-balance approaches (Kjaersgaard et al., 2011). The size of this thermal band means that it can be contaminated from adjacent areas outside of the site boundaries, which imposes a minimum area requirement at which models can be used. This limitation can be resolved by resampling or disaggregating thermal data estimates down to the resolution of multispectral measurements (30 m), but can require a professional who is knowledgeable with image post-processing techniques. In fact, a threshold minimum of expertise is highly recommended to properly execute and interpret these models and assure levels of accuracy needed for effective water supply planning.

Remote sensing techniques continue to improve to address various limitations. For instance, easy access to these models, which are now automated the Google Earth Engine (GEE) on the OpenET webpage (www.etdata.org) based on the work of Melton et al. (2021), somewhat compensates for the expertise needed to execute them, although experience is still necessary in regard to their interpretation (Allen et al., 2011). It has been noted that gaps still exist between research findings and practical applications, so

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[2] Potential ET is the amount of water that is required to grow a well-watered crop under optimal conditions having a full water supply from irrigation and precipitation

evaluation projects are useful for improving awareness among water administrators about the benefits and limitations of remote sensing-based modeling (Bastiaanssen and Bos, 1999; Bastiaanssen et al., 2000; Ambast et al. 2002). Along those lines, the goal of this study is to develop, test, and evaluate spatiallybased ET modeling with remotely sensed data, and contribute to ongoing discussions on approaches to drought resilience and water supply challenges in the Colorado River Basin.

2. Study Location and Methods

The study utilized a hybrid paired site approach as its scientific basis (Clausen and Spooner, 1993). This approach compares conservation practices, or treatment (TRT) conditions, against reference (REF) conditions that are irrigated according to conventional timing and amounts. Paired sites were selected to be closely alike in terms of soil, slope, vegetation, hydrology, and weather (e.g., temperatures, precipitation), with historically similar irrigation and grazing practices. Fields in this region are irregularly shaped, however, so precisely partitioning adjacent irrigated areas equally was not possible. Instead, study locations were delineated into smaller sites where irrigation could be restricted or bypassed. Individual paired sample t-tests comparing the spatially averaged mean ET_a for the REF and TRT locations indicated non-significant differences between these fields during each of the prior years evaluated (2016-2019), thus justifying the assumption that these locations could be used as paired study areas.

The 5 primary REF sites were irrigated according to conventional timing and amounts (Table 2.1). Water conservation evaluation sites include 4 TRT sites under full-season irrigation withdrawal and 2 TRT sites under partial-season withdrawal (Table 2.1). In total, the evaluation used all 5 fully irrigated REF sites totaling 161.9 ha (400.0 ac) and separate 6 TRT sites totaling 404.2 ha (998.9 ac). Although sites BJM T1, HSR T1, JLM T1 and SBT T1 were included in the irrigation withdrawal program and evaluated for ET_a, these sites were not used in the analysis due to a lack of a true reference condition.

Table 2.1. Sites evaluated for CU and CCU in Kremmling, CO

Site Name[†]	Irrigation Practice	Acres	Hectares	Research Instrumentation*
	Included in Remote Sensing Evaluations			
GPR T1 2020	Full season, no irrigation	203.7	82.4	H/L Encl, SMS, GW, NP, EC
GPR T2 2020	Full season, no irrigation	344.9	139.6	H/L Encl, SMS, GW, NP
SBR T1 2020	Full season, no irrigation	70.2	28.4	H/L Encl, SMS, GW, NP
SPR T1 2020	Full season, no irrigation	220.6	89.3	H/L Enc, SMS, GW, NP
RCR T1 2020	Partial Season (no irrigation after June 15)	36.7	14.9	H/L Encl, SMS
RSR T1 2020	Partial Season (no irrigation after June 15)	122.8	49.7	H/L Encl, SMS, GW, NP
	Total Analyzed Treatment Sites	**998.9**	**404.2**	
	Not Included in Remote Sensing Evaluations			
BJM T1 2020	Full season, no irrigation	31.3	12.7	None
HSR T1 2020	Full season, no irrigation	83.6	33.8	None
JLM T1 2020	Full season, no irrigation	15.8	6.4	None
SBT T1 2020	Full season, no irrigation	9.1	3.7	None
	Total Non-Analyzed Treatment Sites	**139.8**	**56.6**	
GPR R1 2020	Reference, historical irrigation	94.5	38.2	H/L Encl, SMS, GW, NP
RCR R1 2020	Reference, historical irrigation	226.8	91.8	H/L Encl
RSR R1 2020	Reference, historical irrigation	20.1	8.1	H/L Encl, SMS, GW, NP

SBR R1 2020	Reference, historical irrigation	28.5	11.5	H/L Encl, SMS, GW, NP
SPR R1 2020	Reference, historical irrigation	30.0	12.1	H/L Encl, SMS, GW, NP
	Total Reference Sites	**400.0**	**161.9**	

[†] R = Reference (Historical Irrigation) and T = Treatment (Conservation Practice)

* H/L Enclosure = High (H) & Low (L) Forage Productivity Enclosure, SMS = Soil moisture sensors, GW = Groundwater observation well, NP = Neutron probe access tube location, EC = Eddy covariance tower

2.1 Study Location and Design

The study was conducted near Kremmling, CO in a headwaters area of the Colorado River over 2,200 (7,219 ft) MSL. Agricultural operations in this area are similar to those in much of the Western Slope of Colorado, where the dominant use of irrigated fields is for hay and livestock grazing. This area receives average annual rainfall of 305 mm (12 in), snowfall of 1,397 mm (55 in) and 70 frost-free days. Ranches in the study area receive irrigation water from the Colorado River and lateral diversions from Bull Run, Pass Creek, Red Dirt Creek, and Williams Fork. Water rights consists of direct flow rights that range widely from 244 – 99198 gallons/min (0.5 – 221 ft^3/s) and storage rights that range from 296,035 – 2,306,608 m^3 (240 – 1,870 ac-ft). The sites are irrigated through 18 separate ditches. It is not uncommon for Western Slope water conveyance networks to be administered with this degree of complexity.

2.2 Modeling Approach for Estimating and Mapping ET

The automated version of the Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) model (Allen et al., 2005; Allen et al., 2007) was applied to estimate ET_a at the study sites. The METRIC model uses a thermal-based energy balance approach, which relies on satellite measurements of surface temperature and surface reflectance combined with other key land surface and weather variables. Allen et al. (2011) determined that modeling by a user competent in the biophysics of modeling can be expected to produce estimates which may be 5-10% in error, but novice users may fare no better than 30-40% error. This automated version and associated calibration algorithms were developed, therefore, to improve user performance (Allen et al., 2013; Morton et al., 2013), and allow the model to be accessed through the Google Earth Engine (GEE) under an automated version of METRIC (eeMETRIC). Results from the eeMETRIC model have demonstrated conformity with other methods, including weighing lysimeter, Bowen ratio, and eddy flux techniques (Tasumi et al., 2005; Allen et al., 2007; Allen et al., 2011; Irmak et al., 2011).

The eeMETRIC model was used to study ET_a for the TRT and REF sites on a spatio-temporal basis. Model results were mapped and evaluated in QGIS (Free Software Foundation, Inc.) as raster data for the study years 2016-2021. The OpenET platform archives baseline data dating back to 2016, allowing access to the 4 years of data before this study was initiated. A paired sample t-test was used to determine significance or lack thereof between the means of the spatially averaged ETa rates for REF vs TRT sites, respectively for the fully and partially restricted conditions.

2.3 Eddy Covariance Measurements

An eddy covariance (EC) tower was constructed at the site GPR T1; 40°08’55.0” N and 106°27’11.0” W which is 2,316 m (7,600 ft) MSL north of Kremmling, CO. This tower was constructed in order to ground-truth the ET_a values provided by remote sensing-based modeling. The theoretical basis of using EC measurements to determine ET is that three-dimensional, circular eddy movement of wind carries water vapor molecules (and CO_2 and CH_4), and the speed of these eddies is measurable. The exchange of these molecules between the Earth and the atmosphere can then be determined. By concurrently using a gas analyzer, the amounts of water vapor contained in the air around the tower can be measured. The pattern of how these two variables (water vapor movement and amount) change together, or simply the covariance, is then used to determine a flux based on Rn (net radiation), LE (latent energy/heat flux), H (heat flux), and G (ground heat flux). This flux is then used to make a final determination of ET_a over the surrounding area (Allen et al., 2011; Glenn et al., 2015).

3 Results

The effect of irrigation withdrawal was quite pronounced when viewed in the field (Figure 3). In most circumstances, the participants maintained a separation between REF and TRT that was unexpectedly precise and impressive, consider the nature of the "wild flood" systems they operate.

Figure 3. Healthy vegetation under irrigated conditions abutting dry conditions where irrigation water was not applied, showing an evident difference between irrigated (REF) and non-irrigated (TRT) at the SPR R1 and T1 sites. Photo taken August 27, 2020.

3.1 Normalized Difference Vegetation Index (NDVI)

Figure 3.1.1 [left] shows the mean Normalized Difference Vegetation Index (NDVI) mapped for the study sites for May-June. The NDVI measurement quantifies the appearance of vegetation by measuring the difference between the magnitudes of near-infrared (NIR) and infrared (IR) radiation from the Earth surface. Healthy vegetation (chlorophyll) reflects more near-infrared (NIR) and green light compared to other wavelengths, but it absorbs more red and blue light. These measurements define an indexed ratio from -1 to +1, which defines a range because the signature for each type of land cover exists along a

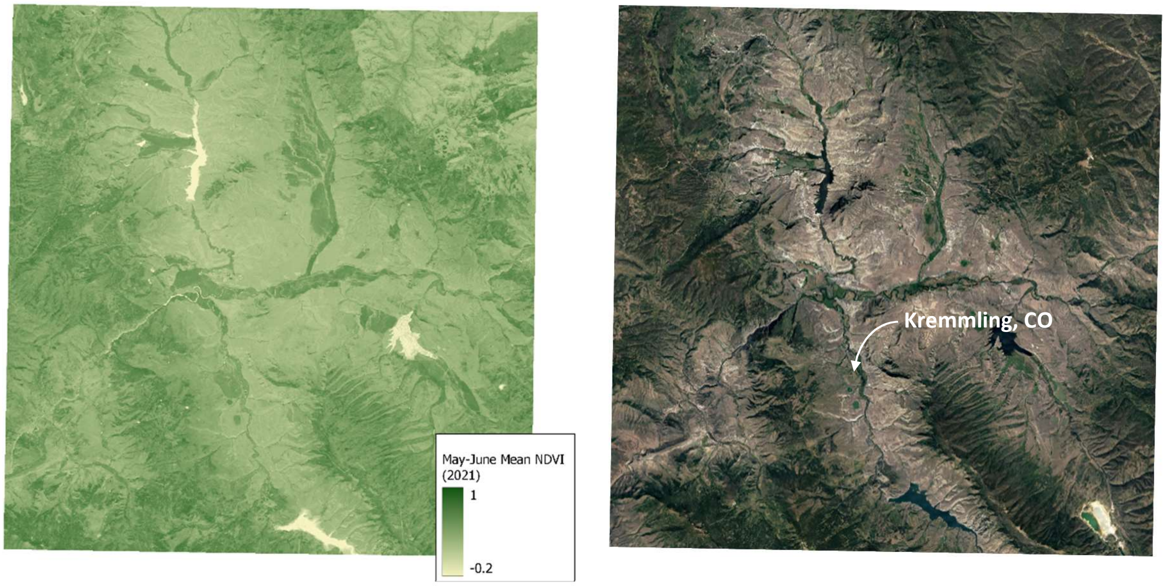

Figure 3.1.1. Mean Normalized Difference Vegetation Index (NDVI) of study area in Grand County at the Upper Colorado headwaters for May-June during the height of the irrigation season (left) and for the entire study area (right).

spectrum. More negative values likely represent water, while values closer to +1 are likely dense green leaves. An NDVI close to zero indicates very few green leaves and bare soil surface.
The various land surfaces are depicted for the entire study area (Figure 3.1.1). The difference in NDVI across the study area near Kremmling, clearly depicts the impact of irrigation the hay production and pastured fields, where these practices are critical to maintaining vegetation.

3.2 Spatial Mapping and Summary of ET rates

Summary ET_a statistics for all pixels that comprise the GIS polygon for each site are provided with the eeMETRIC code outputs. The count of pixels for each site is generally consistent across dates and years, however the values may decrease when clouds are present, as these local weather conditions can invalidate a few of the border pixels.

Figure 3.2.1 shows an example of spatially mapped ET_a. The influence of neighboring conditions on the different sites is evident at the borders, due to irrigation practices and landscape features overlapping between the delineated sites. Despite the management action taken to eliminate water availability to the treatment sites, for instance, the vigor of the grass vegetation still varies spatially. The variations can occur due to subsurface conditions, such as soil types, affected root zone depth, and availability of groundwater from either stored soil moisture or proximity to a neighboring water source, such an active irrigation supply ditch or the river itself. In the case of REF site GPR R1, for instance, there is a dramatic decrease in ET on the southern boundary of the site, adjacent to the TRT site GPR T1. Conversely, the northern boundary of GPR T2 was impacted by seepage from an irrigation water delivery ditch, which sub-irrigated the site and promoted vegetative growth. Neighboring effects such as these are real biophysical processes with actual outcomes, however, which are unavoidable but will also influence spatially aggregated ET data.

Figure 3.2.2 shows other effects of border conditions that were evident at the SBR T1 fields, where the presence of an onsite pond caused an obvious increase in ET_a in the immediate vicinity of this water feature. Additionally, the location of the eastern border of the field was clearly affected by proximity to the Colorado River, although the western border was not impacted by the sharing a boundary with the same watercourse. These maps may also reflect patterns of grazing, animal activity and shading from trees. In the case of SBR, both fields were affected by management decisions regarding the cost of nitrogen fertilizer, which the farmer chose not to apply in 2020. Continued effects of fertilizer prices and other exogenous impacts will impact ET_a rates, as well as underlying biophysical conditions.

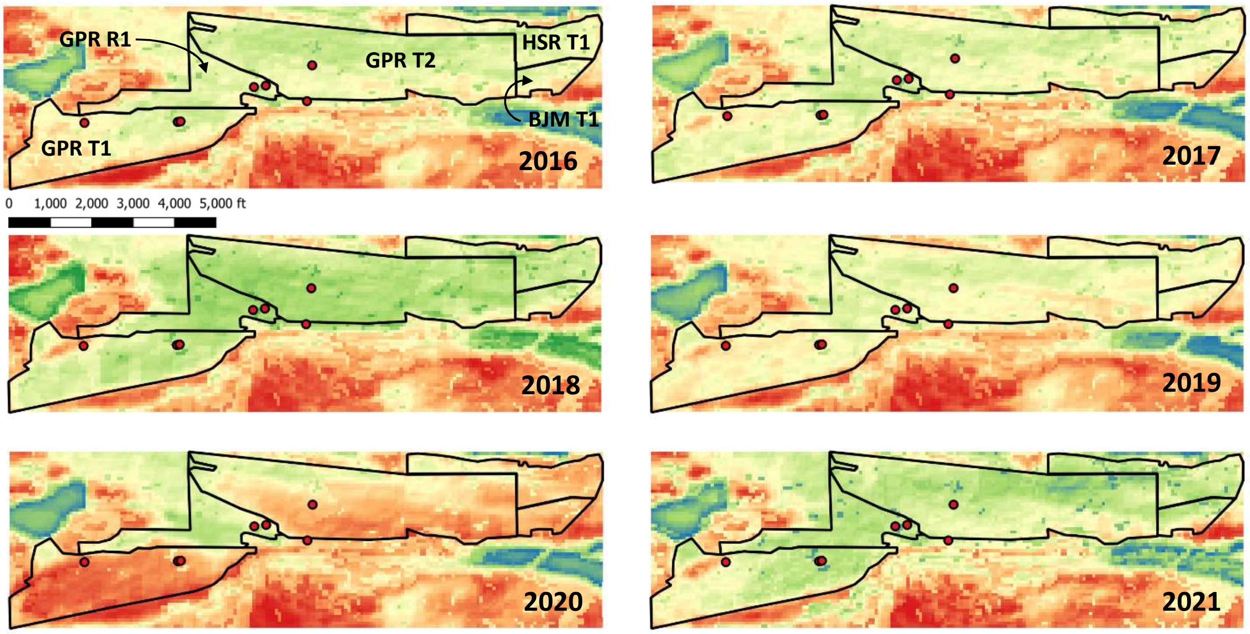

Figure 3.2.1. Spatial distribution of annual ET_a during years prior to curtailment (2016-2019), irrigation shutoff year (2020), and return year (2021) for GPR R1, GPR T1, GPR T2, BJM T1, and HSR T1. Forage and instrumentation enclosures are designated by a red dot symbol. The red to green color ramp is a visual quantification of annual ET_a from 100 mm (3.93 in) to 1,000 mm (39.4 in)

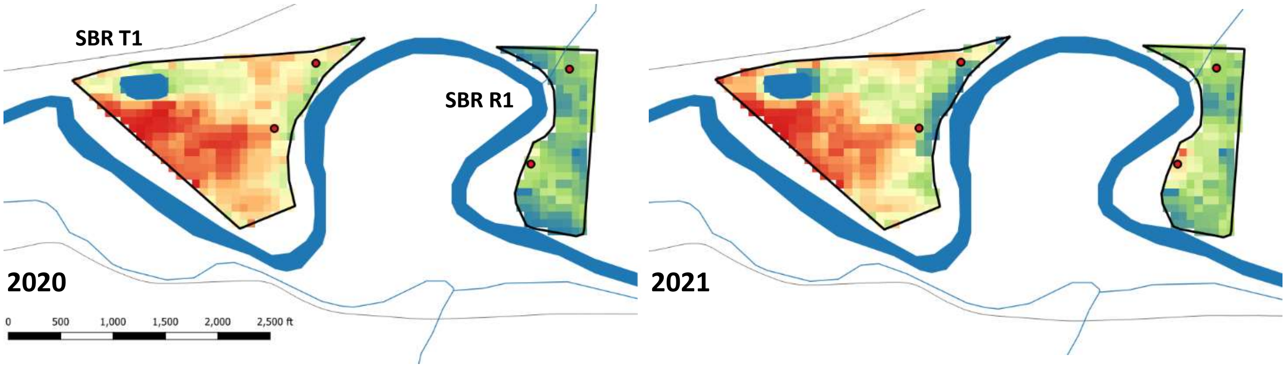

Figure 3.2.2. Spatial distribution of annual ET_a for the irrigation shutoff year (2020) and return year (2021) for SBR R1 and SBR T1. Forage and instrumentation enclosures are designated by the red dot symbol. For these maps, the red to green color ramp is a visual quantification of 100 mm (3.93 in) to 1,000 mm (39.4 in).

3.3 Modeling Consumptive Use

Table 3.3.1 summarizes basic ET data for May through September, which represents the dominant actual growing season of this part of the state. Estimation of wintertime demands are less certain, so the May-Sept timeframe also removes some of this uncertainty, especially since the Carlson et al. (1990) Grand County study did not include estimates for 1987-1990 Jan, Feb, Mar, Nov, and Dec. Thompson (2021) estimated May-Sept ET_p from DWR Mountain Meadow crop coefficients at Kremmling NOAA Weather Station USC00054664 to be 695 mm (27.35 in). Data from the CSU CoAgMet station northeast of Kremmling, CO was used to calculate ET_p using the ASCE Standardized Reference Evapotranspiration Equation (ASCE-EWRI, 2005) and evaluated to be 764 mm (30.08 in). Results from the lysimeter study conducted in Grand County by Carlson et al. (1991) estimated ET for this region at 708 mm (27.87 in) for May-Sept.

Estimates were also made for ET_a using remote sensing-based models. For the summary in Table 3.3.1, the May-Sept monthly ET_a totals from eeMETRIC were based on spatial averages for the GPR T1, GPR T2, RCR T1, RSR T1, SBR T1, SPR T1, GPR R1, RCR R1, RSR R1, SBR R1, and SPR R1 sites in order to determine baseline, pre-withdrawal conditions for all prior years (2016-2019) for the region of the study. This selection of sites represents over 607 ha (1,500 ac), equaling 87.7% of the monitored area, since BJM T1, HSR T1, JLM T1 and SBT T1 are too small to get an accurate estimation. It should be noted that these spatial averages constitute the entirety of pixels analyzed within the field boundaries, and 1 ha (2.47 ac) contains approximately 11 (30 m x 30 m) pixels. The mean site area of the analyzed fields is 51.5 ha (127.2 ac), ranging from 8.1-139.6 (20.1-344.9 ac) so these spatial averages utilize approximately 6,677 individually analyzed pixels. For example, at 82.4 ha (203.7 ac) and 139.6 ha (344.9 ha), the GPR T1 and GPR T2 site ET_a averages are based on 915 and 1,551 separate estimations. Annual ET_a rates for the study sites were then determined from the spatially averaged monthly means and totaled to calculate the May-Sept total ET_a. Across all sites, the spatially averaged May-Sept ET_a rates estimated by eeMETRIC were 601 mm (23.67 in) for the 4 years prior to the study.

The OpenET platform also provides an "Ensemble" average that provides another ET_a estimate based on eeMETRIC, along with four other models, including ALEXI/disALEXi (Anderson et al., (2007, 2018), PT-JPL (Fisher et al., 2008), SIMS (Melton et al., 2012; Pereira et al., 2020), and SSEBop (Senay et al., 2014; Senay et al., 2018) on the Median Absolute Deviation (MAD), explained by Melton et al. (2021) and the OpenET methods: https://openetdata.org/methodologies/. For comparison, May-Sept total ET_a calculated from this Ensemble method was 635 mm (25.00 in), for the 4 years prior to the study, showing the importance that model selection can have on these estimates. Also shown are the results from the SSEBop model, which is a simplified method in which certain components of the energy balance are not estimated or are calculated using simplifying assumptions. The May-Sept total ET_a using this method was calculated as 480 mm (18.89 in).

Table 3.3.1. Comparison of ET_p to ET_a on Evaluation Sites (Average for 2016-2019)*

ET in inches	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	May-Sep
Estimated ET_p[1]	0.14	0.21	0.41	1.28	4.72	7.41	6.54	5.33	3.35	0.52	0.24	0.10	27.35
ASCE-EWRI ET_p[2]	0.00	0.00	0.00	0.60	5.09	6.43	6.98	5.09	4.28	1.21	0.00	0.00	27.87
Lysimeter ET[3]	0.00	0.00	0.00	3.80	5.17	6.42	6.73	6.13	5.63	3.03	1.42	0.73	30.08
SSEBOP ET_a	0.19	0.34	0.43	0.78	2.05	5.20	6.05	3.79	1.79	0.64	0.34	0.18	18.89
eeMETRIC ET_a	0.12	0.39	1.02	1.07	2.56	6.48	7.26	4.98	2.39	1.30	0.57	0.19	23.67
Ensemble ET_a	0.13	0.44	0.98	1.65	3.20	6.64	7.58	5.14	2.44	1.14	0.57	0.19	25.00

*2016-2017 data was not available for ASCE-EWRI ETp calculations

[1] PET calculated using DWR Mountain Meadow crop coefficients at Kremmling NOAA station USC00054664 (Thompson, 2021)

[2] PET calculated with data from CSU CoAgMet station (40°06'55.44" N, 106°16'58.80" , 2,296 m (7,534 ft) MSL northeast of Kremmling, CO using the ASCE Standardized Reference Evapotranspiration Equation (ASCE-EWRI; 2005) with grassy hay crop coefficients.

[3] From Grand County Lysimeter Results from Carlson et al. 1991, as calculated using average of Blaney-Criddle crop coefficients (from Smith et al. 2008) at Kremmling NOAA in StateCU

Similarity between the ET_p and lysimeter rates is expected, given that both of these approaches are designed to estimate ET for well-watered systems. The estimations produced from the remote sensing-based models, however, clearly depict the difference between ET_p and ET_a, observing that the ET_p approaches likely overestimate the amount of water consumed on these landscapes. More specifically, it is recognized that reference ET equations do not represent measurable quantities during non-growing periods, suggesting another value of remote sensing-based modeling lies in the capability for better estimating ET_a at lower temperature ranges. Reference ET equations also do not capture the phase during re-growth after cutting.

3.4 Determining Conserved Consumptive Use

A major premise of this study is that, if all other factors (e.g., crop type, field area) remain the same, sites under irrigation withdrawal are expected to show diminished CU compared with paired reference sites that represent historical irrigation patterns. Foregone diversions and reduced irrigations would therefore shift a proportion of historical, beneficial CU originating from a water right to be made available elsewhere in the system (CAWA, 2008) The basis for these calculations is the timeseries of monthly ET_a rates for the study period between 2016-2021. The ET_a data for the withdrawal year were used to calculate CCU based on two different approaches, similar to other studies that have evaluated the impacts of reduced irrigation (Allen and Torres-Rua, 2018).

Table 3.4.1 summarizes the monthly ET_a for the 161.9 ha (400.0 ac) of REF sites (GPR R1, RSR R1, RCR R1, SBR R1, SPR R1) during the 4-years (2016-2019) prior to the study, during the withdrawal year (2020) when water conservation practices occurred, and the following two years when irrigation was restored to pre-withdrawal practices (2021-2022). Across all years, the REF sites illustrate a relatively stable pattern of May-Sept ET_a, averaging 599 mm (23.59 in) with a coefficient of variation of 1.92%. Based on the TR21 SCS effective precipitation (P_e) method, values acquired from the StateCU model using the USC00054664 KREMMLING station were 116 mm (4.56 in), 102 mm (4.02 in), 40 mm (1.58 in), 72 mm (2.85 in), 85 mm (3.30 in), 87 mm (3.44 in), and 92 mm (3.23 in) for 2022, 2021, 2020, 2019, 2018, 2017 and 2016, respectively. After subtracting these amounts from the total ET_a rates, the May-Sept adjusted ET_a (May-Sep$_{adj}$) can be reported to average 516 mm (20.31 in). The impact of the 2020 drought year is evident. Higher temperatures associated with drought conditions likely drove increases in ET_a which then diminished in subsequent years possibly due to the impact of plant damage suggested by relatively lower May ET_a rates. Despite these diverse weather conditions, ET_a rates from 2016-2022 on the REF sites exhibited a 3.87% coefficient of variation, still well within the range of low variability and indicating reasonable stability in the fraction of water consumption provided by irrigation.

Table 3.4.1 Comparison of ET_a on analyzed Grand County REF sites between 2016-2022 using eeMETRIC.

ET_a (inches)															
Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**May-Sep**	**May-Sep$_{adj}$**	**P_e (in)**
Full Season Irrigation Withdrawal															
2016	0.01	0.13	0.65	0.96	2.26	6.57	7.83	4.90	2.30	2.00	0.50	0.10	23.85	20.62	3.23
2017	0.07	0.64	1.36	0.85	2.70	6.44	6.88	5.25	2.49	1.54	1.05	0.57	23.77	20.33	3.44
2018	0.36	0.49	1.55	1.51	3.36	6.94	7.03	4.13	2.72	1.26	0.33	0.09	24.18	20.88	3.30
2019	0.01	0.11	0.40	1.29	2.41	5.78	7.24	5.84	2.50	1.03	0.46	0.03	23.78	20.93	2.85
2020	0.01	0.05	0.49	1.39	3.57	6.79	7.15	4.78	3.14	0.95	0.20	0.02	25.43	23.85	1.58
2021	0.00	0.10	0.61	1.81	1.79	5.64	6.41	4.83	3.05	2.01	0.92	0.29	21.72	17.70	4.02
2022	0.05	0.00	0.43	0.92	1.84	6.33	6.88	5.03	2.37	1.19	0.42	0.01	22.46	17.90	4.56

3.4.1 Conserved Consumptive Use based on Prior Years ET

One approach to estimate the amount of CCU originating from a site under withdrawal is to use a Prior Years Approach. For this approach, the eeMETRIC-modeled average site ET_a during the withdrawal period is compared with ET_a for the same site during prior years. As such, data from prior years is used to set a baseline ET_a for a selected set of sites. This approach assumes that weather conditions in previous years are similar to the withdrawal year and subsequent recovery years. This assumption is posited to be acceptable, given the relatively low coefficient of variation of ET_a during the period 2016-2022.

Furthermore, analysis of temperature across the study period indicates fairly low variability (< 10%) during the May-September growing season (Table 3.4.1.1)

Table 3.4.1.1 Local Temperature Data (°F) for Kremmling, CO

Month	2021	2020	2019	2018	2017	2016	Mean	CV
January	1.40	13.63	14.91	11.73	18.30	5.90	13.00	50.93%
February	6.36	19.81	10.98	15.93	25.30	17.10	30.30	45.31%
March	20.05	25.26	27.39	24.58	32.20	30.50	36.40	19.37%
April	35.98	36.58	36.29	39.16	42.08	39.00	39.00	5.69%
May	45.88	45.82	48.23	41.88	48.87	46.30	45.80	4.87%
June	55.90	57.91	55.73	52.21	57.27	59.90	58.60	4.39%
July	60.74	61.63	58.54	59.13	61.17	62.40	64.30	3.19%
August	58.32	56.51	57.97	57.20	56.81	58.40	59.40	1.76%
September	51.76	50.16	48.54	51.34	50.57	53.30	53.50	3.42%
October	37.20	37.75	36.07	29.71	38.46	44.40	38.20	11.54%
November	21.09	31.92	26.86	25.75	22.49	33.10	35.40	19.54%
December	12.01	20.37	12.16	11.48	13.33	16.00	19.60	24.84%

The amount of CCU calculated using the Prior Years Approach is equal to the spatially averaged ET_a for the TRT sites during withdrawal, subtracted from the ET_a for these same sites during prior years, thereby ensuring that the analysis is performed on withing the same physical boundaries. The major limitation of this method is that it does not consider if a site may have been historically water-supply limited due to irrigation supply or farming practices or, on the other hand, if P_e rates, early season soil moisture and groundwater contributions have been markedly different in prior years. In other words, using the Prior Years Approach may lower the amount of CCU if the site under withdrawal site has received significantly less irrigation in the past, although this issue is resolved as more data is taken into account with the addition of more analysis from prior years. Rates for P_e can be calculated for each prior year as an additional analysis step analysis but would require instrumentation for monitoring soil moisture and groundwater.

Table 3.4.1.2 summarizes the 2016-2022 ET_a for the TRT sites. Based on the prior years approach, the spatial average of May-Sept ETa was 53.4% lower for sites where irrigation was completely withdrawn in 2020 versus the 2016-2019 baseline average for these same sites. Subsequently, May-Sept ETa rates in 2021 and 2022 were 13.9% and 1.7% lower, respectively, than the same 2016-2019 baseline. The sites that adhered to a partial-season approach where irrigation was withdrawn after June 15, 2020, exhibited May-Sep ETa that was 14.7% lower than the 2016-2019 baseline average for these same sites, then exhibited rates in 2021 and 2022 that were 16.1% and 6.6% lower than the baseline (Table 3.4.1.1). In general, fully restricted treatment fields appeared to return more vigorously to prior year ET_a after the period of water stress, compared with the fields under partial-season withdrawal. This trend continued in the second year, possibly due to more favorable soil conditions or the accumulation of fructans before dormancy, allowing stored energy reserves to aid grasses when conditions are again favorable for growth. Previous studies have also shown that partial-season withdrawal programs generate limited CCU (Allen and Torres-Rua, 2018; Cabot et al., 2018), although there are clear environmental benefits, such as streamflow enhancement.

Table 3.4.1.2 Baseline 2016-2019 TRT Fields ET_a compared with impact and recovery year TRT Fields ET_a

Site Name	2016-2019 Baseline	2020 vs Baseline	2021 vs Baseline	2022 vs Baseline

	TRT ET_a	TRT ET_a	Change	TRT ET_a	Change	TRT ET_a	Change
			Full Season Irrigation Withdrawal				
SPR	22.85	14.45	-36.8%	17.18	-24.8%	21.12	-7.6%
SBR	21.99	11.81	-46.3%	20.51	-6.8%	22.39	1.8%
GPR T1	23.63	6.22	-73.7%	21.12	-10.6%	23.53	-0.4%
GPR T2	25.89	11.15	-56.9%	22.37	-13.6%	25.72	-0.7%
Average	**23.59**	**10.91**	**-53.4%**	**20.30**	**-13.9%**	**23.19**	**-1.7%**
		Partial-Season Irrigation Withdrawal (no irrigation after June 15)					
RSR	24.57	20.45	-16.8%	21.40	-12.9%	22.25	-9.4%
RCR	21.97	19.19	-12.7%	17.73	-19.3%	21.14	-3.8%
Average	**23.27**	**19.82**	**-14.7%**	**19.57**	**-16.1%**	**21.70**	**-6.6%**

One issue that is strikingly obvious from the Prior Years Approach analysis is that there are lingering impacts to fields that are enrolled in irrigation withdrawal programs. As shown in this analysis, these impacts can persist for several years, raising questions as to whether these lag effects of diminished CU should be incorporated into CCU estimates for the entirety of the program.

3.4.2 Spatially averaged Conserved Consumptive Use from Reference Site ET

Another approach to estimating CCU amounts is to compare modeled site ET_a averages between the REF and TRT sites only for the withdrawal year. The Reference Site Approach is simple because it does not require estimating changes in effective precipitation, irrigation, available soil moisture, or groundwater contribution (where applicable) that could affect the baseline used in the Prior Years Approach. Additionally, this approach can obviate the effect of varying local weather conditions, such as drought, since the same year comparison considers local weather conditions as causing equal impact to the REF and TRT fields. Using the Reference Site Approach, the amount of CCU is equal to the ET_a for the TRT sites subtracted from the ET_a for their comparison REF site. The major limitation of this method is that it assumes the selection of a comparable REF condition, and thus does not consider specific site differences that may be caused by pasture health, soil fertility, or underlying soil conditions. The purpose of selecting sites with considerable size and spatial variability for this project was to ameliorate some of these concerns by acquiring large enough datasets.

Using the same-year reference site approach, ETa was 57.5% lower for the TRT sites where irrigation was completely withdrawn versus their companion REF sites and only 20.9% lower for the TRT sites under partial-season irrigation withdrawal. The ETa for TRT sites under full irrigation was then 5.2% lower and 0.6% higher compared with their respective REF sites in 2021 and 2022, indicating an overall effect of the sites returning fairly closely to expected pre-withdrawal rates of water consumption. For the partial-season withdrawal condition, the ETa for the TRT sites was 20.9% lower than for their companion REF sites, 11.9% lower in 2021, then 0.5% higher in 2022.

Table 3.4.2.1 Reference Field ET_a compared with TRT Field ET_a during impact and recovery years

	2020 Impact Year			2021 Recovery Year 1			2022 Recovery Year 2		
Site Name	**REF**	**TRT**	**Change**	**REF**	**TRT**	**Change**	**REF**	**TRT**	**Change**
				Full Season Irrigation Withdrawal					
SPR	23.57	14.45	-38.7%	15.32	17.18	12.1%	19.81	21.12	6.6%
SBR	28.02	11.81	-57.8%	24.45	20.51	-16.1%	23.59	22.39	-5.1%

GPR T1	25.43	6.22	-75.5%	24.48	21.12	-13.7%	25.73	23.53	-8.6%
GPR T2	25.43	11.15	-56.1%	24.48	22.37	-8.6%	25.73	25.72	0.0%
Average	**25.67**	**10.91**	**-57.5%**	**21.42**	**20.30**	**-5.2%**	**23.04**	**23.19**	**0.6%**
Partial-Season Irrigation Withdrawal (no irrigation after June 15)									
RSR	27.60	20.45	-25.9%	23.59	21.40	-9.2%	23.53	22.25	-5.4%
RCR	22.52	19.19	-14.7%	20.76	17.73	-14.6%	19.65	21.14	7.6%
Average	**25.06**	**19.82**	**-20.9%**	**22.18**	**19.57**	**-11.8%**	**21.59**	**21.70**	**0.5%**

Paired sample t-tests comparing the spatially averaged mean ET$_a$ for the REF and TRT (fully restricted) locations in 2020, 2021 and 2022 resulted in p-values of 0.006, 0.244, and 0.539, respectively, indicating a trend towards non-significance in ET$_a$ rates and suggesting a slow return to pre-program conditions after 2 years with continued lag effects.

3.5 Conserved Consumptive Use Amounts for Study Area

Below, we calculate total CCU for a selection of sites that represented 87.7% of the monitored area, since several smaller sites included in the irrigation withdrawal program did not have adequate reference locations. This summary of CCU amounts was based on the acreage of the fields and described an overall impact of the project at a larger scale. Amounts were compared between the Prior Years and Reference Site Approaches (Table 3.5.1 and Table 3.5.2).

Table 3.5.1 Summary of CCU for project evaluation area based on Prior Years Approach.

			2020		**2021**		**2022**		**Overall**
Site	**Site Area** (ac)	**2016-2019 Baseline** (in)	**TRT ET$_a$** (in)	**CCU** (AF)	**TRT ET$_a$** (in)	**CCU** (AF)	**TRT ET$_a$** (in)	**CCU** (AF)	**CCU** (AF)
SPR	220.7	22.9	14.4	154.6	17.2	104.3	21.1	31.8	290.7
SBR	70.3	22.0	11.8	59.6	20.5	8.7	22.4	-2.3	66.0
GPR T1	203.1	23.6	6.2	294.5	21.1	42.4	23.5	1.6	338.6
GPR T2	345.7	25.9	11.2	424.7	22.4	101.5	25.7	5.0	531.2
RSR	123.3	24.6	20.5	42.3	21.4	32.6	22.3	23.8	98.7
RCR	37.6	22.0	19.2	8.7	17.7	13.3	21.1	2.6	24.6
Total				**984.6**		**302.7**		**62.5**	**1349.8**

Table 3.5.1 Summary of CCU for project evaluation area based on Reference Site Approach.

		2020			**2021**			**2022**			**Overall**
Site	**Site Area** (ac)	**REF ET$_a$** (in)	**TRT ET$_a$** (in)	**CCU** (AF)	**REF ET$_a$** (in)	**TRT ET$_a$** (in)	**CCU** (AF)	**REF ET$_a$** (in)	**TRT ET$_a$** (in)	**CCU** (AF)	**CCU** (AF)
Full Season Irrigation Withdrawal											
SPR	220.7	23.6	14.4	167.8	15.3	17.2	-34.2	19.8	21.1	-24.2	109.4
SBR	70.3	28.0	11.8	94.9	24.5	20.5	23.1	23.6	22.4	7.0	125.0
GPR T1	203.1	25.4	6.2	325.1	24.5	21.1	56.9	25.7	23.5	37.2	419.1
GPR T2	345.7	25.4	11.2	411.4	24.5	22.4	60.8	25.7	25.7	0.3	472.5

Partial-Season Irrigation Withdrawal (no irrigation after June 15)											
RSR	123.3	27.6	20.5	73.5	23.6	21.4	22.5	23.5	22.3	13.2	109.1
RCR	37.6	22.5	19.2	10.4	20.8	17.7	9.5	19.7	21.1	-4.7	15.3
Total				**1083.1**			**138.5**			**28.9**	**1250.5**

3.6 Comparison Between Modeled Results and Eddy Covariance Measurements

The modeled ET estimates from eeMETRIC were compared with the onsite measurements of ET_a made from the eddy covariance (EC) tower instrumentation. This comparison consists of assuming that vapor flux conditions in an area near the tower location represent the conditions observed by the flux footprint that contributes to the EC measurements (Heinsch et al., 2006). One approach to selecting the area to compare with the EC tower conditions is to derive a static set of pixels from the Landsat 30-meter grid, based on the long-term daytime wind direction and speed, and site homogeneity. For this comparison, three different static areas were used, determined by 3x3, 5x5, and 7x7 pixel grids, representing surrounding areas of 0.81 ha (2.00 ac), 2.25 ha (5.56 ac), and 4.41 ha (10.90 ac). The second approach is to use a dynamic pixel fetch-footprint to create hourly “dynamic” flux footprints that are weighted by hourly reference ET (ET_r) before making daily and monthly normalized footprints (Kljun et al., 2015). Comparisons were made for the “full period,” which refers to any and all data available. In the case of the Kremmling, CO location, the full period is the same as the growing season, due to the station being powered down from operation during the winter.

Based on the comparison with the ET_a rates derived from the EC technique, eeMETRIC corresponds well at both ends of the vegetative spectrum, showing strong predictive correlation for healthy, well- irrigated vegetation, as well as at the lower ends of the range when sites were subjected to irrigation withdrawal. The selection of eeMETRIC as the preferred model is based on a holistic assessment, taking into account all of the comparative statistical metrics.

Figure 3.5.1 shows the comparison between modeled ET_a from the six remote sensing-based models and the ensemble, compared with EC-derived ET_a on the days of satellite passes.

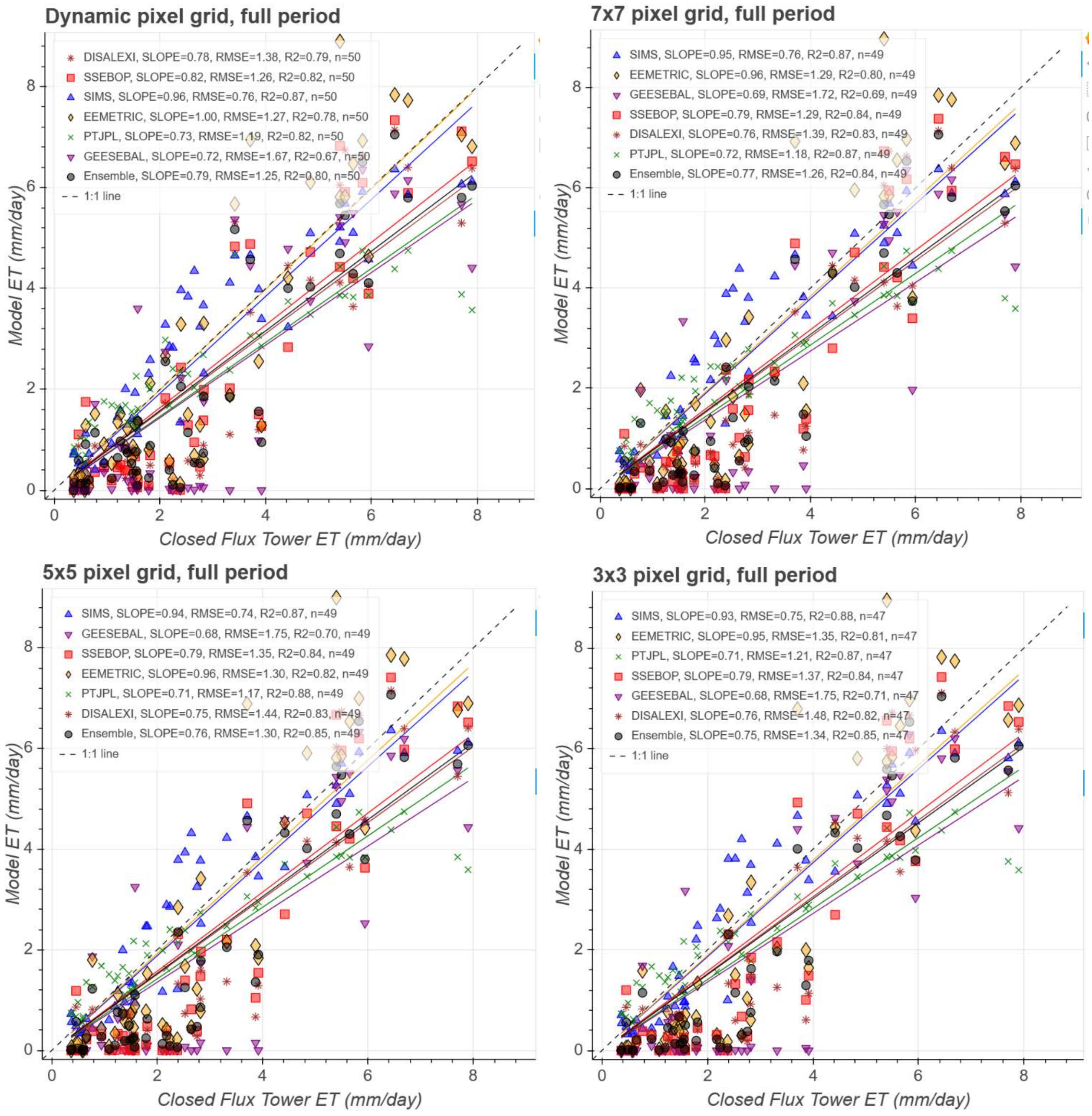

Figure 3.6.1 Plots comparing ET rates from EC Tower against modeled ET rates from remote sensing data. Data for these charts was provided February 7, 2023 by the Desert Research Institute. These plots supercede all others have have been reported prior to the issuance of this technical bulletin.

Among the modeled results, the determinations made by eeMETRIC agreed best with the ET_a derived from the EC tower, based on an average slope = 1.00, RMSE = 1.27, and $R^2 = 0.79$. This comparison indicates that eeMETRIC appears to perform better under a variety of circumstances important to high-elevation pasture. The slope close to 1.0 demonstrates that eeMETRIC performs accurately under the irrigation withdrawal conditions, whereas temperature-based models such as SSEBop and GEESEBAL produced values of near zero during irrigation withdrawal. These low values are not realistic, given residual soil moisture and the data derived from the EC tower. On the other hand, the PT-JPL model agreed well with EC measurements under the water-deficit conditions, but it underpredicted for well-watered conditions. The SIMS model is an idealized model used for irrigation management in California, is entirely based on NDVI and uses a fixed set of crop FAO-56 coefficients from the landcover/crop classification of CDL (USDA Cropland Data Layer). It is built on idealized well-managed, well-watered conditions and considered unsuitable for estimating ET for any sort of deficit irrigation scenarios. One explanation for why eeMETRIC performs relatively better than other models against the ET_a estimates from the EC tower is that it combines the use of NDVI, temperature, and albedo as inputs of an energy balance model, whereas SSEBop relies heavily on temperature, for instance, and a model like SIMS leans almost exclusively on NDVI. These additional parameters likely improve the performance of eeMETRIC in estimating ET_a at both the low and high end of the spectrum (Bromley, 2023).

4. Discussion

Given recent developments in the adoption of remote sensing tools by water administrative agencies, this research lends validation to the use of this technology for individual projects and broader programmatic and policy purposes. In particular, the Upper Colorado River Commission (UCRC) recently issued a resolution on the methods and processes for estimating agricultural CU, stating that the “Commission and Upper Division States unanimously support the Commission's use of eeMETRIC to measure Upper Basin agricultural consumptive use” and instructed UCRC staff to work with the Upper Division States [Colorado, New Mexico, Utah, and Wyoming] to “implement the use of eeMETRIC to measure agricultural consumptive use” (UCRC, 2022). The resolution further stipulates that “as the science evolves and improved consumptive use measurement methods develop, the Commission will continue to work with the Upper Division States and coordinate with Reclamation to monitor progress and institute improvements.”

Results from this study support the UCRC’s decision to select eeMETRIC to provide consistency in how CU is estimated across the Upper Division States. Other models perform reasonably well, still estimating ET_a values below ET_p, but are not as well-correlated with in-field instrumentation. The SIMS model demonstrates a reasonably good level of performance, although it arrives at a suitable answer while using a suboptimal approach. The underestimation presented by the SSEBop model thorough most of the season would affect an estimated CCU rate by suggesting perhaps that the amount of conserved water might be greater than likely, or that less available CU exists in the landscape than might otherwise be the case.

By comparing ET_a modeled with remote sensing data against ET_a derived from eddy covariance instrumentation, water consumption in drier conditions was able to be detected, without forcing estimates to zero. This is an important result, as it can significantly affect the amount of CCU that is presumed for fields that are implementing water conservation activities. The reductions in CU for May-Sept estimated by this study range between 53.4 - 57.5%, for sites under full withdrawal, depending on the analysis method. Similarly, for sites where water conservation was based on a partial-season approach and had irrigation restricted after June 15, CU reductions are estimated to range from 14.7 - 20.9%. As reported by Mefford et al. (2022), caution is warranted in the application of remote sensing models, as the use of these tools involves a degree of expertise that can be consequential to the quality of the results. The procedure to determine the amount of CCU that could originate from water conservation activities should adhere to the same level of diligence. Precipitation (rainfall and snow) in Kremmling has been measured at 226 mm (8.9 in), 215 mm (8.5 in), 124 mm (4.9 in), 142 mm (5.6 in), 338 mm (13.3 in), 259 mm (10.2 in), and 281 mm (11.1 in), for 2022, 2021, 2020, 2019, 2018, 2017 and 2016, respectively. Nevertheless, because precipitation rates have been on the decline in recent years, the slight rate of change may impact the prior year baseline used in this study, although ET_a in previous years did not differ greatly from the evaluation year. It is also noted that because the intent of remote sensing-based modeling is to estimate an actual rate of ET happening in the specific biophysical system where measurements are being taken, this means that all manner of field operations will also be taken into account and thus the assigning of a precise baseline is spurious. All ranching operations, for example, will make management modifications for fertilizer rates, hay cutting schedules, and grazing plans, thereby compelling endogenous variables to affect ET_a as well as local weather.

This study also presents the perspective that water conservation programs must be viewed in the context of a multi-year phased process. One observation made in this study is that sites experiencing full withdrawal clearly affected the conservation of water by the reduction in ET_a during the year of program participation. However, upon receiving irrigation water the following spring, ET_a rates still lagged compared with prior years on the same study sites, and compared with their reference conditions during the same year. On the other hand, the sites where a partial-season form of irrigation withdrawal was practiced showed minor reductions in ET_a during the program year, but also did not rebound as rapidly during the subsequent year. The suppressed CU rates after the program year of irrigation indicate that some water conservation might still be occurring during the years following withdrawal, suggesting that multiple years of consideration could be part of the measurement and verification aspects of any water conservation program.

5. Conclusions

This study has demonstrated that remote sensing and modeling are important tools for estimating ET_a on high elevation pastures and hay fields in Western Colorado under both irrigation withdrawal and full irrigation. While fields exhibit geographic and biophysical variability due to the influence of underlying conditions, the eeMETRIC model produces valuable spatial averages that are not overly influenced by this natural heterogeneity or the special conditions of high-elevation pastures and fields under dryup conditions.

Further analysis is recommended in order to develop the findings of this study in greater detail. Two outstanding questions emerged during the ongoing analysis of the spatial data. The first question deals with whether the spatially averaged ET_a rates assigned to the fields change measurably if the pixels used in calculating these results are selected using another heuristic beside a spatial average for the whole field. For instance, subsequent analysis will examine the change in both the ET_a as well as CCU if the spatial average is based on a different "core" group of pixels that have been screened for neighboring effects. Possible approaches might include a surrounding buffer of 1 or 2 pixels to remove any edge effects, using a statistical approach to dealing with outliers near underlying water sources such as ponds, ditches or watebodies, taking only those measurements within a single standard deviation of the mean, or basing an acceptable population of measurements on a median value, rather than an average. The second question entails using other spatial statistical variables or forms of analysis that can be used to understand the patterns of ET_a rates. These approaches would include evaluations of spatial autocorrelation or semivariograms for the spatial data.

There are several next steps in this research process to continue performing evaluations. First, the remote sensing-based model results will be compared with a data set of soil moisture measurements collected at the sites. These measurements were taken using Acclima TDR-315 sensors and Solar DataSnap SDI-12 data loggers (Acclima, Inc., Meridian, ID) for soil moisture sensor measurement at depths of 6, 18, 30 and 42 cm. Using this data, effort will be made to develop a water balance that can be used to further compare the ground conditions with the satellite-based modeling results. Additional utilization of local atmometer (ETgage Company, Loveland, CO) and raingage data will assist in understanding the local water balance and performing comparisons. Secondly, the ET_a data will also be utilized to produce crop production functions that help normalize the amount of CU required to produce a unit of dry matter forage. Understanding this relationship better can increase communication during negotiations for water sharing. Lastly, further data will be made available for the remainder of 2022 and be included in subsequent reports, as well as data from the 2023 cropping season.

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Appendix

Comparison of ET_a on Grand County TRT sites between 2016-2022 using eeMETRIC.

	ET_a (inches)													P_{eff} (in)	
Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**May-Sep**		**May-Sep**
Full Season Irrigation Withdrawal															
2016	0.02	0.07	1.04	1.63	2.36	7.11	7.94	4.74	2.12	1.54	0.37	0.07	24.27	3.23	21.04
2017	0.06	0.74	1.00	0.57	2.78	7.23	7.20	4.93	2.06	1.10	1.24	0.48	24.19	3.44	20.75
2018	0.29	0.62	1.65	1.24	3.45	7.44	6.63	3.07	2.44	1.05	0.29	0.09	23.03	3.30	19.73
2019	0.02	0.21	0.44	0.98	2.13	5.55	7.34	6.03	2.40	0.86	0.42	0.07	23.46	2.85	20.61
2020	0.05	0.19	0.57	0.98	2.27	2.56	2.66	2.09	1.13	0.21	0.08	0.03	10.71	1.58	9.13
2021	0.00	0.10	0.59	2.25	2.00	5.60	6.23	4.70	2.60	1.19	0.84	0.35	21.13	4.02	17.11
2022	0.04	0.01	0.45	0.72	2.61	7.24	6.83	4.67	2.20	1.31	0.34	0.01	23.56	4.56	19.00
Partial-Season Irrigation Withdrawal (no irrigation after June 15)															
2016	0.00	0.07	0.54	0.24	1.68	5.19	7.77	5.78	2.41	1.74	0.37	0.10	22.82	3.23	19.59
2017	0.05	0.72	1.92	0.60	1.62	5.49	6.69	5.98	3.15	1.53	1.00	0.58	22.93	3.44	19.49
2018	0.54	0.62	1.41	0.71	2.50	6.41	7.37	5.77	2.97	1.37	0.34	0.05	25.02	3.30	21.72
2019	0.02	0.23	0.46	0.69	1.78	5.13	7.32	6.26	1.81	0.86	0.40	0.01	22.29	2.85	19.44
2020	0.02	0.04	0.26	0.59	2.77	6.24	5.86	3.38	1.58	0.35	0.07	0.00	19.82	1.58	18.24
2021	0.00	0.03	0.40	1.67	1.26	4.19	5.14	5.16	3.81	1.96	0.81	0.28	19.56	4.02	15.54
2022	0.08	0.00	0.35	1.35	1.66	4.88	6.74	5.36	3.05	1.00	0.45	0.00	21.69	4.56	17.13

Table. Comparison of ET_a for Grand County REF and TRT sites in 2020 and 2022 using eeMETRIC.

ET_a in inches	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**May-Sep**
Full Season Irrigation Withdrawal													
2020 (REF)	0.02	0.08	0.38	1.17	3.68	6.83	7.02	4.95	3.19	0.83	0.19	0.02	25.67
2020 (TRT)	0.06	0.20	0.65	0.97	2.27	2.56	2.66	2.09	1.13	0.21	0.08	0.03	10.71
2021 (REF)	0.01	0.16	0.65	1.89	1.89	5.31	6.15	4.68	2.98	1.82	0.85	0.30	21.01
2021 (TRT)	0.01	0.12	0.60	2.16	2.09	5.44	6.19	4.61	2.50	1.16	0.84	0.43	20.83
2022 (REF)	0.04	0.00	0.52	0.83	1.96	7.00	6.75	4.86	2.48	1.35	0.42	0.01	23.04
2022 (TRT)	0.05	0.01	0.46	0.79	2.08	6.94	6.95	4.86	2.37	1.41	0.39	0.01	23.19
Partial-Season Irrigation Withdrawal (no irrigation after June 15)													
2020 (REF)	0.00	0.01	0.81	1.65	3.41	6.71	7.34	4.52	3.07	1.14	0.22	0.03	25.06
2020 (TRT)	0.02	0.04	0.26	0.59	2.77	6.24	5.86	3.37	1.58	0.35	0.08	0.00	19.82
2021 (REF)	0.00	0.05	0.60	1.56	1.76	5.60	6.68	4.72	2.83	2.16	1.03	0.32	21.58
2021 (TRT)	0.00	0.03	0.42	1.59	1.25	4.01	5.11	5.03	3.67	1.91	0.82	0.27	19.07
2022 (REF)	0.07	0.00	0.29	1.05	1.66	5.33	7.08	5.30	2.21	0.95	0.42	0.00	21.59
2022 (TRT)	0.08	0.00	0.35	1.35	1.66	4.88	6.74	5.36	3.05	1.00	0.45	0.00	21.69

Table 3.6.1 Comparison of Growing Season Water Use (eeMETRIC ET_a), TRT Sites (2020 vs 2021)

Site Name	Year	Monthly ET_a					May-Sept ET_a	Annual Total ET_a
		May	June	July	Aug.	Sept.		
						ET_a (in)		
SPR T1	2020	3.11	4.66	3.57	2.02	1.08	14.44	15.90
	2021	2.49	4.98	4.82	2.02	2.39	16.71	23.17
	2022	2.25	6.26	6.51	3.32	2.79	21.12	24.60
	$\Delta_{20, 21}$	**-20%**	**7%**	**35%**	**0%**	**122%**	**16%**	**46%**
SBR T1	2020	1.62	2.06	3.67	2.90	1.55	11.80	13.40
	2021	1.52	4.97	5.93	4.26	3.35	20.03	24.66
	Δ	**-7%**	**142%**	**62%**	**47%**	**116%**	**70%**	**84%**
GPR T1	2020	1.68	1.61	1.34	1.00	0.60	6.23	7.96
	2021	0.86	4.98	6.84	6.21	2.01	20.90	26.23
	Δ	**-49%**	**210%**	**412%**	**518%**	**236%**	**236%**	**230%**
Table 3.6.1 Comparison of Growing Season Water Use (eeMETRIC ET_a), TRT Sites (2020 vs 2021) - continued								
GPR T2	2020	2.06	2.28	2.75	2.51	1.56	11.16	13.93
	2021	1.04	4.15	7.39	6.69	2.95	22.22	27.11
	Δ	**-49%**	**82%**	**169%**	**167%**	**89%**	**99%**	**95%**
BJM T1	2020	2.54	2.03	1.35	1.21	0.76	7.90	10.35
	2021	2.76	6.45	6.58	3.97	1.61	21.36	26.76
	Δ	**8%**	**217%**	**386%**	**226%**	**113%**	**170%**	**158%**
HSR T1	2020	2.61	2.71	3.32	2.86	1.21	12.70	15.85
	2021	3.88	7.10	5.56	4.55	2.69	23.78	29.03
	Δ	**49%**	**162%**	**68%**	**59%**	**122%**	**87%**	**83%**
RSR T1*	2020	3.16	6.91	5.88	3.01	1.48	20.4	22.7
	2021	1.00	5.68	7.16	4.97	2.08	20.89	24.75
	Δ	**-68%**	**-18%**	**22%**	**65%**	**41%**	**2%**	**9%**
RCR T1*	2020	2.38	5.56	5.83	3.74	1.68	19.19	19.62
	2021	1.50	2.33	3.06	5.09	5.25	17.23	23.46
	Δ	**-37%**	**-58%**	**-48%**	**36%**	**212%**	**-10%**	**20%**

*Sites with partial season withdrawal in 2020. All others had full season withdrawal

Table 3.6.2 Comparison of Growing Season Water Use (METRIC ET_a), REF Sites (2020 vs 2021)

Site Name	Year	Monthly ET_a					May-Sept ET_a	Annual Total ET_a
		May	June	July	Aug.	Sept.		
						ET_a (in)		
SPR R1	2020	4.50	6.37	5.90	4.20	2.59	23.57	26.62
	2021	2.56	3.66	3.87	2.75	2.03	14.87	21.49
	Δ	**-43%**	**-43%**	**-34%**	**-35%**	**-22%**	**-37%**	**-19%**
SBR R1	2020	4.72	7.86	7.99	4.87	2.58	28.02	29.70
	2021	2.03	6.41	7.00	4.45	3.99	23.89	29.15

	Δ	**-57%**	**-18%**	**-12%**	**-9%**	**55%**	**-15%**	**-2%**
GPR R1	2020	1.83	6.26	7.17	5.76	4.40	25.43	28.79
	2021	1.07	5.84	7.58	6.85	2.92	24.27	29.43
	Δ	**-41%**	**-7%**	**6%**	**19%**	**-34%**	**-5%**	**2%**
RSR R1	2020	3.78	6.99	7.89	4.97	3.97	27.60	33.29
	2021	1.72	6.49	7.30	4.63	2.86	23.01	27.29
	Δ	**-55%**	**-7%**	**-7%**	**-7%**	**-28%**	**-17%**	**-18%**
RCR R1	2020	3.04	6.44	6.80	4.07	2.17	22.51	24.55
	2021	1.79	4.70	6.05	4.80	2.81	20.15	27.33
	Δ	**-41%**	**-27%**	**-11%**	**18%**	**29%**	**-11%**	**11%**