Evaluation of hydrologic impact of an irrigation curtailment program using Landsat satellite data

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Abstract
Upper Klamath Lake (UKL) is the source of the Klamath River that flows through southern Oregon and northern California. The UKL Basin provides water for 81,000 + ha (200,000+ acres) of irrigation on the U.S. Bureau of Reclamation Klamath Project located downstream of the UKL Basin. Irrigated agriculture also occurs along the tributaries to UKL. During 2013–2016, water rights calls resulted in various levels of curtailment of irrigation diversions from the tributaries to UKL. However, information on the extent of curtailment, how much irrigation water was saved, and its impact on the UKL is unknown. In this study, we combined Landsat-based actual evapotranspiration (ETa) data obtained from the Operational Simplified Surface Energy Balance model with gridded precipitation and U.S. Geological Survey station discharge data to evaluate the hydrologic impact of the curtailment program. Analysis was performed for 2004, 2006, 2008–2010 (base years), and 2013–2016 (target years) over irrigated areas above UKL. Our results indicate that the savings from the curtailment program over the June to September time period were highest during 2013 and declined in each of the following years. The total on-field water savings was approximately 60 hm³ in 2013 and 2014, 44 hm³ in 2015, and 32 hm³ in 2016 (1 hm³ = 10,000 m³ or 810.7 ac-ft). The instream water flow changes or extra water available were 92, 68, 45, and 26 hm³, respectively, for 2013, 2014, 2015, and 2016. Highest water savings came from pasture and wetlands. Alfalfa showed the most decline in water use among grain crops. The resulting extra water available from the curtailment contributed to a maximum of 19% of the lake inflows and 50% of the lake volume. The Landsat-based ETa and other remote sensing datasets used in this study can be used to monitor crop water use at the irrigation district scale and to quantify water savings as a result of land-water management changes.
1 | INTRODUCTION

The increasing pressure to meet human demand for food for continuously growing populations is depleting water resources and leading to global water scarcity. It is estimated that over two-thirds of the global population is currently suffering from lack of water at least 1 month out of the year (Mekonnen & Hoekstra, 2016), and up to 700 million people could be displaced by intense freshwater scarcity by 2030 (Hameeteman, 2013). Agriculture consumes up to 70% of global human water use. Within the agricultural sector, water used for irrigation accounts for nearly 65% of the world's freshwater withdrawals excluding thermoelectric power (Hutson et al., 2004). Over the last several decades, increases in global food production were to a large extent possible due to (a) doubling of the irrigation area, (b) corresponding increases of water withdrawal for irrigation, and (c) increased usage of fertilizer (Oki & Kanae, 2006). The increase in water use for irrigation is depleting surface water resources (Rodell et al., 2018; William Darwall William Darwall et al., 2018), depleting groundwater resources (Wada et al., 2010), reducing water quality (Gallardo et al., 2018), and impacting ecosystem biodiversity (Clausen & York, 2008; Falkenmark, 2003; Gallardo et al., 2018; Garcia-Moreno et al., 2014).

Within the United States, agriculture is a major consumer of groundwater and surface water. About 80% of the Nation's consumptive water use (> 90% in the western United States) is attributed to crop irrigation. The arid/semiarid climate of the western United States with low rainfall distribution has resulted in increased pressure for freshwater for use in irrigated agriculture. Recently, water management programs have been implemented to reduce agricultural water use in the western United States. These programs are often supported by the government and water management authorities, which are implementing policies to promote water conservation rather than water use (Peck, 2015). A well-studied example is the crop fallowing program in the Palo Verde Irrigation District (PVID) on the border between California and Arizona, where a water management agreement between the PVID and the Metropolitan Water District of Southern California left a fraction of PVID fields intentionally fallow, so water could be transferred to meet domestic water demand in municipal areas (Senay, Schauer, Friedricks, Velpuri, & Singh, 2017). Similarly, a farmland fallowing and forbearance project in Arizona was implemented in 2014 to increase water in the Colorado River system by saving about 25 to 74 cubic hectometers (hm³, 1 hm³ = 10,000 m³ or 810.7 ac-ft) of water and improving Lake Mead water levels (https://wrrc.arizona.edu/arizona-land-fallowing, last accessed: Nov 12, 2019). Other examples of irrigation water curtailment include reducing water permits for extraction of surface and groundwater, termination of water rights, or economic payouts to compensate the forbearance of water rights.

This study focuses on quantifying the effects of curtailment of irrigation diversions in the Upper Klamath Lake (UKL) Basin in southern Oregon. Since 2013, when water claims were determined in the basin, water users with senior water rights (who do not receive the water they are entitled to) may request that state water regulators shut off or curtail diversions to junior water rights users. Regulators and water users need to understand the effect of curtailing diversions, specifically how curtailment affects streamflow and inflows to UKL. The impact of the curtailment in the UKL Basin and quantifying the additional water that remained in the stream from curtailment were first studied by Hess and Stonewall (2014), where they compared the measured U.S. Geological Survey (USGS) 2013 streamflow data with curtailments with those data from hydrologically similar years without curtailments. That study found that streamflow from the Williamson and Wood Rivers to UKL increased by approximately 17 hm³ (14,100 ac-ft) and 7 hm³ (5,500 ac-ft), respectively, between July and September. However, the Hess and Stonewall study was limited to analysis of instream river flows only in 2013. Furthermore, information on temporal and spatial variability in the water savings (2013–2016) across the UKL Basin and from which crop types/landscapes savings originated were not addressed.

The goal of this current study was to use Landsat-derived ETa to quantify the hydrologic impact of the 2013–2016 curtailment program. The primary objectives of this study were to (a) quantify the on-field water savings and how these water savings affected streamflow due to irrigation curtailment, (b) understand the spatial and temporal variability in water savings, (c) estimate and quantify water savings by crop type during the curtailment period, and (d) understand the impact of water savings on the UKL Basin water budget.

2 | STUDY AREA AND DATA USED

2.1 | Study area

The UKL Basin is on the eastern slopes of the Cascade mountains in southern Oregon and is characterized by low rainfall and semiarid conditions. UKL is the largest freshwater body in the state of Oregon. It is the source of the Klamath River that flows through southern Oregon and northern California and is a crucial source of water for irrigation up to 202,000 ha (~500,000 ac) including 81,000+ ha (200,000+ ac) of the U.S. Bureau of Reclamation irrigation project located downstream of the lake (Marshall, Robles, Majka, & Haney, 2010). UKL is a shallow lake with an average depth of 2 m and an average volume of approximately 546 hm³ (Walker, Walker, & Kann, 2012). Hubbard (1970) provided a detailed account of the UKL primary water budget components. Principal inflows into UKL are contributed by streams, irrigation canals, agricultural drainage, springs, seeps, and direct precipitation on the lake. Surface inflow provides about 79% of the lake inflows (Hubbard, 1970). The Williamson and the Wood Rivers contribute nearly 49% and 16%
of the UKL inflows, respectively. These two rivers together contribute more than 80% (66% of the total 80% surface inflows) of the surface inflows to the lake. The streams that drain from the Cascade ranges on the west side of the lake (Cherry, Sevenmile, Fourmile, Three mile Creeks, and Central Canal) together contribute up to 8% of the lake inflows. Other minor creeks, such as Rock, Varney, Moss, and Denny, contribute up to another 2% of the lake inflows. It is reported that about 4% of the total inflows comes from agricultural drainage, and the remaining inflows (up to 14%) are contributed by springs and seeps around the lake; precipitation directly contributes to the remaining 7% of inflows to the lake (Hubbard, 1970). Because it is hard to delineate watersheds for these small to minor creeks at the scale presented in Figure 1, we combined their watersheds with the Wood River basin.

2.2 | Data used

The top-of-atmosphere reflectance Landsat data (Collection 1) were obtained from https://earthexplorer.usgs.gov (last accessed: Nov 12, 2019). In this study, a total of 1,066 Landsat 5/7/8 images with 60% cloud cover or less from paths 44–45, rows 30–31, which covered the basin, were processed for the base (2004, 2006, and 2008–2010) and target years (2013–2016). Base and target years were selected based on recommendations from the USGS Oregon Water Science Center. The number of Landsat imagery and sensor types used in this study is presented in Table 1. The Landsat quality assessment band was used to flag and mask out clouds, cloud shadows, and Landsat 7 scan-line errors, and these pixels were gap-filled with simple linear interpolation using Landsat images in a 48-day window (Senay et al., 2019).

Landsat-based ETa data used in this study were modelled using the Operational Simplified Surface Energy Balance (SSEBop) algorithm (Senay et al., 2013) that uses model-assimilated weather datasets and Landsat thermal data to produce ETa for the UKL Basin. Monthly total precipitation for the study area over the base years and target years was summarized from 4-km monthly Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation datasets (Daly et al., 2000; Daly, Smith, & McKane, 2007) obtained from the PRISM

FIGURE 1  The Upper Klamath Lake Basin covering Sprague, Williamson, and Wood River basins (shown in grey shades) are available at https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/newsroom/features/?cid=nrcs143_023452. The area under irrigation is shown as coloured polygons
Climate Group website (http://www.prism.oregonstate.edu/, last accessed: Nov 12, 2019). River discharge data were obtained from the USGS National Water Information System database (U.S. Geological Survey, 2019; https://waterdata.usgs.gov, last accessed: Nov 12, 2019). Locations of gaging stations used in this study are presented in Figure 1. Data from two eddy covariance sites were obtained from Stannard et al. (2013). We used a 10-m USGS National Elevation Dataset digital elevation model to derive watersheds for the selected streamflow gaging stations. We also used gridded 30-m U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) products (2008–2010 and 2013–2016) to summarize crop-wise water savings over the target years. An irrigated area mask showing areas under which water rights are in place was obtained from the Oregon Water Resources Department. This irrigated area mask identifies irrigated areas within the Sprague, Williamson, Wood Rivers, and other small watersheds. The mask also provides information on the source of water (surface water, groundwater, or conjunctive use).

3 | METHODS

3.1 | Modeling ET data using SSEBop model

Landsat ET is modelled using the SSEBop approach, which leverages the thermal band from Landsat along with weather datasets to generate a daily total of ETa (Senay et al., 2013). The Landsat thermal band is converted into land surface temperature using emissivity derived from the normalized difference vegetation index. The primary product of the SSEBop model is the daily ET fraction, which is an index between 0 (dry, bare surface with no ET) to 1 (wet, green, irrigated land with maximum ET). The ET fraction is then used to reduce the grass-reference potential ET dataset derived from GridMET (Abatzoglou, 2013). GridMET is a gridded 4-km dataset of daily weather variables for the continental United States provided from 1979 to the present and available from the University of Idaho http://www.climatologylab.org/gridmet.html. SSEBop actual ET can be summarized with the following equation:

$$ETa = (1 - γs(Ts − Te)) * k * ETo$$

(1)

where ETa is the daily total actual ET in millimetre for the Landsat image; γs is the surface psychrometric constant (K) derived from a radiation budget; Ts is the land surface temperature derived from the Landsat thermal band (K); Te is cold/wet reference limit, derived from the daily maximum air temperature (K); k is a scaling factor (fixed at 1.25) to convert grass reference to alfalfa reference; and ETo is the gridded grass-reference (short crop) potential ET from GridMET (Abatzoglou, 2013). Equation (1) calculates the daily total actual ET for each Landsat image, which is then aggregated to monthly, seasonal, and annual ET. For a more detailed description of the SSEBop model, please refer to Senay (2018) and Senay et al. (2019).

3.2 | Validation of ET datasets

Modelled SSEBop ET estimates have been thoroughly validated over multiple sites in the past. Velpuri, Senay, Singh, Bohms, and Verdin (2013) indicated a reasonable match between SSEBop ETa versus flux tower sites at pixel-scale validation and with Max Planck Institute's gridded monthly estimates of ET at the basin scale. Senay et al. (2017) compared monthly SSEBop ETa to monthly Max Planck Institute ETa from 1984 to 2011 for eight hydrologic unit code-8 sub-basins in the middle and lower Central Valley of the United States and found an average R² of .76 and average root mean square error (RMSE) of 11.7 mm. More recently, monthly SSEBop ETa and Ameriflux eddy covariance flux tower monthly ETa were compared in the Upper Rio Grande Basin of the southwestern United States for noncropland environments such as forest, shrubland, and grassland sites from 2007 to 2014 and found an average R² of .85 and average normalized RMSE of less than 10% (Senay et al., 2019).

In this study, validation of SSEBop ETa was carried out using observed data from two eddy covariance flux tower sites located within the Upper Klamath National Wildlife Refuge: (a) Bulrush site (42°30′48.88″N, 122°2′4.89″W, 1261.9-m above mean sea level) and (b) Mixed site (42°28′36.80″N, 122°4′6.05″W, 1260-m above mean sea level), Observed ETa data from these two sites were collected and published by Stannard et al. (2013). The Bulrush site is dominated by hard-stem bulrush (Scirpus acutus, Schoenoplectus acutus), whereas the Mixed site is 70% bulrush (S. acutus, S. acutus), 15% cattail (Typha latifolia), and 15% wocus (Nuphar polysepalum). The SSEBop ETa was validated at both daily and monthly time scales. Validation was performed by comparing observed ETa with a 3 × 3 pixel mean sample ETa from the SSEBop ETa dataset.
3.3 | Quantifying the on-field water savings

The modelled seasonal SSEBop ETa provides a direct measure of on-field water use per pixel over base years (2004, 2006, and 2008–2010) and target years (2013–2016). As the curtailment in irrigation is expected to reduce the Landsat ETa, any reduction in ETa over target years with respect to the base years would indicate water savings. Hence, using ETa, we computed water savings (the deviation in ETa or \( \Delta ETa \)) for each target year with respect to the base year as

\[
\Delta ETa_i = ETa_i^{TY} - ETa_i^{BY}, \tag{2}
\]

where \( i \) ranges from target years 2013–2016, and \( j \) ranges from base years (2004, 2006, and 2008–2010). Based on Equation (2), we get a set of 5 values for each target year. Mean \( \Delta ETa \) (\( \Delta ETa_{mean} \)) was also computed for each target year using the mean of all the base years as shown below:

\[
\Delta ETa_{mean} = ETa_i^{TY} - ETa_{mean}^{BY}, \tag{3}
\]

where \( ETa_{mean}^{BY} \) is the mean estimate of SSEBop ETa for all the base years.

3.4 | Computation of extra water available

The deviation in ETa does not necessarily reflect the extra water available (EWA) in the streams resulting from the curtailment because any changes in ETa over the target year can be partially attributed to the differences in precipitation between target and base years. Hence, to compensate the impact of precipitation on the \( \Delta ETa \) estimates, we used gridded estimates of precipitation over base year and target year to compute the deviation in precipitation (\( \Delta PPT \)) and average deviation in precipitation (\( \Delta PPT_{mean} \)) between base and target years as shown below.

\[
\Delta PPT_{ij} = PPT_i^{TY} - PPT_i^{BY}, \tag{4}
\]

\[
\Delta PPT_{mean} = PPT_i^{TY} - PPT_{mean}^{BY}, \tag{5}
\]

EWA for each of the target year (with respect to the base year [s]) and average EWA (with respect to the average of the base years) are then computed as

\[
EWA_{ij} = \Delta PPT_{ij} - \Delta ETa_i, \tag{6}
\]

\[
EWA_{mean} = \Delta PPT_{mean} - \Delta ETa_{mean}. \tag{7}
\]

The parameters \( \Delta ETa \) and EWA are computed per pixel and are summarized as polygon averages over irrigated areas in a river basin. The data are also presented for the river basin irrigation (Sprague River, Williamson River, Wood River, and Upper Klamath Agency Lakes irrigation) and irrigation type (surface water, groundwater, and conjunctive use).

3.5 | Analysis of crop-wise water savings

To investigate the impact of water savings on crop types and vice versa, we used the USDA-NASS CDL dataset over 2008–2010 and 2013–2016. The CDL is considered the best crop-specific gridded dataset for the conterminous United States (Lark, Mueller, Johnson, & Gibbs, 2017). We clipped out CDL crop type information for the irrigated area within the study site. To obtain a clean map and to remove the unwanted single pixels with random crop types, we ran a generalization procedure suggested by Lark et al. (2017) to retain only pixel clusters of eight or more neighbouring pixels and identified eight crop types for the analysis. Out of eight crop classes, we identified four grain crop and four non-grain crops classes that were widespread in the UKL Basin. Because we ignored isolated pixels and classes that were less than eight-pixel clusters, the eight classes covered >75% of the total irrigated area. For each crop type, we computed the mean savings over the base year and target years and computed crop type savings in water use for the target years.

3.6 | Impact of water savings on Upper Klamath Lake water budget

Curtailment of surface water should result in more flow in streams and inflow to UKL than if curtailment did not occur. Hence, the impact of savings from the irrigation curtailment on the UKL was investigated by comparing the savings computed from Equations 6 and 7 with surface inflows (\( Q_{in,i} \)), surface outflows (\( Q_{out,i} \)) and lake volume (\( L_i \)). We computed lake inflows (\( Q_{in,i} \)) as shown below:

\[
Q_{in,i} = Q_{hi} + Q_{wo} + Q_{oth}. \tag{8}
\]

where \( Q_{hi} \) is the average annual discharge estimates over 2003–2012 (33 cubic metre per second [m³/s] or 1,171 cubic feet per second, [ft³/s]) for Williamson River obtained from the USGS gaging station #11502500 (Williamson River below Sprague River near Chiloquin; 42°33’51.75”, 121°52’46.97”). The data from this station include combined discharge from Sycan, Sprague and Williamson Rivers and contribute up to 49% of UKL inflows. \( Q_{wo} \) represents the average annual discharge data over 2014–2018 for Wood River into UKL obtained from USGS gaging station #11504115 (Wood River near Klamath Agency). \( Q_{oth} \) represents other smaller tributaries that flow into UKL and contribute nearly 16% of inflows. Because data on \( Q_{oth} \) are not available, we omitted this parameter from the analysis. Only discharge data obtained from the Williamson River gaging station (\( Q_{wo} \)) and the Wood River gaging station (\( Q_{wo} \)) which together contribute nearly 80% of the surface inflows, were used to compute \( Q_{in,i} \). The lake outflows were obtained from USGS discharge station #11507500, (station name: Link River at Klamath Falls). Average annual discharge data over 2003–2012 were used to compute outflows from the lake. The mean lake volume (\( L_i \)) of 541.6 hm³ was obtained from Walker et al. (2012).
4 | RESULTS

4.1 | Seasonal SSEBop ETa estimates

Basin-wide seasonal SSEBop ETa estimates were produced for the June–September months corresponding to the irrigation curtailment during the peak growing season. Figure 2 shows the total seasonal ETa for the base and target years. In the figure, the areas of low ETa < 100 mm (in yellow) are concentrated in the northwestern and eastern regions of the basin. The areas of high ETa > 800 mm (in dark blue) represent water bodies or marsh lands. During June to September, the UKL Basin was mostly dry as it received average rainfall of about 50–60 mm. However, the seasonal SSEBop average ETa was roughly four times higher than the rainfall received (up to 260 mm) during June–September.

4.2 | Validation results

Validation was carried out at two scales. First, we compared daily summaries of ETa obtained from the eddy covariance tower sites with overpass ETa modelled using SSEBop model. Comparison between...
the estimated daily ETa and measured ETa showed decent correlation at both sites (Pearson’s $r$, Figure 3). SSEQop ETa was found to capture the temporal variability seen at both the sites. The SSEQop model-based ETa reasonably captured the daily variation of ETa at the Bulrush site with an adjusted $R^2$ of .75 (2008), .75 (2009), and .61 (2010) with percent mean bias error of −0.3% (2008), 8% (2009), and 10% (2010). The RMSE ranged from 0.99 mm/day (2008) to 1.19 mm/day (2009) at the Bulrush site. For the Mixed site, modelled ETa showed an adjusted $R^2$ of .68 (2008), .79 (2009), and .71 (2010) with percent mean bias error of −0.4% (2008), −9% (2009), and 7% (2010). The RMSE for the Mixed site was 1.12 mm/day (2008), 1.21 mm/day (2009), and 0.97 mm/day (2010).

Monthly observed ETa data from both sites (Bulrush and Mixed) were summarized and compared with the monthly SSEQop ETa data. Validation at a monthly time step showed high correlations (adjusted $R^2 > .92$) in Figure 4. At both sites, SSEQop ETa was slightly underestimated. The RMSE at the monthly scale was found to be 22 mm (25%) and 21 mm (22%), respectively, for the Bulrush and Mixed sites. However, at the seasonal scale, the RMSE was found to be about 72 mm (12%) and 46 mm (6%), respectively, for the Bulrush and Mixed sites. The percent bias error at the monthly scale indicated an underestimation up to 15 mm (16%) and 11 mm (12%), respectively, for the Bulrush and Mixed sites. However, the percent bias error at the seasonal scale was 71 mm (12%) and 30 mm (5%), respectively, for the Bulrush and Mixed sites.

### 4.3 Basin-scale ETa and ΔETa

The deviation in ETa (ΔETa), or water savings for each target year, was computed using Equations 2 and 3. Figure 5 shows the comparison of average ETa over the base years versus the ΔETa for the target years. The base year average ETa shows irrigated areas and marshlands in darker shades of green with seasonal ETa estimates greater than 400 mm (Figure 5). The ΔETa for the target years clearly shows areas where water savings occurred (in shades of yellow to red). Whereas most water savings occurred over the irrigated regions, some of the highest water savings (in the order of 200 to 424 mm) were observed over the irrigated area and marshlands of the UKL Basin (Sycan and Klamath marshes). Most of the increase in ETa over the target years occurred outside the irrigated areas.

Figure 5 shows that water savings were large in 2013 and 2014 and relatively smaller in 2015 and 2016. Although Figure 5 provides some information on the general trend and spatial variability in water savings across the basin, it does not provide quantitative information about the water savings exclusively for the irrigated regions (Sprague, Williamson, Wood River irrigation, and Upper Klamath Agency Lakes irrigation), and how they change over the target years. Figure 6 shows a simple bar plot of total seasonal precipitation and ETa for base years and target years summarized for basin irrigated areas in the UKL Basin. The seasonal precipitation is low when compared with the seasonal ETa. The mean precipitation and ETa over the base years was found to be 55 and 310 mm, respectively. Over the target years, precipitation increased by around 30% on average with a mean seasonal rainfall of 70 mm. However, due to the curtailment, the mean ETa over the target year decreased by 22% (with a mean ETa of 242 mm).

The ETa over the target years gradually increased from 2013 to 2016.

### 4.4 Temporal analysis of ETa

The mean irrigated area ETa over the base years was 310 mm, with a standard deviation of 38 mm. The highest ETa was observed in 2008 (346 mm), and the lowest ETa was observed in 2010 (254 mm). Irrigated area within the Sprague River basin showed similar trends, with highest ETa observed in 2008 (367 mm) and lowest ETa observed in 2010 (283 mm). However, irrigated area within the Williamson River Basin showed the highest ETa in 2006 (317 mm) and the lowest in

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**FIGURE 4** Validation of monthly Operational Simplified Surface Energy Balance actual evapotranspiration (ET) data using for Bulrush and Mixed sites over 2008–2010. Data from May 2008 to September 2010 are shown
FIGURE 5  Difference in ET between the base year average (2004, 2006, and 2008–2010) and each target year (2013–2016). ETa, actual evapotranspiration
FIGURE 6  Total seasonal precipitation and actual evapotranspiration (ETa) for base years (2004, 2006, and 2008–2010) and target years (2013–2016) summarized for irrigated areas in the Upper Klamath Lake basin. Change in mean ETa and precipitation from base to target years is highlighted in red. The mean precipitation increased from 55 to 70 mm, and ETa decreased from 310 to 242 mm.

FIGURE 7  Histograms of the irrigated area pixels extracted from the actual evapotranspiration (ETa) images over the base year (average of 2004, 2006, and 2008–2010) and the target years (2013–2016) computed for (a) all irrigated areas, (b) Sprague River irrigation, (c) Upper Klamath Agency Lakes irrigation, (d) Williamson River irrigation, and (e) Wood River irrigation. The vertical red line indicates the mean of the histogram.
2010 (192 mm). The irrigated area within the Wood River Basin and Upper Klamath Agency Lakes basin showed the highest ETa in 2009 (389 and 339 mm, respectively) and the lowest in 2010 (298 and 235 mm, respectively). The irrigated area within the Upper Klamath Agency Lakes basin showed the highest ETa in 2006 (317 mm) and the lowest in 2010 (192 mm).

To further understand the changes in on-field irrigation water savings (defined as water savings over the irrigated areas) during target years, we plotted histograms of the images corresponding to the irrigated area pixels. Figure 7 shows histograms of the irrigated area pixels extracted from the ETa images for the average of base years on the left and the target years to the right. The top panel (Figure 7a) shows the histograms for all irrigated pixels in the UKL Basin. The histogram for the base year closely resembles a normal distribution with a mean ETa of about 310 mm when analysed for all irrigated areas combined. Over the target years, decline in ETa has resulted in a leftward shift of the histogram with mean values of about 240 mm. This negative shift in the histogram is even more prominent in 2013 and 2014, indicating greater water savings in the first 2 years with respect to all target years. Over 2015 and 2016, the mean of the histogram slightly increased (>240 mm), indicating a reduction in savings. Similar observations can be made for the irrigated area in the Sprague River (Figure 7b) and Williamson River Basins (Figure 7d) with the highest savings occurring in 2013 and 2014 and reducing considerably thereafter. By 2016, the mean of the histograms in these basins tends to move towards the mean of the base years, indicating a reduced impact from the curtailment. Across irrigated areas from the Upper Klamath Agency Lakes basin (Figure 7c), although some savings occurred over 2013 and 2014, histograms from 2015 and 2016 closely resemble the base years, indicating minimal savings after 2014. The irrigated areas in the Wood

![Figure 7a](image_url)
![Figure 7b](image_url)
![Figure 7c](image_url)
![Figure 7d](image_url)

**FIGURE 8** Plots shows the percent irrigated area that showed water savings (ΔETa) over the target years computed for (a) all irrigation (58,065 ha), (b) Sprague river irrigation (27,562 ha), (c) Upper Klamath Agency lakes irrigation (252 ha), (d) Williamson river irrigation (20,362 ha), and (e) Wood river irrigation (10,466 ha). All the area left of vertical red line (zero crossing) indicates water savings. ETa, actual evapotranspiration.
River Basin do not show marked differences in the histograms (Figure 7e), even though a slight decline in ETa was observed.

4.5 | Variability in area under irrigation water savings

To quantify the water savings from irrigated lands during the target years, we first computed histograms from the ∆ETa images for all irrigated areas within the river basins. Then, we computed the area under each bin (bar) in the histogram and plotted the percentage of area covered under each bin against mean ∆ETa values for each bin (Figure 8). Results indicate that for all irrigation (Figure 8a), about 91% of the total irrigated area (out of a total of 58,605 ha) had water savings (∆ETa < 0) in 2013. Irrigated areas show water savings steadily declined thereafter from 88% of all irrigated areas in 2014 to 72% in 2016. Except for the Upper Klamath Agency Lakes basin (Figure 8c), the irrigated areas in the Sprague, Williamson, and Wood River irrigated areas (Figure 8b, d, and e) showed the largest area with savings in 2013 and declining areas of savings from 2014 to 2016. In the Upper Klamath Agency Lakes irrigated area (Figure 8c), 2013 showed savings for almost 97% of the area (out of a total of 252 ha). However, the area under savings steeply declined from 82% in 2014 to 47% in 2015 and increased up to 59% in 2016. The magnitude of water savings in this basin was the smallest (up to 350 mm) when compared with other irrigated areas in this study.

4.6 | Summary of on-field water savings (∆ETa)

The savings in irrigation due to a curtailment estimated using Equation 2 are presented in the top row of Figure 9 for Sprague, Upper Klamath Agency Lakes, Williamson, and Wood River irrigation regions. Estimates of irrigation water savings were also computed for different irrigation types (surface water, groundwater, and conjunctive use) and are shown in the bottom row of Figure 9. Results indicate that estimates of water savings showed an overall decreasing trend, but for Sprague, Williamson, and all irrigation, 2013 and 2014 showed the highest savings. Although estimates of mean irrigation water savings changed from year to year, the interquartile range of Sprague, Williamson, and Wood River irrigation savings remained relatively similar. However, the Upper Klamath Agency Lakes showed higher year to year variability in irrigation water savings and interquartile range over the target years. However, the irrigated area under Upper Klamath Agency Lakes basin is small (252 ha), and the magnitude of water savings in this basin is less than 0.2 hm³ (196 ac-ft). Of all the irrigation regions, the Sprague River Basin irrigation showed the highest irrigation water savings on the order of 35 hm³ (28,164 ac-ft) in 2013 to 19 hm³ (15,662 ac-ft) of irrigation water savings in 2016 (Table 2). After Sprague, the next highest water savings occurred in the Williamson River Basin with 18 hm³ (14,537 ac-ft) of savings in 2013 to 11 hm³ (9,182 ac-ft) of savings in 2016. Wood River irrigation showed savings of 7 hm³ (5,951 ac-ft) in 2013 to 1 hm³ (990 ac-ft) in 2016.
ft) of savings in 2016. The total savings for 2013 and 2014 was about 60 hm³ (49,000 ac-ft); however, total water savings decreased by nearly 14 hm³ (~13,000 ac-ft) in 2015 and declined further by another 12 hm³ (~10,000 ac-ft) in 2016.

The water savings from the surface water irrigation was found to be the largest of all irrigation types with 2013 showing the highest mean savings and 2016 showing the lowest (Figure 9). The water savings from groundwater-irrigated areas showed the highest mean savings in 2014 and the lowest in 2015 (Figure 9). The water savings from the conjunctive use irrigation followed the trend from surface water irrigation. The total irrigation for target years (the sum of all irrigation water savings from different basins is equal to the sum of water savings from the three irrigation types) shows higher water savings in 2013 and 2014 and a gradual reduction in water savings over 2015 and 2016 (Figure 9).

### Summary of EWA

Figure 10 presents the EWA estimated over target years using Equation 6 for each irrigation region and type. Unlike irrigation water savings, the year to year variability in EWA is unidirectional as EWA gradually reduced over the irrigation curtailment period. Out of four irrigation regions, the Williamson River Basin irrigation area showed the highest interquartile range in EWA, whereas the Wood River irrigation area showed the lowest. Similarly, surface water irrigation area showed the highest interquartile range in EWA, whereas groundwater irrigation area showed the lowest. The EWA estimates from all irrigation (sum of EWA from four irrigation regions is equal to the sum of EWA from the three irrigation types) indicate a similar declining trend from 2013 to 2016. Of all the irrigation areas, the Sprague River Basin irrigation area showed the highest EWA, 48 hm³ (38,877 ac-ft) of water in 2013 and declined to 18 hm³ (14,536 ac-ft) of irrigation water savings in 2016 (Table 2). The next highest EWA was in the Williamson River irrigation area with 31 hm³ (24,988 ac-ft) of EWA in 2013, which declined to 9 hm³ (7,027 ac-ft) of EWA in 2016. The Wood River irrigation area showed EWA up to 13 hm³ (10,286 ac-ft) in 2013 but then declined to nearly negligible EWA (40 ac-ft) in 2016. The total EWA for 2013 was about 92 hm³ (74,500 ac-ft); however, the EWA reduced dramatically to 26 hm³ (21,421 ac-ft) in 2016.

### Crop type water savings

We used USDA-NASS CDL data to understand crop type water savings. The results in Table 3 indicate that out of four grain crop classes, the water requirement for alfalfa was the highest with up to 10 hm³ during the base year. Other grain crops such as barley, spring/winter wheat, and oats/rye consumed relatively negligible amounts of water over the base years when compared with the water requirement of non-grain crop types. During the target years, most grain crop savings came from alfalfa fields; however, the amount of savings gradually reduced from 8 hm³ (6,204 ac-ft) in 2013 to 4 hm³ (3,593 ac-ft) in 2016. Barley was grown only during 2013 (consuming more water than during the base years) and was absent on fields over

### Table 2

| Scenario          | Year | P (hm³) | ETa (hm³) | ΔP (hm³) | ΔETa (hm³) | EWA (hm³) |
|-------------------|------|---------|-----------|----------|------------|-----------|
| Sprague           | 2013 | 24      | 56        | 13       | -35        | 48        |
|                   | 2014 | 13      | 56        | 2        | -35        | 38        |
|                   | 2015 | 14      | 67        | 3        | -24        | 27        |
|                   | 2016 | 9       | 71        | -1       | -19        | 18        |
| Upper Klamath     | 2013 | 0.2     | 0.5       | 0.1      | -0.2       | 0.4       |
| Agency Lake       | 2014 | 0.2     | 0.6       | 0.1      | -0.1       | 0.2       |
|                   | 2015 | 0.1     | 0.7       | 0.0      | 0.0        | 0.0       |
|                   | 2016 | 0.1     | 0.7       | 0.0      | -0.1       | 0.1       |
| Williamson        | 2013 | 22      | 36        | 13       | -18        | 31        |
|                   | 2014 | 13      | 34        | 4        | -20        | 24        |
|                   | 2015 | 7       | 40        | -2       | -14        | 12        |
|                   | 2016 | 7       | 43        | -3       | -11        | 9         |
| Wood              | 2013 | 9       | 29        | 5        | -7         | 13        |
|                   | 2014 | 6       | 31        | 2        | -5         | 7         |
|                   | 2015 | 5       | 31        | 1        | -6         | 6         |
|                   | 2016 | 3       | 35        | -1       | -1         | 0         |
| Total             | 2013 | 56      | 121       | 32       | -60        | 92        |
|                   | 2014 | 33      | 121       | 8        | -60        | 68        |
|                   | 2015 | 26      | 138       | 1        | -44        | 45        |
|                   | 2016 | 19      | 150       | -6       | -32        | 26        |

Abbreviations: ETa, actual evapotranspiration; EWA, extra water available.
2014–2016. Similarly, oats/rye were grown in 2015 and 2016 and absent during 2013 and 2014.

Out of the four non-grain crop types, herbaceous wetlands and grassland/pasture have large water requirements in the basin and showed the most savings during the target years. The herbaceous wetlands class showed the highest savings in 2013, and savings reduced gradually thereafter. Conversely, the grassland/pasture class showed a gradually increasing trend in water savings, where the increase in ETa could be attributed to the increase in precipitation over the target years. The positive values in Table 3 indicate no savings (i.e., more water was consumed by these crop types during the target years). For example, other hay crop types did not show any savings over the target years; instead, their crop water use increased. The four non-grain crop classes account for more than 50% of the total irrigated area because the classification of areas as irrigated for this study was guided by the water rights and included areas such as grassland, pastures, and herbaceous wetlands, which are widely used for grazing cattle.

![Figure 10](image-url)  
**FIGURE 10** Box plots showing the variability in extra water available (EWA) over the target years for Sprague, Upper Klamath agency lakes, Williamson, and Wood river irrigation. The mean of the distribution is represented by the horizontal black line, the box indicates upper 75th and lower 25th percentiles, and the whiskers above and below the boxes indicate the maximum and the minimum estimates of EWA. Absence of whiskers for Williamson river irrigation indicates that the minimum and maximum estimates of EWA are well above the 1.5 times the 25th and 75th percentile estimates.

| Crop type         | Base year average | 2013  | 2014  | 2015  | 2016  |
|-------------------|-------------------|-------|-------|-------|-------|
| Barley            | 0.04              | 0.03  |       |       |       |
| Spring/winter wheat| 0.04              | −0.01 | 0.02  | 0.3   | 0.8   |
| Oats/rye          | 0.2               |       | −0.2  | −0.2  |       |
| Alfalfa           | 10                | −8    | −6    | −6    | −4    |
| Other hay         | 2                 | 0.2   | 0.6   | 0.03  | 4.8   |
| Shrublands        | 6                 | −2    | −4    | −0.9  | 0.4   |
| Grass/pasture     | 40                | −6    | −10   | −14   | −16   |
| Herbaceous wetlands| 65                | −24   | −23   | −13   | −7    |

**TABLE 3** Crop type water savings (ΔETa) in hm³ with respect to the base year average ETa (in hm³)

Note: A negative value indicates lower than base year average ETa (savings), and a positive value indicates higher than base year average ETa (no savings).

Abbreviation: ETa, actual evapotranspiration.
4.9  Impact of water savings and EWA on UKL water levels

Water savings from the curtailment are assumed to add to streamflow and result in higher inflows into the UKL Basin. Hence, we obtained river inflows from Equation 8 and computed the percentage of irrigation water savings and EWA with respect to lake surface inflows, lake outflows, and average lake volume. Table 4 indicates that the savings generated during the curtailment program contributed to a maximum of 19% of the lake inflows, 27% of the lake outflows, and 50% of the lake volume.

5  DISCUSSION

The possibility of using remotely sensed data for routinely monitoring agricultural water use is a priority for water managers and planners around the world (Senay et al., 2019). This study presents an application of Landsat-based ETa for solving real-world problems. The benefit of using remote sensing is its capability to produce spatially and temporally explicit information on agricultural water use. This study provides insights into the hydrologic impacts of an irrigation curtailment in the UKL Basin. The value of remote sensing estimates often depends on the accuracy and uncertainty of the data and models used. In this study, the errors in the estimation of water savings from the curtailment program arise from (a) error in the ETa estimates and (b) error in the precipitation estimates. The accuracy of seasonal ETa was quantified to have uncertainty up to 10–15% at basin scale (Velpuri et al., 2013). However, validation of seasonal ETa estimates using two eddy covariance sites used in this study indicates an underestimation up to 16%. Uncertainties in the PRISM rainfall data used in this study are thoroughly investigated by (Daly et al., 2008) who found that uncertainties reduce considerably when averaged over spatial domains with $R^2$ as high as .85 (with very low bias error approximately ±0–5%) when compared with other gridded rainfall datasets. Based on these estimates, we expect a bias in the range of ±0–2% in our estimates for absolute magnitudes, but water savings are based on relative differences from base years and thus less affected by bias errors.

In this study, we estimated ETa over irrigated areas within the UKL Basin and computed the ΔETa in the target years compared with the ΔETa from the base years. The ΔETa represents direct savings in water use over the fields that are irrigated. To normalize the impact of precipitation on changes in ETa, we computed the EWA parameter, which is more important in predicting the flow in streams; however, the direct impact of curtailment may be better quantified by a decrease in ETa alone, as the EWA includes assumptions on the transport of excess precipitation/irrigation to the river system. Generally, some years have more precipitation, which could increase ETa over
fallow lands, thus appearing to confound the effectiveness of the curtailment program in the wetter years. For example, 2013 was much wetter than the base years (four times the precipitation of 2014). Thus, the water savings in 2013 and 2014 are comparable in terms of ETa, but EWA in 2013 was much higher than EWA in 2014. One way of interpreting the 2013 and 2014 ETa and EWA disparity is that although fallow lands used much of the increased precipitation in 2013, the crop water demand on irrigated areas was partially met by the precipitation, and thus, farmers did not need to apply as much water on the fields or excess precipitation/irrigation found its way to the river system, thus increasing the streamflow (higher EWA).

Irrigation water savings could be a result of (a) the direct curtailment of irrigation, (b) changes in the water management practices, (c) changes in crop type, (d) changes in the agronomic practices such as irrigation scheduling, or (e) a combination of all. The water savings estimated in this study (Table 2) quantifies the total savings and does not provide the information on the actual cause of the savings. If we assume minimal change in management and agronomic practices between base and target years, then we can conclude that most of the savings are attributable to the curtailment program.

The estimation of impact of the curtailment on the lake inflows, outflows, and lake volume (Table 4) is illustrated using the data available at the time of the study. We used pre-curtailment data (2003–2012) for the estimation of inflows from the Williamson River. However, because pre-curtailment data for Wood River inflows were not available, data from the post-curtailment period (2014–2018) were used, which could report a higher flow due to reduced irrigation. Hence, the real impact of curtailment on total lake inflows may be slightly underestimated. Similarly, the surface outflow estimated using data obtained from the Link River at Klamath Falls constitutes about 85% of the outflow from the lake (Hubbard, 1970). Direct pump irrigation from the lake and direct evaporation losses from the lake were not considered.

Since the irrigation curtailment is scheduled mostly during the June–September months, the estimates of EWA correspond to the seasonal savings because EWA is calculated using June–September precipitation and ETa variability only. However, the antecedent soil moisture and the end of season precipitation are not accounted for in the EWA estimation. Because the basin is arid/semiarid, the monthly ETa is higher than precipitation for most months. Hence, the impact of antecedent rainfall would be low at the beginning of the cropping season. Also, high precipitation occurring towards the end of the season may not be completely captured in the seasonal ETa estimate. Generally, off-season antecedent soil moisture and end of season precipitation equate to about 10–15% of the seasonal ETa. Hence, the direct use of seasonal EWA (June–September) would be different from annual (water year) EWA estimates. Moreover, the impact of the off-season (October–May) hydrologic regime outside of the irrigated areas and change in storage should be considered to accurately predict basin-scale EWA estimates. Further studies are needed to understand (a) the water budget dynamics of the off season and its impact during the curtailment, (b) impact of seasonal curtailment on the off-season hydrologic regime, and c) the overall impact of the curtailment on the ecohydrology of the basin.

6 | CONCLUSIONS

The goal of this study was to use Landsat-derived ETa to quantify the hydrologic impact of the 2013–2016 curtailment program in the Upper Klamath Lake Basin. The following four objectives were addressed to meet this goal: (1) We quantified the on-field water savings by comparing remotely sensed ETa during base (2004, 2006, and 2008–2010) and target years (2013–2016). The study results show that the target (curtailment) years had lower ETa than the base years, confirming the implementation of the curtailment program and demonstrating the capability of remote sensing in monitoring and assessing water management programs in a spatially explicit manner. Precipitation differences between base and target years indicated that the target years were slightly wetter than the base years. A small increase in precipitation may have resulted in increased flows (EWA) during the target years. (2) We analysed satellite-based ETa and precipitation data to understand the spatial variability in water savings. Both the ∆ETa savings and EWA showed that the curtailment program saved more water in the first 2 years (2013 and 2014) and saved the lowest in the final year (2016), implying the program was more effective in making more EWA during the first year. The volume of water saved varied by basin owing to the differences in the size of the irrigated area; the Sprague River showed the highest savings. Similarly, water savings were observed on surface-irrigated systems compared with groundwater-irrigated systems, which makes sense as the curtailment program primarily applied to surface water irrigation. (3) We analysed the data to estimate and quantify water savings by crop type during the curtailment period. Water savings by cover/crop type showed that most savings occurred in herbaceous wetlands followed by alfalfa. (4) Lastly, we quantified the hydrologic impact of irrigation water savings. The overall impact of the irrigation curtailment program on the basin’s water resources was quantified to increase the extra water available as percent of lake inflow and lake storage by as much as 19% and 50%, respectively, during the peak curtailment year of 2013. This study demonstrated a promising application of the Landsat data archive and the SSEBop ETa model for monitoring and assessing ecohydrological parameters in space and time to guide water management decisions. Similar approaches can be applied anywhere in the world due to the availability of uniformly acquired remote sensing and hydroclimatic data since the early 1980s.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available with the USGS earth explorer at https://earthexplorer.usgs.gov for Landsat imagery and at http://www.climatologylab.org/gridmet.html for reference ET. The overall documentation for the USGS data release is reported at Velpuri et al. (2020). Precipitation data is downloaded from the PRISM Climate Group website (http://www.prism. oregonstate.edu/); river discharge data were obtained from the USGS water data website (https://waterdata.usgs.gov).

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