Estimating irrigation water use from remotely sensed evapotranspiration data: Accuracy and uncertainties at field, water right, and regional scales

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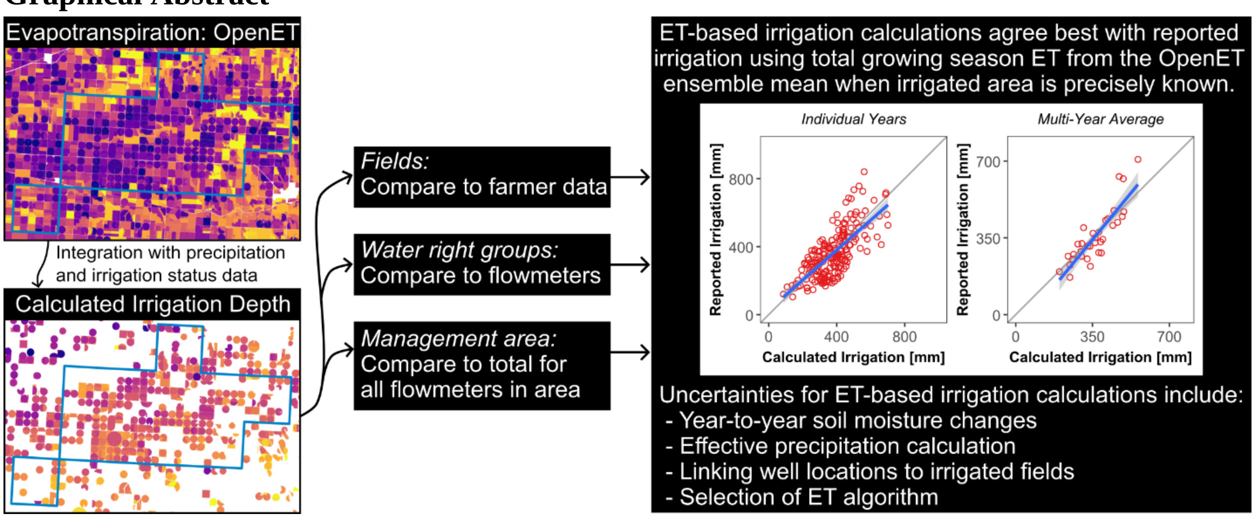
Abstract

Irrigated agriculture is the dominant user of water globally, but most water withdrawals are not monitored or reported. As a result, it is largely unknown when, where, and how much water is used for irrigation. Here, we evaluated the ability of remotely sensed evapotranspiration (ET) data, integrated with other datasets, to calculate irrigation water withdrawals and applications in an intensively irrigated portion of the United States. We compared irrigation calculations based on an ensemble of satellite-driven ET models from OpenET with reported groundwater withdrawals from hundreds of farmer irrigation application records and a statewide flowmeter database at three spatial scales (field, water right group, and management area). At the field scale, we found that ET-based calculations of irrigation agreed best with reported irrigation when the OpenET ensemble mean was aggregated to the growing season timescale (bias = 1.6% to 4.9%, R^2 = 0.53 to 0.74), and agreement between calculated and reported irrigation was better for multi-year averages than for individual years. At the water right group scale, linking pumping wells to specific irrigated fields was the primary source of uncertainty. At the management area scale, calculated irrigation exhibited similar temporal patterns as flowmeter data but tended to be positively biased with more interannual variability. Disagreement between calculated and reported irrigation was strongly correlated with annual precipitation, and calculated and reported irrigation agreed more closely after statistically adjusting for annual precipitation. The selection of an ET model was also an important consideration, as variability across ET models was larger than the potential impacts of conservation measures employed in the region. From these results, we suggest key practices for working with ET-based irrigation data that include accurately accounting for changes in soil moisture, deep percolation, and runoff; careful verification of irrigated area and well-field linkages; and conducting application-specific evaluations of uncertainty.

Graphical Abstract



Keywords: OpenET, remote sensing, evapotranspiration, water management, High Plains Aquifer, uncertainty

1. Introduction

Irrigated agriculture is the dominant global user of water. Groundwater supplies an estimated 40% of global irrigation, with this figure rising even higher in semi-arid/arid regions or in drought years when surface water availability is limited (Gleeson et al., 2020). As such, groundwater use plays a critical role in global food production and trade (Dalin et al., 2017) and sustaining local and regional economies (Deines et al., 2020). However, groundwater use can also lead to detrimental outcomes, such as the depletion of interconnected surface water resources (de Graaf et al., 2019; Zipper et al., 2022), declining water levels and storage capacity in regionally and globally important aquifers (Hasan et al., 2023; Jasechko et al., 2024), and associated water scarcity and insecurity (D'Odorico et al., 2019; Marston et al., 2020). In many agricultural settings without alternative water sources, pumping reductions are the only currently viable tool available to reduce water abstraction and water table decline rates (Butler et al., 2020).

Making informed management decisions requires information about pumping rates and the anticipated impacts on the environment (Foster et al., 2020). However, management is challenging because data on the locations, schedules, and volumes of groundwater withdrawals are rarely available, even in data-rich countries like the United States (Marston, Abdallah, et al., 2022). Given the paucity of groundwater pumping data, emerging application-ready remote sensing products may be a valuable tool to fill this data gap (Melton et al., 2022). While flowmeters on pumping wells directly monitor the amount of water coming out of the ground, which we refer to here as 'irrigation water withdrawals', remotely sensed approaches typically provide data for spatially distributed evapotranspiration (ET) rates. Satellite-based ET data can then be incorporated into a water balance or statistical model to infer 'irrigation water applications', or the amount of water that is applied to a field after accounting for losses (Dhungel et al., 2020; Folhes et al., 2009; Foster et al., 2019; Laluet et al., 2024). These models can range from simple annual water balances to detailed daily soil water balance models tracking multiple components of the water balance such as infiltration, deep percolation, and runoff. Like all modeled quantities, however, these ET-based calculations of irrigation are subject to numerous uncertainties, which can lead to inefficient or inequitable water management decisions if not well-characterized (Foster et al., 2020).

Unfortunately, due to the lack of reliable irrigation water withdrawal and application data for ground reference, there have been limited opportunities to evaluate the ability of ET-based approaches to calculate irrigation withdrawals and applications. While many past studies have sought to estimate irrigation water use using satellite-based ET data and other hydrological variables such as soil moisture (Brocca et al., 2018; Dari et al., 2020; Ketchum et al., 2023), these estimates have typically been evaluated against aggregated statistics or synthetic model estimates of water use. Other studies use statistical or machine learning approaches to relate ET to observed water use, but these approaches are limited in terms of their applicability outside of the model training region (Filippelli et al., 2022; Majumdar et al., 2022; Wei et al., 2022). As a result, there is a lack of knowledge about how effectively ET data can be translated into irrigation water withdrawals and applications across different spatial scales, from an individual field to a region, which are relevant to regulatory and management purposes.

Here, we address this gap by comparing calculations of ET-based irrigation applications and reported irrigation at multiple spatial scales (field, water right group, management area) within the heavily irrigated High Plains Aquifer in the State of Kansas (USA). Reported irrigation data are from both direct farmer-provided records of irrigation water applications and a high-quality flowmeter database of irrigation water withdrawals (Figure 1). Specifically, we ask:

(1) How well do irrigation calculations derived from remotely sensed data and other spatial datasets agree with water withdrawal and application data from flowmeters and farmer records?

(2) What are the major sources of uncertainty in calculating irrigation withdrawals and applications using remotely sensed ET data?

Addressing these questions provides insights into the potential for remotely sensed ET products to address critical water challenges and highlights key future research needed to operationalize ET data for agricultural water management.

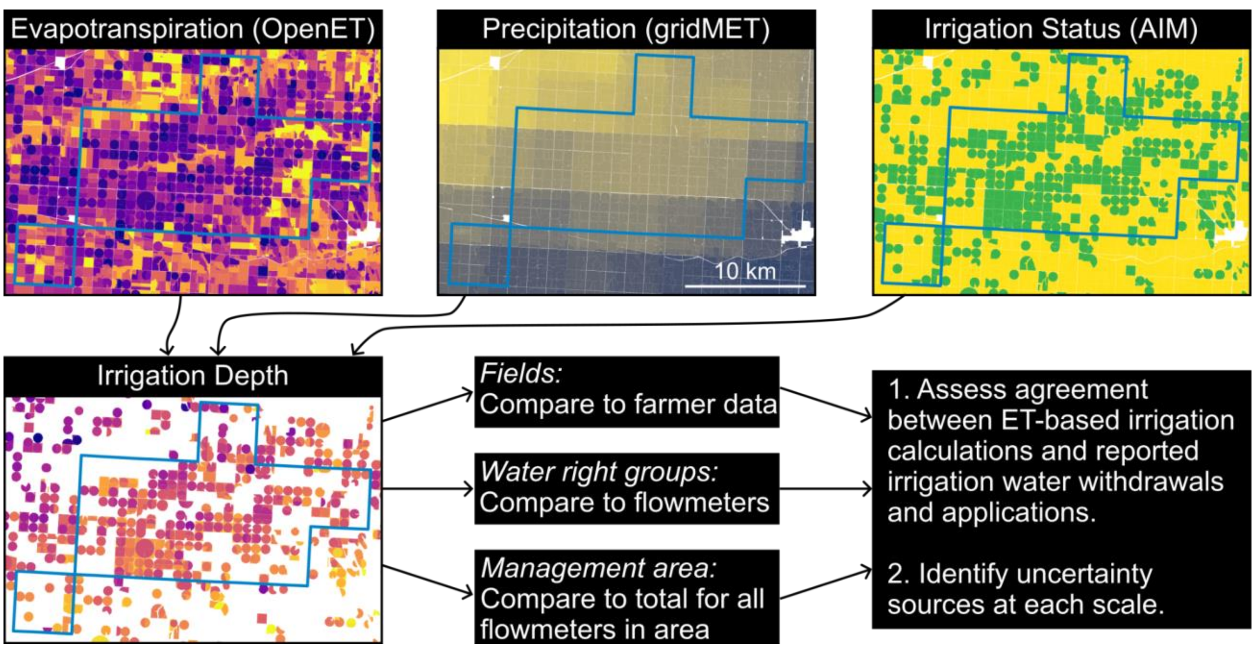


Figure 1. Overview of study including key input datasets (OpenET: Melton et al., 2022; gridMET: Abatzoglou, 2013; AIM: Deines, Kendall, Crowley, et al., 2019), spatial scales, and study objectives. The images show the area in and around the Sheridan-6 Local Enhanced Management Area (blue outline), the location of which is shown in Figure 2.

2. Methods

2.1 Study areas and irrigation ground data

We conducted comparisons of ET-based irrigation calculations to in-situ measurements of groundwater withdrawals and applications at three spatial scales that address different potential use cases for remotely sensed irrigation data:

(1) At the field scale (Section 2.1.1), we compared ET-based calculated irrigation depths to field-resolution irrigation water application data from fields where farmers voluntarily shared irrigation records (field-years of data by region shown in Figure 2 in parenthesis).

(2) At the water right scale (Section 2.1.2), we focused on a 255 km^2 groundwater management area, the Sheridan-6 Local Enhanced Management Area (SD-6 LEMA; blue area in Figure 1 and Figure 2). We subdivided the SD-6 LEMA into water right groups (WRGs) made up of non-overlapping combinations of pumping wells, fields, and authorized places of use and compared ET-based irrigation volumes to total water withdrawals within each WRG.

(3) At the management area scale (Section 2.1.2), we compared ET-based irrigation volumes to total reported irrigation water withdrawals within the entire SD-6 LEMA.

Conducting our analysis at these three spatial scales allowed us to leverage independent data sources for comparison (farmer records at the field scale, a state database at the water right and management area scales) and assess different aspects of uncertainty.

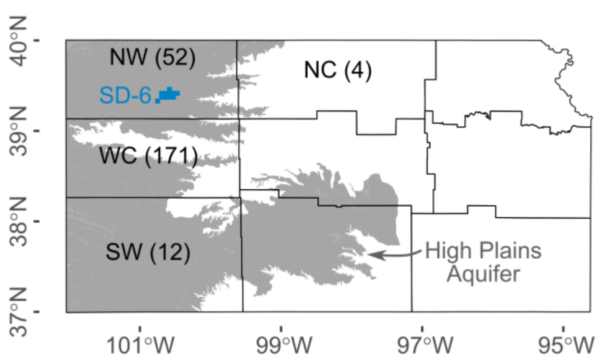


Figure 2. Map of the state of Kansas subdivided into agricultural reporting districts. The number of field-years of data at the field scale are shown in parentheses for the northwest (NW), north-central (NC), west-central (WC), and southwest (SW) reporting districts within the state. The location of the Sheridan-6 (SD-6) Local Enhanced Management Area is shown in blue. The Kansas portion of the High Plains Aquifer is shown in gray.

2.1.1 Individual fields

We collected field-resolution irrigation application information from four farmers willing to share this information with us. Farmers were contacted directly based on existing personal relationships and through regional organizations such as groundwater management districts and asked to provide applied irrigation volumes for as many fields as they were willing to share at the finest possible temporal resolution. We also requested either data files or annotated pictures showing the irrigated extent for each field so we could extract satellite-based ET data for each field. Therefore, unlike the management area and WRG scale comparisons described in Section 2.1.2, for the field-scale comparison we had information on actual places of use and irrigated extent. Irrigation data varied in format, including minute-resolution water use from irrigation control software, irregularly timed sub-annual water use based on periodic visits to flowmeters, and annual values based on flowmeter data that farmers associated with specific fields. For this study, all data were aggregated to the annual total depth of applied irrigation. In total, we received data for 43 fields between 2016 and 2022, totaling 239 field-years of data. Following Ott et al. (2024), we screened out any fields where the ratio of irrigation to the difference of ET (from the OpenET ensemble mean) and effective precipitation was <0.5 or >1.5, since this suggests potential errors in reported irrigation data. To protect the privacy of the farmers involved (Zipper, Stack Whitney, et al., 2019), the locations of the fields are only shown here at the resolution of federal agricultural reporting districts (Figure 2). The data span three of the five reporting districts that overlie the High Plains Aquifer, with the most fields in west-central and northwest Kansas (note: one field, just across the border in Nebraska, is included with the NW Kansas district). None of the fields included within this dataset are within the SD-6 LEMA.

2.1.2 Sheridan-6 Local Enhanced Management Area

The SD-6 LEMA covers 255 km^2 in northwest Kansas, much of which is used to grow irrigated corn, soybeans, sorghum, and wheat (Figure 2). The SD-6 LEMA was formed when local irrigators, concerned about declining groundwater levels, proposed an allocation of 1397 mm (55”) of water over a five-year period, which represented an approximate 20% reduction in pumping rates compared to historical averages (Drysdale & Hendricks, 2018). After approval by the state’s chief engineer, this allocation was codified in law for a five-year period beginning in 2013. The irrigators within the SD-6 LEMA have since renewed for two additional five-year periods (2018-2022 and 2023-2027). To date, the SD-6 LEMA exceeded the original conservation goals and reduced irrigation water withdrawals by 26-31% (Deines, Kendall, Butler, et al., 2019; Drysdale & Hendricks, 2018) and slowed water table decline rates (Butler et al., 2020; Whittemore et al., 2023) with only minor negative impacts on yield and none on profitability (Golden, 2018). As such, the SD-6 LEMA is a successful example of irrigator-driven groundwater conservation (Marston, Zipper, et al., 2022) and has motivated the development of additional conservation approaches around the state (Steiner et al., 2021).

We selected the SD-6 LEMA as the focus of our management area and water right scale comparison because conservation practices have led to high irrigation efficiencies of producers in the SD-6 LEMA with relatively little wasted irrigation water (e.g., deep percolation from return flows or major fluxes of soil evaporation caused by excessive irrigation; Deines et al., 2021). High irrigation efficiency suggests that irrigation water withdrawals and applications should be approximately equal, and ET-based approaches should be particularly effective for calculating irrigation volumes in this setting. Additionally, due to numerous past studies of groundwater use in the SD-6 LEMA (Deines et al., 2021; Deines, Kendall, Butler, et al., 2019; Dhungel et al., 2020; Drysdale & Hendricks, 2018; Glose et al., 2022; Whittemore et al., 2023), we have a high degree of confidence in the accuracy of the irrigation withdrawal data for the SD-6 LEMA.

Irrigation withdrawal data were aggregated from the Water Information Management and Analysis System (WIMAS; https://geohydro.kgs.ku.edu/geohydro/wimas/) database maintained by the Kansas Department of Agriculture - Division of Water Resources and the Kansas Geological Survey. Withdrawal data are at the resolution of points of diversion, which in the SD-6 region correspond exclusively to pumping wells since there are no surface water resources used for irrigation. The data are high quality, as all non-domestic pumping wells in the state of Kansas are required to use a totalizing flow meter subject to accuracy checks from the Kansas Department of Agriculture with strong penalties for falsifying flow meter data or drilling illegal wells (Butler et al., 2016). Therefore, we do not believe there is significant under-reported or non-reported irrigation water use in the area. The WIMAS database also includes reported total irrigated acreage in each year, though unlike water use, the reported irrigated acreage is not subject to verification and therefore the accuracy is unknown. In the SD-6 LEMA, we conducted our comparison at two spatial scales:

- For the water right group (WRG) scale comparison, we established non-overlapping groups of water withdrawals and applications by combining wells, water rights, and authorized places of use as in Earnhart & Hendricks (2023). This aggregation was necessary due to the complexities of agricultural water management that make it impossible to quantify the water use for a specific field from the WIMAS data alone: (i) a single well may provide water to multiple fields; (ii) a single field may receive water from multiple wells; (iii) a single water right may cover multiple wells and fields; and (iv) irrigators are only required to report the authorized place of use and the total number of acres irrigated, not the specific locations where water was used within the authorized area in a specific year. For each WRG, we then summed the total reported annual water withdrawals for all wells within the WRG.
- For the management area scale comparison, we summed the total annual withdrawals from all irrigation wells within the SD-6 LEMA boundaries. For any water rights that had authorized places of use both inside and outside the LEMA (n = 9, or 6% of the total water right groups), we scaled the total water use based on the proportion of total estimated irrigated area that was within the LEMA for that well. This is the approach used in Brookfield et al. (2023) and is extended here through additional analyses of uncertainty, the use of effective precipitation for estimating irrigation depths, and comparison to other spatial scales.

The SD-6 LEMA comparisons were conducted for the period 2016-2020, as that is the extent covered by all necessary input datasets (described in Section 2.2).

2.2 Calculating irrigation from ET data

We integrated ET data with several other geospatial datasets to calculate irrigation volumes and/or depths (Figure 1). We extracted OpenET data from Google Earth Engine at a monthly time step for 2016-2022 (Melton et al., 2022). OpenET includes ET data from six different satellite-driven models, as well as an ensemble mean. The models included are DisALEXI (Anderson et al., 2007, 2018), eeMETRIC (Allen et al., 2005, 2007, 2011), geeSEBAL (Bastiaanssen et al., 1998; Laipelt et al., 2021), PT-JPL (Fisher et al., 2008), SIMS (Melton et al., 2012; Pereira, Paredes, Melton, et al., 2020), and SSEBop (Senay et al., 2022). The ensemble mean was calculated as the mean of all models, with outlier values from the ensemble identified based on median absolute deviations and removed prior to averaging (Volk et al., 2024). The OpenET products were validated against 70 eddy covariance towers deployed at agricultural sites spanning a range of climate and land cover conditions across the western US and generally had a strong agreement, with all models within +/- 15% of growing season mean flux tower ET averaged across all sites (Melton et al., 2022). A subsequent evaluation affirmed the accuracy of the ET data from OpenET via comparison to a total of 141 sites with eddy covariance towers, along with seven sites with Bowen ratio systems and four weighing lysimeters, finding that the growing season ensemble ET values for cropland had a mean absolute error of 78.1 mm (13.0%) and a mean bias error of -11.9 mm (2.0%). The overall accuracy for cropland sites was the best of any land cover type evaluated, and performance for annual crops, including corn, soybeans, and wheat, was particularly strong (Volk et al., 2024). However, there were no eddy covariance towers near our study area - the closest irrigated fields with eddy covariance towers were in Mead, NE, where annual precipitation is ~50% greater than western Kansas - and therefore OpenET's accuracy for irrigated agriculture in semi-arid conditions typical of the western High Plains Aquifer has not been locally assessed.

OpenET data and precipitation data (from the 4 km gridMET data; Abatzoglou, 2013) were averaged for each field. For the field-resolution comparison, field boundaries, crop type, and irrigation status were defined based on information provided by farmers. For the management area and WRG comparisons, field boundaries were defined based on a Kansas-specific modification of the US Department of Agriculture (USDA) Common Land Unit dataset (Gao et al., 2017; MardanDoost et al., 2019), annual crop type from the USDA Cropland Data Layer (USDA, 2022), and field-resolution irrigation status from the Annual Irrigation Maps (AIM) dataset (Deines, Kendall, Crowley, et al., 2019). For crop type and irrigation status, we summarized the rasterized input data to a single categorical value for each field based on the most common raster value.

To estimate irrigation using our ET data (Figure 1), we calculated the precipitation deficit (ET - effective precipitation) for each field (Figure S1) and masked it to only fields mapped as irrigated by AIM (Figure S2). Effective precipitation was calculated as precipitation from gridMET minus deep percolation out of the bottom of the root zone, which we estimated as a function of precipitation based on 2013-2017 deep percolation estimates from Deines et al. (2021) (regressions shown in Figure S3). This method does not account for soil moisture storage from year-to-year, so we did these calculations at three timescales: the growing season (April-October), the calendar year (January-December), and the water year (October-September). This allowed us to test the degree to which the timescale of aggregation influenced agreement between calculated and reported irrigation withdrawal data. Since negative irrigation depths are not physically possible, for any irrigated fields with a negative precipitation deficit we set the irrigation depth to 0 mm, though this was rare and negative precipitation deficits were typically associated with fallow, non-irrigated fields (Figure S1). Irrigation depth was calculated separately for each year and each model (six ET models, as well as the ensemble mean). To convert field-resolution irrigation depths to irrigation volumes for comparison with pumping data, we multiplied the calculated irrigation depth by the area within each field that was mapped as irrigated in AIM. Since there are no surface water rights in this region, we assumed that all irrigation was sourced from groundwater.

2.3 Assessing approaches for improving irrigation calculations

Our approach to estimating irrigation adopts several assumptions, including that there is minimal runoff or fluxes of water apart from precipitation, irrigation, deep percolation and evaporation. While past work has suggested that there is virtually no runoff under conservation practices in the SD-6 LEMA (Deines et al., 2021), these assumptions may be less appropriate in other parts of the state, in particular the 4 field-years of data in the north-central region (Figure 2). Additionally, there may be differences in the relationship between precipitation and deep percolation in other regions given that irrigation efficiency is particularly high in the SD-6 LEMA.

We assessed both our confidence in and potential impacts of errors in irrigated area classification. In the SD-6 LEMA area, we evaluated confidence in the field-resolution irrigation classifications by evaluating the area of fields with a mixture of irrigated and non-irrigated pixels in the AIM dataset. The irrigation confidence results suggested that this irrigation status mapping approach was more likely to overestimate, rather than underestimate, irrigated area (Figure S4, Figure S5) due to field boundaries not perfectly aligning with on-the-ground management divisions. To address this, we used the fraction of each field that was mapped as irrigated to scale from calculated irrigation depths to irrigation volumes so that potentially non-irrigated portions of otherwise irrigated fields were not included in volume estimation. To determine the potential impacts of uncertainty in irrigated area on our results, as well as potential errors associated with defining WRGs, we also compared reported irrigated acreage for all the wells in the WRG (from the WIMAS database) to the estimated irrigated acreage from AIM for irrigated fields in the WRG. We then repeated our comparison of WRG-scale reported and calculated irrigation water use for only WRGs where the reported and estimated irrigated area agreed within 10%.

Additionally, at the management area scale, we evaluated the degree to which a locally-informed bias correction approach could be used to improve agreements between calculated and reported irrigation. This approach, which we call ‘precipitation-adjusted irrigation calculations’, involved developing a linear regression between the irrigation volume residual and precipitation, and then using this linear relationship to adjust ET-based irrigation calculations. This adjustment is useful in both highlighting potential mechanisms for disagreement between calculated and observed irrigation and to demonstrate an approach for either spatial or temporal extrapolation from locations/time periods with well-monitored irrigation to locations/time periods where irrigation is not monitored.

3. Results

3.1 Field-scale comparison

At the field scale, we first evaluated the timescale for aggregating the calculated precipitation deficit at which calculated and reported irrigation agreed best. We found that using the growing season for aggregation consistently provided the best agreement in terms of percent bias, mean absolute error (MAE), slope of the relationship between calculated and reported irrigation, and R^2 (Figure 3). This was true across most ET algorithms and fit metrics, and for all subsequent analyses at the field, WRG, and management area scale, we used the growing season timescale of aggregation for irrigation calculations. Slope values tended to be <1 for all ET models at the annual scale (Figure 3, Table 1). The slope of the relationship between calculated and reported irrigation can be an indicator of irrigation efficiency (Ott et al., 2024), and the slope < 1 may reflect lower irrigation efficiencies and increased non-evaporative losses (such as deep percolation or runoff), particularly since our effective precipitation relationship was based on the data from the SD-6 LEMA and the field-scale analysis did not include fields within the LEMA (Figure S3). Agreement for individual years did not appear to vary systematically as a function of the region within the state, though the dataset was not evenly distributed among regions with most of the fields in either west-central or northwest Kansas (71.5% and 21.8% of total field-years, respectively; Figure 2) which are climatically very similar.

Comparing across OpenET models, we found that the OpenET ensemble mean tended to provide the best agreement with reported irrigation at the annual timescale, with a MAE of 81 mm, bias of 4.9%, slope of 0.88, and R^2 of 0.53 (Table 1). This slope (0.88) closely matches typical irrigation efficiencies for the region (0.9; Deines et al., 2021), suggesting that losses in the irrigation conveyance system and wind-drift evaporation are approximately 12% of pumped water. When averaged across multiple years, the error in each model was substantially reduced (Figure 4, Table 1). The choice of model also contributed to variability for both individual years and multi-year averages. While the ensemble mean provided the best overall agreement between calculated and reported data, there was also good agreement with reported data for irrigation calculations using DisALEXI and PT-JPL. In contrast, eeMETRIC and SSEBop tended to overestimate at high levels of irrigation, geeSEBAL tended to underestimate across the range of irrigation depths, and SIMS tended to overestimate across the range of irrigation depths (Figure 4). The high calculated irrigation volumes from SIMS make sense due to the formulation of this model, which assumes well-watered conditions sufficient to meet the needs of the satellite-observed crop density (Melton et al., 2012). Even irrigated crops in this region likely experience periodic water stress during the growing season, as evidenced by the narrow distribution of SIMS ET data with respect to other models (Figure S6).

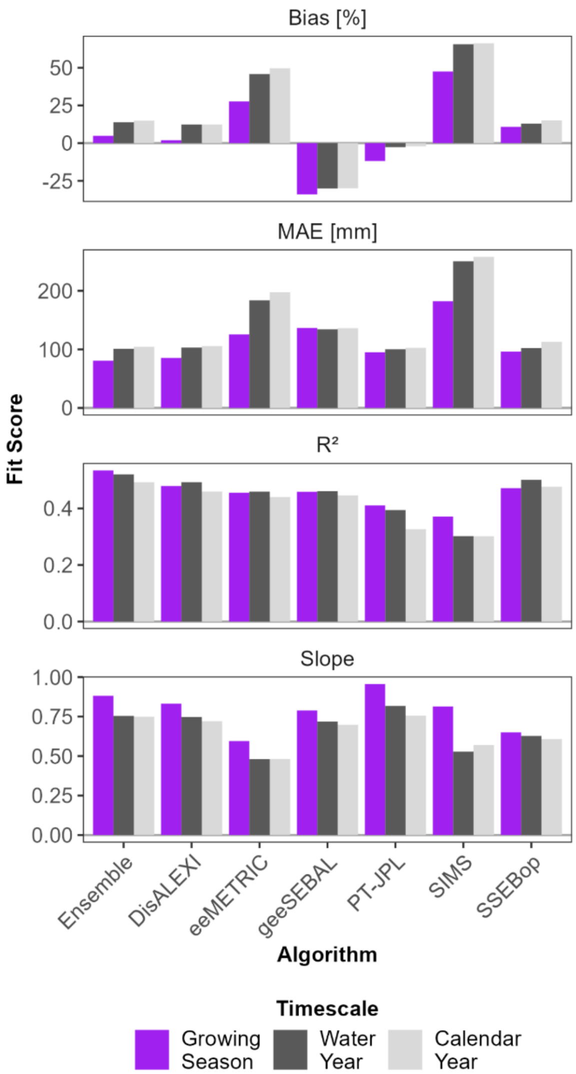


Figure 3. Agreement between field-resolution reported and calculated irrigation based on different aggregation timescales. Fit metrics shown include bias (better performance = closer to 0), mean absolute error (MAE; better performance = closer to 0), R^2 (better performance = closer to 1), and slope (better performance = closer to 1).

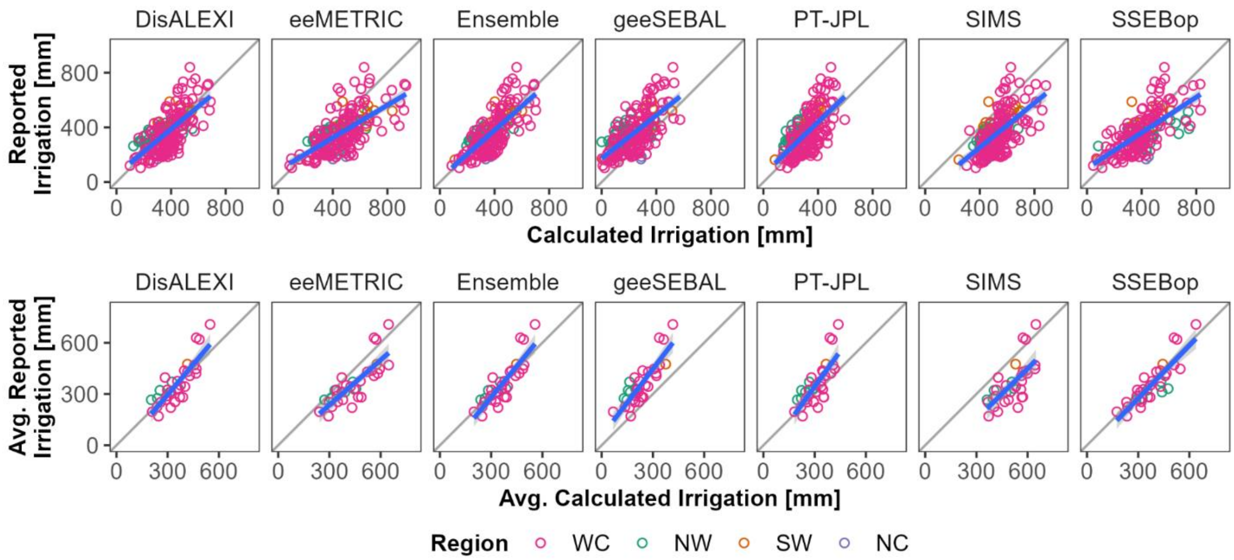


Figure 4. Comparison between reported and calculated irrigation for individual fields. The top row shows annual irrigation and the bottom row shows the multi-year average, both colored by the region within the state. Calculated irrigation is based on growing season timescale of aggregation. In each panel, the gray line indicates 1:1 agreement and the blue lines in the bottom panels show a linear best-fit with a shaded standard error confidence interval.

Table 1. Fit statistics for field-resolution comparison between calculated and reported irrigation application depths based on growing season timescale of aggregation.

	MAE [mm]		**Bias [%]**		**Slope**		**R^2**	
Model	*Annual*	*Multi-Year*	*Annual*	*Multi-Year*	*Annual*	*Multi-Year*	*Annual*	*Multi-Year*
DisALEXI	85	52	1.9	-1.5	0.83	1.18	0.48	0.71
eeMETRIC	126	93	27.7	22.7	0.59	0.88	0.46	0.66
Ensemble	81	48	4.9	1.6	0.88	1.22	0.53	0.74
geeSEBAL	136	126	-34.0	-35.2	0.79	1.31	0.46	0.73
PT-JPL	95	69	-11.9	-13.3	0.96	1.38	0.41	0.60
SIMS	182	158	47.5	41.8	0.81	0.99	0.37	0.47
SSEBop	96	52	10.8	6.5	0.65	1.03	0.47	0.76
Average	*115*	*86*	*6.7*	*3.2*	*0.79*	*1.14*	*0.45*	*0.67*

3.2 SD-6 LEMA water right group comparison

For the WRG-scale comparison, the growing season-based irrigation volumes from the ensemble ET were used, since this had the best agreement at the field scale where there are fewer sources of uncertainty (Section 3.1). The calculated irrigation volumes showed substantially more interannual variability than reported irrigation volumes at the WRG scale, with ET-based irrigation volumes positively biased relative to reported volumes for most WRGs (Table 2). While there was a positive bias across all years, the greatest positive bias was during dry years such as 2020 (Figure 5a). When averaged across all five years, the scatter in the agreement between estimated and reported irrigation volumes was dramatically reduced (Figure 5c), leading to a decrease in MAE and increase in slope and R^2 relative to the annual-resolution comparison (Table 2).

The correlation between calculated and reported irrigation was worse for irrigation depths (Figure 5b, Figure 5d) than volumes (Figure 5a, Figure 5c), though irrigation volumes were more consistently positively biased than depths (Table 2). Overall, our results indicate that uncertainty in estimated irrigation depth is greater than uncertainty in estimated irrigated volume, which is further supported by the field-scale comparison in Section 3.1 and has been observed in other ET-based irrigation comparisons in Nevada and Oregon (Ott et al., 2024). Nevertheless, place of use and irrigation status are important potential drivers of disagreement between calculated and reported irrigation volumes. While there was a positive correlation between reported and estimated irrigated area, the irrigated area within WRGs based on AIM only matched the reported irrigated area in the WIMAS database for approximately half of WRG-years (321 of 680 within 10%). Differences between reported and calculated irrigated area were mostly distributed around the 1:1 line, with a slight positive bias for calculated irrigated area (Figure 6). On average, the estimated irrigated area was 6.9% higher than the reported irrigated area (median = 1.1%).

This disagreement may be due to errors in reported irrigated area and calculated irrigated area as well as difficulties in identifying annual places of use for each WRG. While irrigated area is required for annual water use reports, water use reports do not include spatial information specifying where the water was actually used, and total irrigated area is not subject to verification or enforcement penalties (unlike reported water use). Therefore, it is unknown how accurate the reported data are, but one plausible explanation for the disagreement in estimated and reported irrigated area is uncertainty in field or parcel boundaries, particularly related to corners of parcels that are irrigated with center-pivot systems. Since the field boundary dataset we are using was originally based on 2007 common land units (CLUs) mapped by the USDA with some refinements (Gao et al., 2017), it may not accurately delineate fields that harbor differently managed component areas. For example, a square quarter section containing a center pivot might consist of separate CLUs for the irrigated circle and the non-irrigated corners, or it might simply be the quarter section boundary with multiple records for differently managed subfields used when the farmer signs up for federal government programs such as crop insurance. In the latter case, the entire field would be classified as irrigated based on our assignment of irrigation by majority, even though the ~20% of the field in the corners would not be reported as irrigated by the farmer. This is consistent with our observation that there tended to be more low-confidence classifications for irrigated fields than non-irrigated fields (Figure S4), and supports our approach using the fraction of the field that was mapped as irrigated to scale from calculated irrigation depth to volume (see Section 2.2). Areas of low-confidence classifications were often field corners (Figure S5), suggesting that the misclassification of non-irrigated corners as irrigated due to insufficiently refined field boundaries may have a slight contribution to overestimated irrigation volumes at both the WRG and management area scales. To assess the potential impacts of errors in irrigated area classification, we repeated the analysis using only WRGs and years where the reported and estimated irrigated area agreed within 10% (Figure 7 and 'Area Agree' columns in Table 2). The results of this comparison had a smaller positive bias for both irrigation volumes and depths, with overall the best agreement observed for multi-year average volumes (Figure 7c). While the annual-resolution irrigation depths had a similar overall correlation (R^2 = 0.35 in Figure 5b and R^2 = 0.40 in Figure 7b), the correlation between five-year average calculated and reported irrigation depth improved when only using WRGs with strong irrigated area agreement (R^2 = 0.32, Figure 7d) compared to using all WRGs within the LEMA (R^2 = 0.05, Figure 5d).

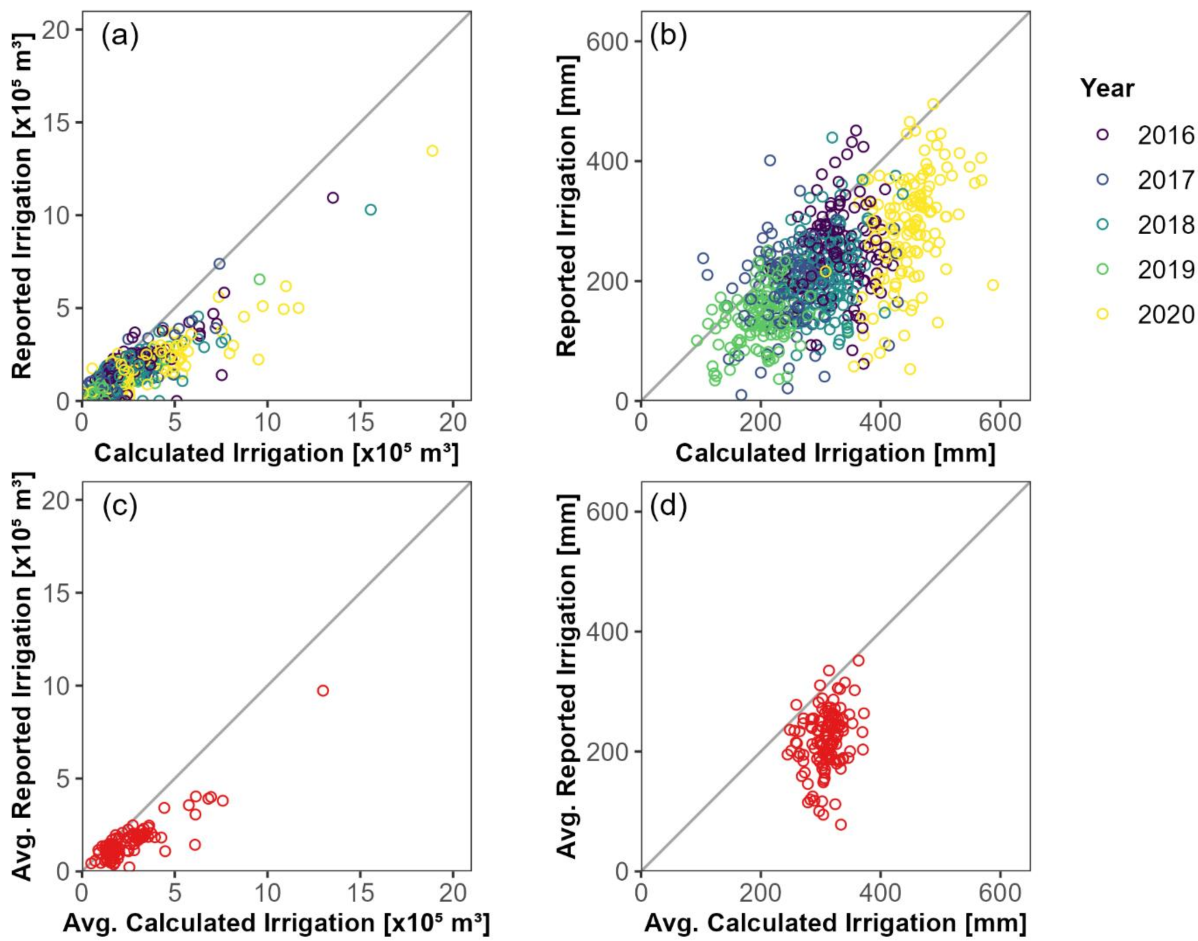


Figure 5. Comparison of reported irrigation for each water right group (WRG) to ET-based irrigation calculation using the ensemble ET. (a) Annual irrigation volume for each WRG; (b) Annual irrigation depth for each WRG; (c) Average irrigation volume for each WRG; (d) Average irrigation depth for each WRG. In each plot, the gray line shows a 1:1 agreement between reported and estimated irrigation. Calculated irrigation is based on growing season timescale of aggregation.

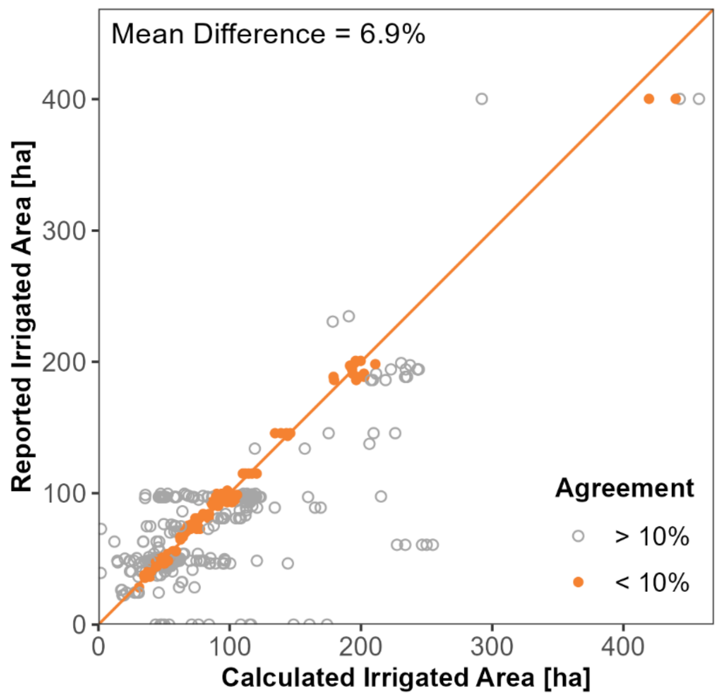


Figure 6. Comparison between reported irrigated area (from WIMAS) and estimated irrigated area (from AIM and authorized places of use) within each water right group in the SD-6 LEMA. Points colored orange have an agreement within 10% and the orange line shows 1:1 agreement.

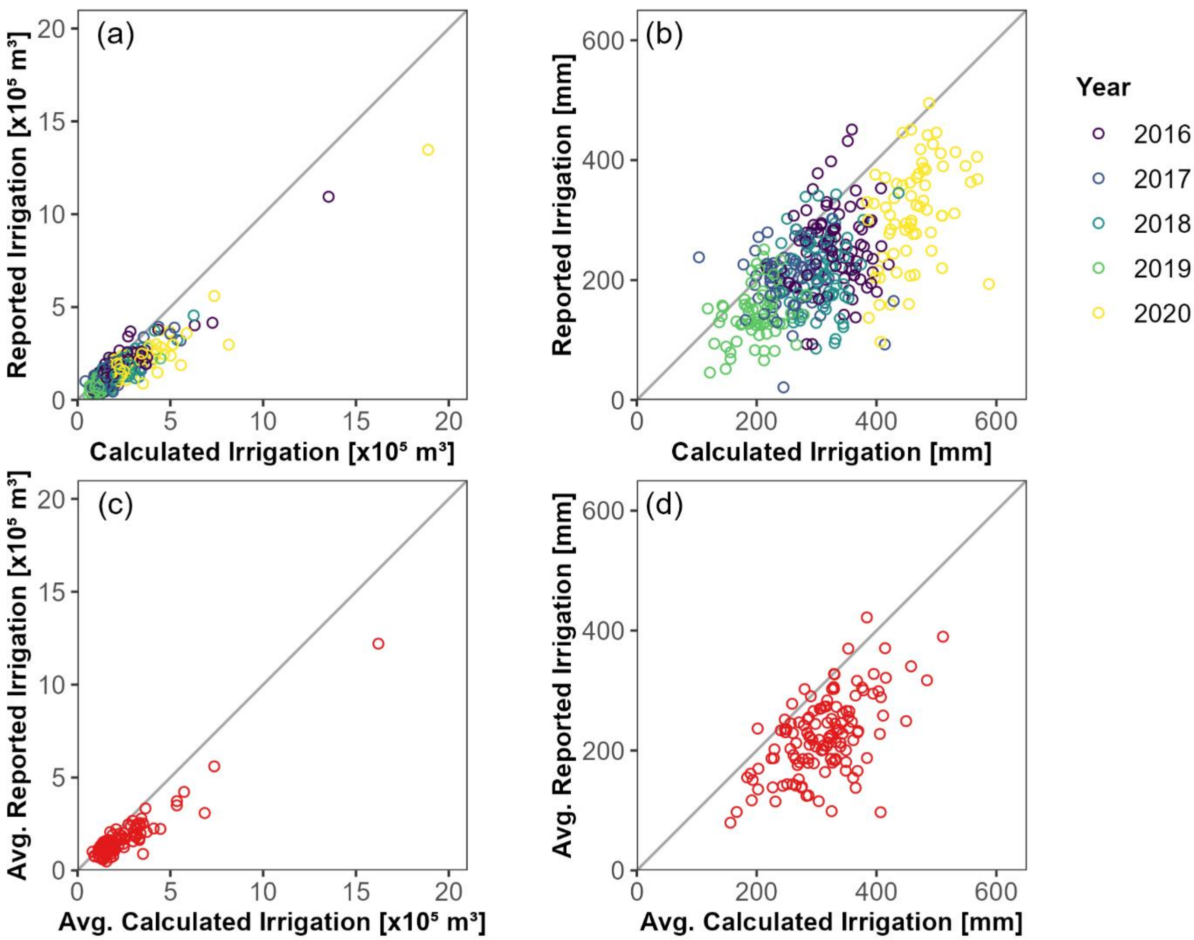


Figure 7. Same as Figure 5, but only for WRGs where reported and calculated irrigated area agreed within 10% (i.e., orange points in Figure 6). Each panel shows: (a) Annual irrigation volume for each WRG; (b) Annual irrigation depth for each WRG; (c) Average irrigation volume for each WRG; (d) Average irrigation depth for each WRG. In each plot, the gray line shows a 1:1 agreement between reported and calculated irrigation. Calculated irrigation is based on growing season timescale of aggregation.

Table 2. Fit statistics for WRG comparison for all WRGs (data points shown in Figure 5) and those with irrigated area agreement (data points shown Figure 7).

	MAE		**Bias [%]**		**Slope**		**R^2**	
Model	*All WRGs*	*Area Agree*	*All WRGs*	*Area Agree*	*All WRGs*	*Area Agree*	*All WRGs*	*Area Agree*
Annual Irrigation Volume [x10^5 m^3]	0.92	0.66	57%	40%	0.53	0.64	0.72	0.83
Annual Irrigation Depth [mm]	98.76	93.81	42%	38%	0.54	0.56	0.35	0.40
Average Irrigation Volume [x10^5 m^3]	0.86	0.67	57%	41%	0.57	0.68	0.79	0.89
Average Irrigation Depth [mm]	90.97	89.88	41%	39%	0.44	0.58	0.05	0.32

3.3 Management area comparison

At the scale of the SD-6 LEMA, the ET-based irrigation volumes are the same order of magnitude as the reported withdrawal volumes but have a positive bias and greater interannual variability (Figure 8a, Table 3). The best-performing model depends on the fit metric being used (Table 3, ‘Calc.’ column). For instance, the average MAE and bias values were lowest for geeSEBAL, while SIMS had the slope closest to 1 and the ensemble mean and SIMS had the highest R^2. Since we observed an overestimate across all models, the relatively lower MAE and bias for geeSEBAL reflects its consistently low estimates of ET relative to other algorithms (as observed for the field-scale analysis; Figure 4). The high R^2 values we observe across all models (generally $R^2 \sim 0.9$), combined with the relatively high MAEs (~0.5-2.5 x10^7 m^3, which is approximately equal to typical irrigation withdrawals for the management area) and a slope substantially lower than one (Table 3) collectively support our interpretation that the ET-based irrigation calculations capture appropriate temporal patterns of variability in estimated irrigation, but tend to overestimate both the average magnitude and degree of interannual variability in irrigation volumes.

Subsequent analyses suggest that estimates of non-evaporative components of the water balance, such as deep percolation and root zone soil moisture storage changes, are a potential mechanism for this positive bias and increased variability because they can represent a potential source or sink for water that is not captured by our precipitation deficit calculation. The potential importance of deep percolation and soil moisture storage are suggested by Figure 8b, which shows that growing season precipitation is strongly correlated with the difference between the ET-based irrigation volumes and the reported groundwater withdrawals. The consistent positive bias in all years indicates that our effective precipitation estimates may be too low, while the strong correlation with precipitation suggests that the difference is driven by hydrologic dynamics. The ET-based approaches overestimated the reported irrigation volumes by the greatest amount in dry years, such as 2020, and the smallest amount in wet years, such as 2019 (Figure 4a). We found that a precipitation-based bias correction (described in Section 2.3 and shown as precipitation-adjusted annual irrigation in Figure 8c) had a substantially better agreement with reported irrigation values, with reductions in MAE by an order of magnitude, and four of the models and the ensemble mean had slopes between 0.9 and 1.1 after adjustment (Table 3, ‘Precip-Adj.’ column).

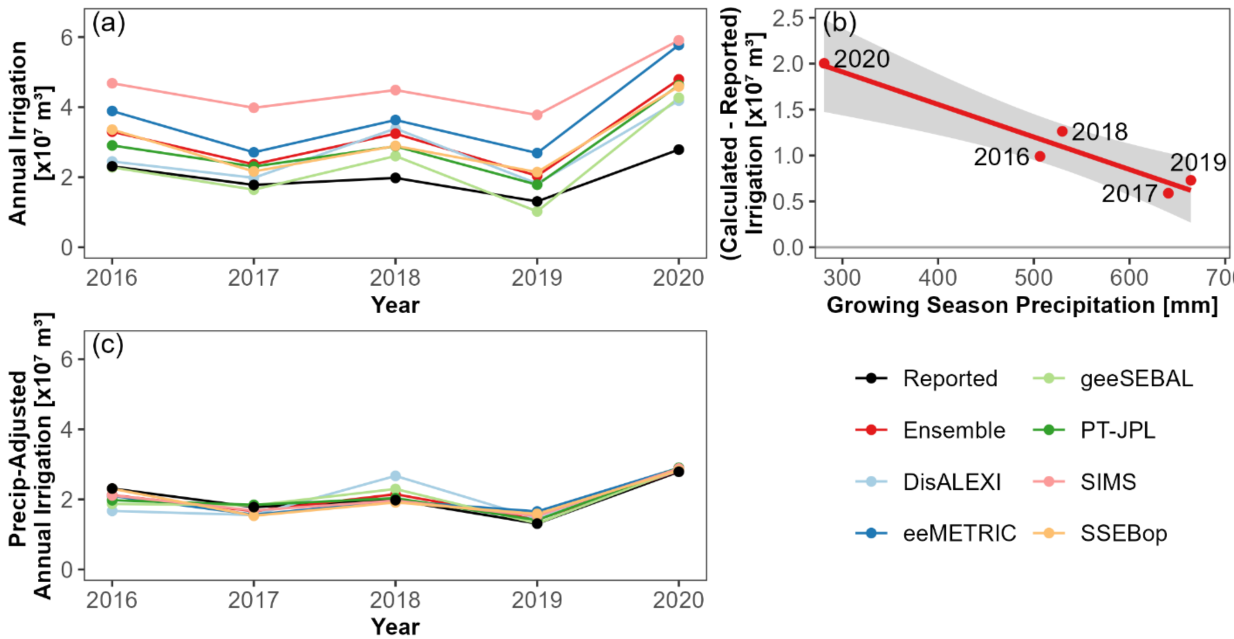


Figure 8. (a) Comparison between reported WIMAS pumping and ET-based irrigation volumes over the entire SD-6 LEMA. (b) Difference between ET-based calculated irrigation volume (from the OpenET ensemble) and reported water withdrawals for the SD-6 LEMA as a function of total growing season precipitation. The red line indicates a linear best-fit with a shaded standard error confidence interval (R^2 = 0.93) and points are labeled by year. (c) Comparison of reported and calculated irrigation for the SD-6 LEMA following precipitation adjustment based on Figure 8b. In all panels, calculated irrigation is based on growing season timescale of aggregation.

Table 3. Fit statistics for LEMA-scale OpenET-WIMAS comparison for each timescale of aggregation and model. 'Calc.' = calculated irrigation without adjustment (Figure 8a), 'Precip.-Adj.' = precipitation-adjusted irrigation (Figure 8c). Calculated irrigation is based on growing season timescale of aggregation.

	MAE [x10^7 m^3]		**Bias [%]**		**Slope**		**R^2**	
Model	*Calc.*	*Precip-Adj.*	*Calc.*	*Precip-Adj.*	*Calc.*	*Precip-Adj.*	*Calc.*	*Precip-Adj.*
DisALEXI	0.73	0.35	36%	0%	0.46	0.58	0.68	0.47
eeMETRIC	1.71	0.18	84%	0%	0.41	0.95	0.86	0.82
Ensemble	1.11	0.12	55%	0%	0.50	1.00	0.92	0.93
geeSEBAL	0.51	0.18	16%	0%	0.43	0.85	0.88	0.78
PT-JPL	0.87	0.13	43%	0%	0.50	0.96	0.90	0.89
SIMS	2.53	0.12	125%	0%	0.64	1.01	0.91	0.92
SSEBop	1.00	0.13	49%	0%	0.52	0.97	0.90	0.88

4. Discussion

We found that there was generally a positive correlation between calculated and reported irrigation at the field, WRG, and management area scales. The agreement was the best at the field scale, where we found that the growing season timescale of aggregation and the OpenET ensemble mean provided the closest match to reported irrigation. At the WRG and management area scales, we observed substantially more variability in the ET-based irrigation calculations than reported irrigation, which appeared to be associated with uncertainties in linking irrigated areas to places of use and non-evaporative components of the water balance, such as deep percolation and runoff used to calculate effective precipitation and year-to-year variability in soil moisture storage. Here, we discuss key sources of uncertainty that may have contributed to differences between reported and calculated irrigation and how those may affect the utility of ET-based irrigation products for research and management.

4.1 Sources of uncertainty in estimating irrigation from ET data

We identified and evaluated several sources of uncertainty that may explain differences between satellite ET-based and reported irrigation water withdrawals and applications, including (i) accounting for non-evaporative water balance components such as changes in soil moisture storage and effective precipitation; (ii) accurate identification of irrigated area, including linking fields to wells; and (iii) variability among ET models.

<u>4.1.1 Soil moisture changes and effective precipitation</u>

Quantifying non-evaporative components of the water balance such as year-to-year changes in soil moisture, deep percolation, and runoff appeared to be an important driver of uncertainty in our analysis at all three spatial scales. Since our approach relies on a relatively simple water balance (ET - effective precipitation) to estimate applied irrigation, the positive bias we observe at the WRG and management area scales suggests that we may be underestimating effective precipitation. Therefore, one contributing factor to our observed overestimates of irrigation may be the relatively simple approach we used to estimate effective precipitation, which was based on a regional regression for deep percolation (Figure S3). While runoff may be a source of error in our simple water balance approach for some locations (e.g. fields with larger slopes), it is regionally a small component of the water balance and is unlikely to explain systematic patterns of model errors observed across our study area (Deines et al., 2021). The consistent positive precipitation deficit for rainfed corn (Figure 9) further suggests that effective precipitation is being underestimated by our approach, and calculating effective precipitation using a field-specific soil water balance model approach such as ETDemands (Allen et al., 2020) could help to improve overall agreement. Issues with ET data may also be greater during wet conditions, as we would expect greater errors in calculated ET, and therefore irrigation, for periods or regions with increased cloud cover that affect the optical and thermal bands of satellites used by ET models. Since cloud cover is associated with precipitation events, this may have an outsized effect on estimating ET and irrigation during times when soil moisture is being replenished.

While the overall positive bias suggests issues with effective precipitation calculations, the strong relationship between the calculated irrigation residual and precipitation (Figure 8b) suggests that year-to-year changes in root zone soil moisture are also a source of uncertainty. Holding all other aspects of the water balance constant, if soil moisture storage decreased during the dry 2020 growing season, this would cause an increased overestimate of irrigation since some of the ET in 2020 was using soil moisture that fell in previous years, such as the relatively wet 2019. However, variability in individual producer irrigation behavior across years may also contribute to the increased interannual variability in the ET-based irrigation volumes observed in Figure 8 compared to the reported irrigation volumes. For example, previous research in the neighboring state of Nebraska has shown that metered groundwater use typically exceeds crop water requirements in wetter and average rainfall years while farmers are observed to adopt more water-efficient irrigation practices in drier years to reduce non-consumptive water losses, likely motivated by a combination of the higher costs of irrigation and greater likelihood of experiencing irrigation system capacity constraints in drought years (Foster et al., 2019).

Furthermore, our ET-based irrigation volumes did not account for leakage in irrigation systems and other losses of water between where it is pumped from the ground but before it reaches the field, though based on the high efficiency in the SD-6 LEMA area we expect that these losses are minimal (~10%, consistent with other estimates). However, in settings with lower irrigation efficiencies, non-consumptive losses of applied irrigation water such as deep percolation or runoff would likely be missed by ET-based irrigation estimation methods and can have a significant impact on estimated irrigation water use (Puy et al., 2022). Our analysis suggests that, for annual or finer temporal resolutions and/or settings with lower irrigation efficiency, the use of more complex water balance approaches, such as soil water balance models (Dhungel et al., 2020; Kharrou et al., 2021; Pereira, Paredes, & Jovanovic, 2020; Zhang et al., 2023), will be necessary to accurately disentangle the rates, locations, and timing of irrigation applications. To facilitate these approaches, there may be promise through the assimilation of additional data sets such as in situ or remotely sensed soil moisture (Dari et al., 2020; Filippelli et al., 2022; Jalilvand et al., 2019, 2023; Laluet et al., 2024; Paolini et al., 2023).

4.1.2 Linking wells to irrigated fields

Challenges in linking specific wells to irrigated fields appeared to cause disagreement between reported and calculated irrigation at the WRG spatial scale. This source of uncertainty is supported by several lines of evidence. At the field scale, where irrigated extents were known and verified by the farmers sharing their irrigation data, we generally saw the best agreement between calculated and reported irrigation (Figure 4), while at the WRG scale there was substantial disagreement between estimated and reported irrigated area (Figure 6). At the WRG scale, our ET-based calculations of irrigation volume were better correlated with flowmeter data than calculations of irrigation depth (Figure 5), consistent with results from the nearby Colorado portion of the Republican River Basin (Filippelli et al., 2022), and agreement improved when focusing only on WRGs where reported and estimated irrigated area were similar (Figure 7). The weaker relationship between calculated and reported irrigation depth, compared to irrigation volume, reflects the importance of irrigated area as a determinant of overall irrigation volumes (Lamb et al., 2021; Puy et al., 2021; Wei et al., 2022).

While the irrigation extent dataset we used is the best-available for this region and consistently shows differences in precipitation deficit between irrigated and rainfed corn, there is also substantial overlap between their distributions, suggesting that some degree of misclassification is practically assured (Figure 9). Based on our analysis, local errors in irrigation status maps are likely fairly evenly distributed between under- and over-estimating irrigated area, with a slight bias towards overestimated irrigated area (Figure 6). This may be particularly challenging in relatively small unirrigated portions of otherwise irrigated fields, such as the non-irrigated corners of center-pivot systems (Figure S5). Additionally, irrigation mapping can be particularly challenging during wet years, such as 2019 when there is the greatest overlap between rainfed and irrigated distributions, because the differences in canopy cover and greenness between irrigated and rainfed fields are smaller (Xu et al., 2019).

Accurately linking the point of water diversion with the place where that water is applied was a major challenge in our analysis and has been identified as a key source of uncertainty in other domains (Ott et al., 2024). While developing these links may not be needed for many applications, such as regional water balance assessments, connecting the point of diversion with place of use is critical to evaluate irrigation application depths and to assess the effectiveness of conservation measures and the ultimate impacts of pumping on other aspects of regional agrohydrological systems such as streamflow (Kniffin et al., 2020; Zipper, Carah, et al., 2019; Zipper et al., 2021), aquifer dynamics (Feinstein et al., 2016; Peterson & Fulton, 2019; Wilson et al., 2021), or groundwater-dependent ecosystems (Tolley et al., 2019). Despite exceptionally high-quality water use data for the state of Kansas, the limited linkages between the point of diversion and actual place of use highlights a key data gap for the application of remotely sensed irrigation data for hydrogeological research and management, and a necessary improvement for field-level operationalization.

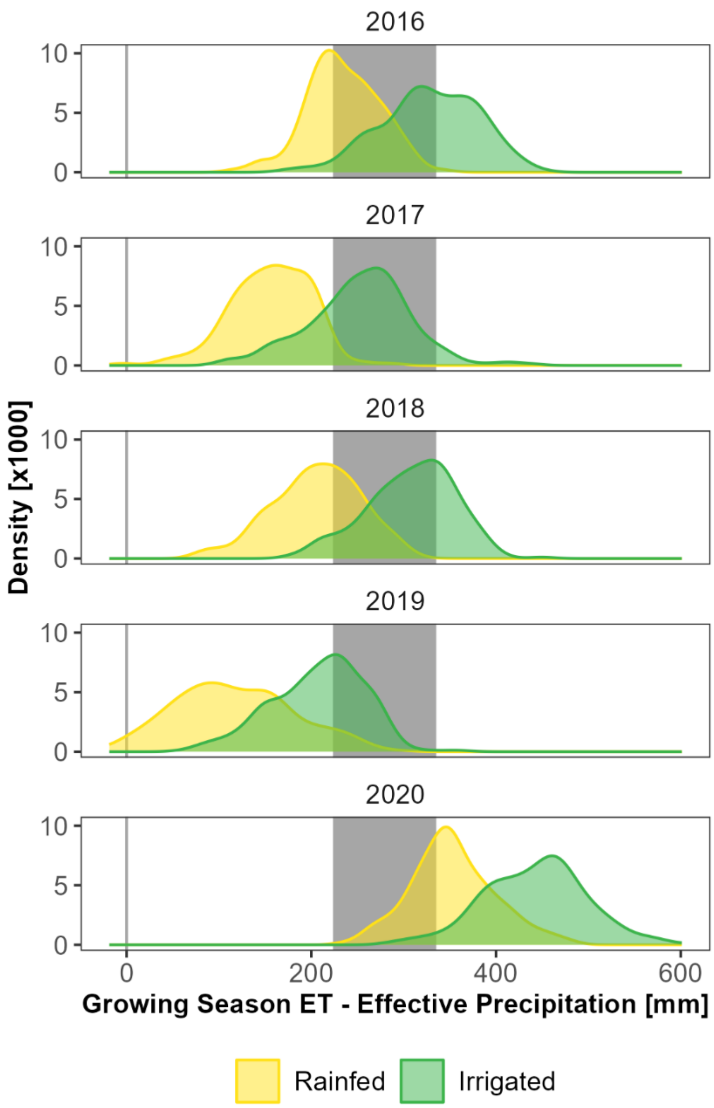


Figure 9. Distribution of field-resolution growing season ensemble ET - Effective Precipitation for corn fields in the SD-6 LEMA, separated by year and colored by irrigation status. The gray shaded interval shows the average annual LEMA irrigation allocation (279.4 mm) +/- 20%.

4.1.3 Variability among ET models

The selection of ET model also led to substantial variability in the estimated irrigation depths, with a relatively consistent ordering across models (from lowest to highest): geeSEBAL, DisALEXI, PT-JPL, SSEBop, Ensemble, eeMETRIC, SIMS (Figure 4, Figure 8). Since the effective precipitation input data used to estimate irrigation was the same for all models, this variability in estimated irrigation among the models can be attributed entirely to differences in the approaches used by each ET model, and variability can be quite substantial. For example, for irrigated corn in the SD-6 LEMA, the medians span 156-270 mm across ET models in a given year (Figure 10), which approaches the magnitude of total applied irrigation water and greatly exceeds the magnitude of the conservation actions put in place in this region (Whittemore et al., 2023). The variability among models may be due to differences in the approaches to computation of the sensible heat flux used in each of the five energy balance models, differences in the spatial scale of key meteorological inputs for the DisALEXI, PT-JPL and geeSEBAL models, and model assumptions, especially for SIMS, which assumes well-watered conditions. This underscores the importance of local model accuracy assessments to identify the models that perform best for the crop types and irrigation management practices that are most prevalent in the region.

In the absence of suitable independent dataset for use in a local or regional accuracy assessment, OpenET recommends use of the ensemble ET value, which has been shown to perform best overall for the western U.S. across most accuracy metrics (Melton et al., 2022; Volk et al., 2024). Our results support this recommendation, as we found that the model ensemble was generally among the best-performing approaches to calculating irrigation (Table 1, Table 3), particularly after statistically adjusting to account for potential errors in effective precipitation calculations (Figure 8c). This suggests that the ensemble mean would be a reasonable approach to use across our study region until additional local accuracy assessments can be conducted.

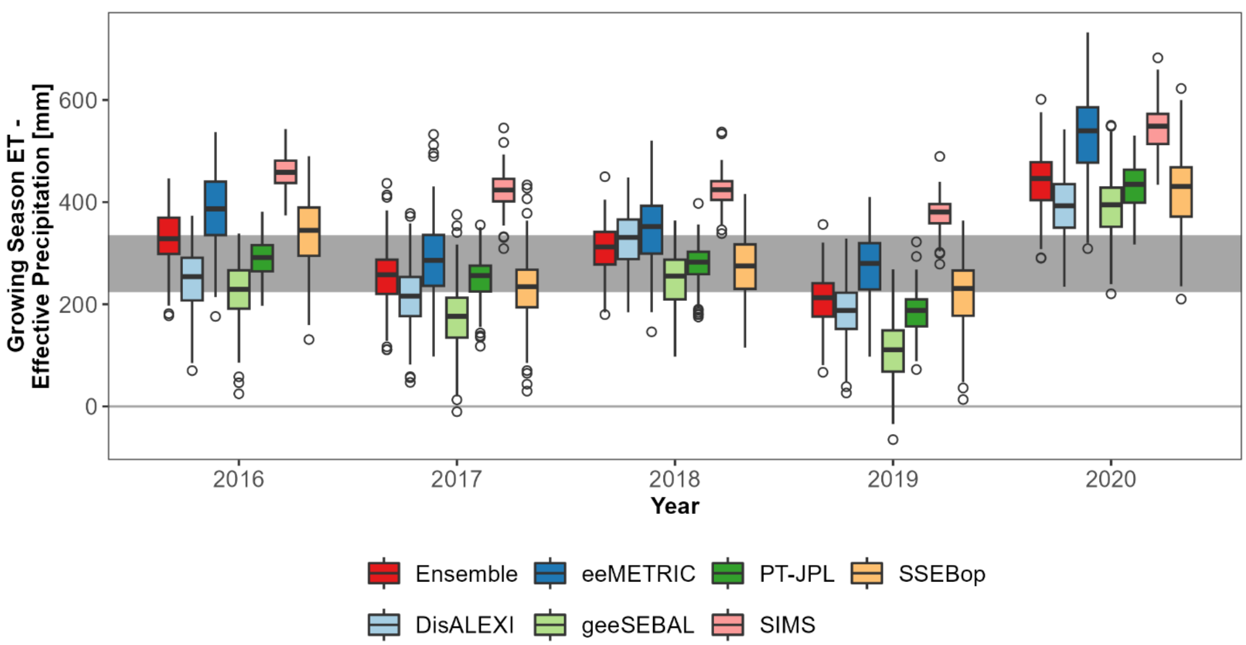


Figure 10. Distribution of ET - precipitation for all irrigated corn fields in the LEMA, colored by model. The gray shaded interval shows the average annual LEMA irrigation allocation (279.4 mm) +/- 20%.

4.2 Utility for research and management purposes

As water becomes increasingly scarce, the importance of accurate accounting of how, where, when, and how much water is being used is becoming more critical. In the US, each state is responsible for administering water rights and regulating water use within their jurisdictional boundaries. Water use metering and reporting requirements vary significantly between states.

Satellite-based ET data could provide a nationally consistent approach to computing consumptive use of water applied for irrigation, and potentially for estimating the volume of water applied for crop irrigation, which is the largest source of consumptive water use in the US (Marston et al., 2018). However, these satellite-based irrigation calculations need to be comparable to what is actually happening on the ground, demonstrating the importance of high-fidelity in situ measurements of irrigation. This study was made possible by metered groundwater pumping records detailing the location, amount, and timing of irrigation. Outside of Kansas, metered records of irrigation are rare, with many states not requiring flowmeters on agricultural water uses (Marston, Abdallah, et al., 2022). This gap is increasingly being filled with reanalysis and ET-based water use products (Haynes et al., 2023; Martin et al., 2023). For ET-based irrigation data to become more useful to researchers, irrigators, regulators, and policymakers, metered irrigation records are needed for other areas with different soils, climate, irrigation practices, and cropping patterns to evaluate the performance of ET-based irrigation calculations under these different conditions.

The sources of uncertainty we discuss in Section 4.1 contributed to variable levels of agreement between ET-based and reported water withdrawals and applications across the comparisons we conducted. At the field scale, we found a generally low bias and slope approaching one for the ensemble mean irrigation (Table 1), though the R^2 and MAE we observed was lower than assessments elsewhere (e.g., Ott et al., 2024). At the management area, we found a strong positive correlation (e.g., R^2 generally above 0.85; Table 3), comparable to other studies using remotely sensed data to estimate irrigation depths with statistical models (Filippelli et al., 2022; Majumdar et al., 2022; Wei et al., 2022). However, we observed a general positive bias and more year-to-year variability in ET-based irrigation than in the reported data, with substantial improvements in agreement after adjusting for potential effective precipitation (Figure 8c). Agreement between calculated and reported irrigation was the worst for the WRG-scale comparison, in particular for irrigation depths, highlighting the major challenges in linking points of diversion to irrigated field extents.

Since errors in estimated irrigation can lead to significant economic and hydrological impacts if used for management purposes (Foster et al., 2020), continued methodological development to overcome the uncertainties described above will be important to advance these tools for some applications. For instance, for purposes that require estimating long-term average consumptive use, such as calculating the water balance for a large (10s to 100s of km) region, the precipitation-adjusted spatially- and temporally-aggregated results we show in Figure 8c might be sufficient. For example, the precipitation-adjusted irrigation calculation approach we show could be effective for providing accurate irrigation calculations extrapolated through space or time. Potential applications may include extending irrigation records backwards to years prior to the onset of irrigation monitoring, providing rapid information on annual irrigation volumes prior to reporting volumes becoming available (a process which typically takes several months in this region), or estimating irrigation in neighboring areas where agricultural practices are similar, but monitoring is unavailable. In areas without any metered data that would be capable for training models, approaches based solely on irrigated area may provide sufficiently accurate water use estimates (Puy et al., 2021), assuming irrigated area is mapped with sufficient accuracy.

In contrast, using these data for other purposes, such as monitoring within-season irrigation timing and volume from a specific well, would require significant improvements in the accuracy of calculated irrigation at these finer spatial and temporal scales and careful selection of an appropriate ET model. We found that statistical adjustments to ET-based irrigation calculations can substantially improve agreement with reported values at annual resolution (Figure 8c), potentially suggesting a path towards greater local accuracy, and highlighting the critical importance of accurate effective precipitation values and ground-based data for comparison. While our precipitation-adjusted approach required reported irrigation data, and therefore would not be tractable in locations without existing withdrawal monitoring, it may be possible to use a limited subset of reporting locations to develop relationships that can be applied more broadly (Bohling et al., 2021). Additional products, such as high-resolution soil moisture data from remote sensing-model integration (Vergopolan et al., 2021), may also provide a pathway for bias-correction and/or temporal disaggregation when integrated with field-specific water balance modeling tools (Hoekstra, 2019). Given that OpenET is a relatively new product (Melton et al., 2022), continued work on specific research and management applications will provide useful targets for prioritizing efforts to reduce existing uncertainties.

5. Conclusions

We evaluated ET-based calculations of irrigation using a simple water balance approach and compared to reported irrigation from farmer records and a statewide database. We found that the agreement between calculated and reported irrigation was best at the field scale, where irrigated extent was precisely known, and when aggregating ET calculations using the OpenET ensemble mean at the growing season timescale. At the WRG and management area scales, there were generally positive correlations between the ET-based approaches and reported data, but the ET-based approaches typically demonstrated more variability than reported values and overestimated irrigation, particularly during dry years. This may be partially attributed to changes in soil moisture storage, the approach used to calculate effective precipitation, and challenges linking irrigated area to specific fields. The choice of an ET model is an additional source of uncertainty. The uncertainties in ET-based irrigation calculations likely exceed the signal of management activities in this region, suggesting further methodological refinement is needed for applications requiring precise quantification of irrigation depth for a given location and/or single year. However, for applications focused on relative differences in irrigation intensity across space and/or multi-year average irrigation applications, some of these uncertainties may safely be ignored. This work suggests that ET-based approaches to calculating irrigation are a potentially valuable tool for developing improved spatial and temporal water use data and will likely require application-specific targeted improvements to reduce key uncertainties.

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