Combining Remote Sensing and Crop Models to Assess the Sustainability of Stakeholder-Driven Groundwater Management in the US High Plains Aquifer

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Key Points:

- We assessed management impacts with a satellite-driven crop model, well data, commodity prices, and energy costs
- Groundwater reductions minimally decreased crop yields; improved irrigation efficiency limited the benefits to the aquifer water balance
- Energy cost savings exceeded yield penalties, increasing net profits while saving water

Keywords: water management, irrigation, agriculture, farmer adaptation, groundwater sustainability, remote sensing, crop modeling

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ABSTRACT

Non-renewable groundwater contributes approximately 20% of global irrigation water. As a result, key agricultural regions around the world are on unsustainable trajectories due to aquifer depletion, threatening food production and local economies. With increasing resource scarcity in the central High Plains Aquifer in the United States, an innovative stakeholder-driven groundwater management framework emerged in Kansas referred to as the Local Enhanced Management Area (LEMA) program; this framework enables groups of irrigators to join together to implement measures to conserve groundwater. Here, we assessed the efficacy of the first LEMA to move the region towards sustainability with a process-based crop model driven by well records and satellite-derived annual land use. We found increased irrigation efficiency under the LEMA program reduced groundwater extraction by 25% (40 million m^3). However, only 22% of pumping reductions benefitted the net water balance (9 million m^3) due to decreased irrigation return flow resulting from increased irrigation efficiency. We then estimated economic impacts using simulated crop yields, commodity prices, and estimated energy saved from reduced groundwater pumping. Cost savings from reduced pumping were about 4.5 times greater than the income lost from minor yield penalties. This suggests the program promotes both economic and water sustainability, but water targets may need to be more strict to stabilize groundwater levels. As aquifer depletion threatens crop production in many parts of the world, approaches that integrate dynamic process-based models with in-situ and satellite data can inform economically and hydrologically sustainable management strategies. Our work highlights the need to consider both economic factors and root zone processes when evaluating irrigation conservation programs.

1. INTRODUCTION

Over the latter half of the twentieth century, the use of non-renewable groundwater resources for irrigated agriculture more than tripled provide approximately 1/5 of global irrigation water (Wada et al., 2012). As a result, key agricultural regions around the world are on unsustainable trajectories due to aquifer depletion, including California's Central Valley (Faunt et al., 2016; Scanlon et al., 2012), the North China Plain (Cao et al., 2013), and northern India (Rodell et al., 2009; Tiwari et al., 2009). In the central United States, the High Plains Aquifer provides water for over 6 million hectares of irrigated land (Deines, Kendall, Crowley, et al., 2019), accounting for approximately 30% of US groundwater irrigation (Dennehy, 2000; Scanlon et al., 2005) and underpinning a significant portion of the region's $7.5 billion agricultural net income (NASS, 2019; Waskom et al., 2006). However, water use exceeds recharge over much of the aquifer, particularly in the central and southern regions (Breña-Naranjo et al., 2014; Haacker et al., 2016; Scanlon et al., 2012). Under current use, approximately 24% of irrigated area could be lost by the end of the century due to falling groundwater levels (Deines et al., 2020).

With limited water resources defining the 21st century (Rodell et al., 2018), it is crucial to find ways to maximize water use and operate within system boundaries (Basso et al., 2013; Zipper et al., 2020). Historically, water management systems over the High Plains Aquifer often exacerbated the problem. For example, farmers in Kansas formerly could lose a portion of their ground- and surface water rights for non-use, providing perverse incentives for farmers to use their full water allocation even in years when this did not benefit crop yield (Peck, 2003). However, management is changing across the aquifer. States such as Nebraska, Kansas, and Texas are gradually establishing local groundwater management areas that have more power to restrict existing allocations (Smidt et al., 2016). For example, Nebraska's 2005 Ground Water Management and Projection Act enabled its 23 Natural Resource Districts to regulate groundwater, including restricting pumping (Peck, 2007). In other cases, litigation has forced increased regulation, such as in the interstate Republican River Basin (Kuwayama & Brozović, 2013; Peck, 2007). Despite diverse perspectives, a recent survey of agricultural producers across the aquifer found broad support for groundwater conservation to sustain water and economic resources into the future (Lauer & Sanderson, 2019).

In Kansas, 2012 legislation created the Local Enhanced Management Area (LEMA) program, which established a framework for stakeholder groups to work with local and state officials to create enforceable management plans for groundwater conservation (K.S.A. 82a-1041, 2012). LEMAs operate on 5-year cycles and combine key factors identified for successful management of common resources, including self-organization, local focus, active monitoring, and enforcement (Ostrom, 2009). In 2013, the first LEMA went into effect for a 256 km^2 region of high groundwater stress in northwest Kansas known as Sheridan-6, which includes portions of Sheridan and Thomas counties (hereafter SD-6, Figure 1) (KDA, 2013). Due to a lack of surface water resources, many agricultural fields in SD-6 are reliant on groundwater to meet water demand unfulfilled by precipitation, with May 1 – Oct. 15 growing season precipitation ranging between 190 – 612 mm between 2008-2017 (mean: 400 mm). The SD-6 LEMA included restrictions to reduce total groundwater pumping by 20% compared to 2002-2012 levels (NW KS GMD 4, 2016). This plan restricted existing groundwater rights to a 5-year allocation of 139.7 cm (55 inches) per irrigated ha, with the flexibility to roll over up to 27.6 cm (11 inches) of unused water to the next LEMA cycle.

Initial assessments of SD-6 LEMA effectiveness for the first 5-year cycle (2013-2017) show promising results. Farmers exceeded the 20% pumping reduction targets for this period (Butler et al., 2020; Deines, Kendall, Butler, et al., 2019), resulting in an estimated 67% reduction in the rate of water table decline (Butler et al., 2018). Water savings have largely been accomplished with a modest 2 to 5% reduction in irrigated area through improved management, including increased water use efficiency and use of crops with lower irrigation demand such as sorghum (Deines, Kendall, Butler, et al., 2019; Drysdale & Hendricks, 2018). Moreover, a preliminary anecdotal analysis indicates that despite slight yield loses (~1.2% for corn, the predominant crop), net profits have been stable or increased due to reduced energy and input costs (Golden, 2018). Stakeholders renewed the LEMA for 2018-2022, indicating the program's continued support among producers.

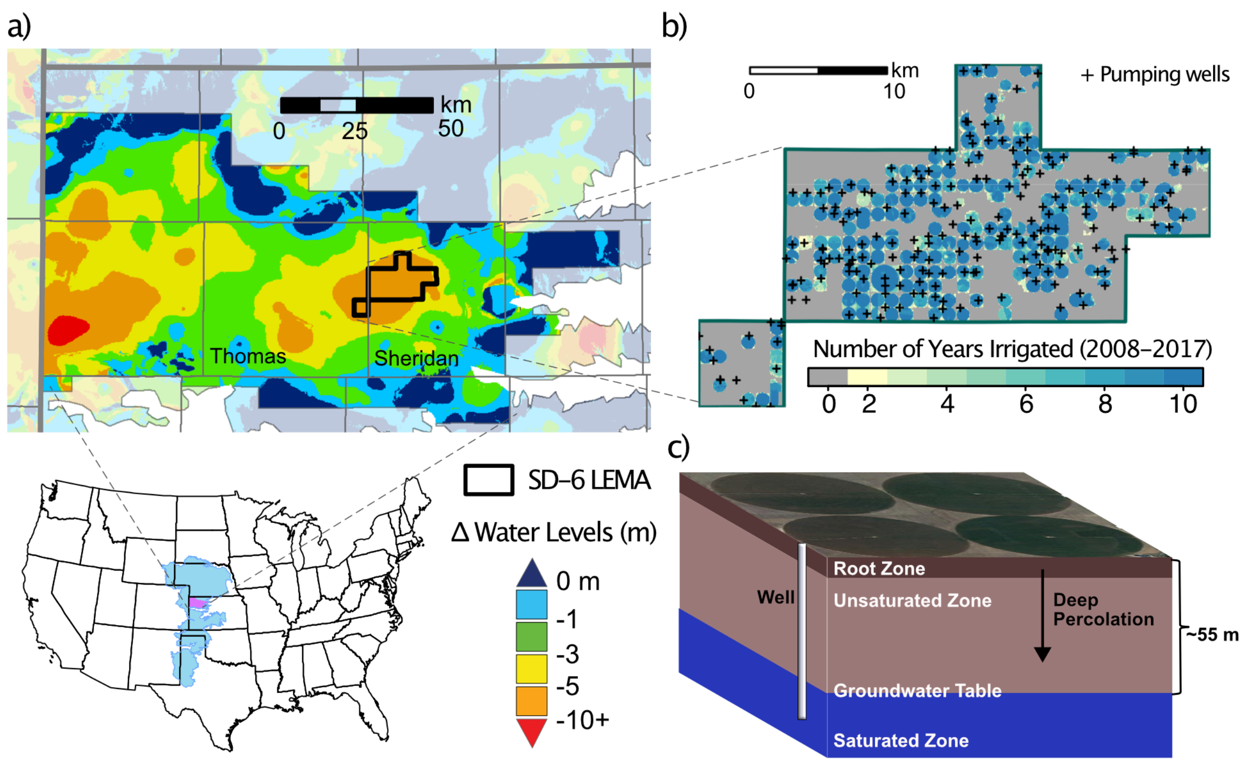

Figure 1. Study area. (a) Location of the Sheridan-6 (SD-6) Local Enhanced Management Area (LEMA) within Groundwater Management District 4 (bold colors) in the United States High Plain Aquifer (inset, blue), including change in groundwater level between 1996-2012 prior to the start of the LEMA in 2013. County borders are shown in light gray, with Thomas and Sheridan counties labelled. (b) Irrigated area, frequency, and groundwater wells in SD-6. Data from Deines, Kendall, Crowley, et al. 2019. (c) Schematic of the hydrological system in SD-6. With no perennial streams, the region relies on groundwater irrigation from a deep water table approximately 55 m below the surface during the study period.

There remains a need, however, to robustly quantify the effects on the full water budget and trade-offs in crop yield and farmer profits, particularly as the LEMA program expands. A second LEMA was started in the spring of 2018 for most of the surrounding Groundwater Management District 4 (Figure 1a), and discussions for additional LEMAs in parts of two other Kansas groundwater management districts are ongoing. Understanding the effectiveness of the SD-6 LEMA can help inform economically and hydrologically sustainable management strategies across the High Plains Aquifer and elsewhere.

Although the state of Kansas is relatively data rich (Butler et al., 2016), existing datasets are inadequate to evaluate the SD-6 LEMA. For example, a reliably curated water use dataset is publicly available to track annual groundwater pumping volume by individual well location (KDA DWR, 2017), but this data cannot quantify how reduced irrigation applications affect the aquifer water balance due to the complexities of irrigation efficiency. In this relatively flat region with no perennial streams, excess irrigation water generally infiltrates back into the ground as irrigation return flow, enhancing deep percolation below the root zone and eventually returning to the aquifer. Because reduced groundwater extraction often reduces this excess irrigation, the irrigation return flow is reduced. In this example of the "paradox of irrigation efficiency" (Grafton et al., 2018), net changes to the aquifer are not equivalent to reduced pumping volumes. Effective aquifer conservation cannot be determined without factoring in changes to both pumping and irrigation return flow, and data on irrigation return flow is not available. Water level data is not useful for evaluation over short time frames in this region due to the time lag for irrigation return flow to reach the aquifer though the deep unsaturated zone (Figure 1c, section 2.3). As of early 2020, water level data indicate little to no irrigation return flow from the LEMA period has reached the water table (Butler et al., 2020).

Similarly, remote sensing products specifying annual agricultural land use at high resolution (30 m) provide information on annually varying crop types (USDA-NASS, 2017) and irrigated areas (Deines, Kendall, Crowley, et al., 2019) from 2006 to present (Figure 1b). However, these land use maps cannot be translated to changes in crop income without simultaneously measuring or modeling changes in crop yields compared to business-as-usual conditions. Yield data representative of the SD-6 region is not available. The region includes small portions of two counties (Figure 1a), and agricultural yield statistics are not reported by irrigation status after 2014. This, combined with limited empirical data that relates reduced water use to producer net profits (Drysdale & Hendricks, 2018; Golden, 2018), limits the ability to quantify the economic feasibility of programs such as this LEMA.

Validated process-based crop models provide an opportunity to simulate these difficult to measure quantities such as irrigation return flow, evaporative water losses, and yield responses to different irrigation regimes (Basso et al., 2016); such crop models can quantify water budgets and crop yields both for observed conditions during the LEMA and for business-as-usual scenarios to estimate the water use and yield outcomes in the absence of the LEMA. With this information, water reductions can be translated into estimated income loss from yield penalties due to reduced irrigation application as well as energy cost savings from reduced groundwater pumping. These components are vital to assess agricultural sustainability, which must consider local socio-economic conditions in addition to environmental protections (Häni et al., 2003).

Here, we applied the System Approach to Land Use Sustainability (SALUS) crop model (Basso et al., 2006; Basso & Ritchie, 2012, 2015) to simulate historic cropping and water use in SD-6 and evaluate the sustainability implications of the LEMA program. To accurately quantify changes in crop yields, water use, and irrigation return flow, we developed a new approach to drive the SALUS model with spatially explicit annual crop and irrigation information based on remote sensing imagery. We used this modeling framework to ask the following questions: 1) What was the effect of the LEMA program on the net water balance, considering changes in both groundwater extraction and irrigation return flows? and 2) How did the LEMA program affect crop yields and net profits, incorporating both yield penalties and reduced energy costs associated with reduced pumping? We address these questions by comparing simulations parameterized with historic data against simulations of a business-as-usual (BAU) scenario. We model changes during 2006-2017 to include the five-year LEMA period (2013-2017), a five-year Pre-LEMA period (2008-2012), and a two-year model spin-up period.

Using the approach presented here, we simulated water savings due to changes in aggregate irrigation behavior, thus using the historically obsersved spatial distribution and annual sequence of crop types and irrigated area for both the BAU and LEMA scenarios. Improving irrigation efficiency is one of three key strategies available for farmers to reduce water use, in addition to changing crop types and reducing irrigated areas (Hendricks & Peterson, 2012). For this LEMA, we previously estimated that improved irrigation efficiency accounted for ~72% of reduced groundwater pumping during the 2013-2017 LEMA cycle, with remaining savings coming form changes in crop type and reductions in irrigated area (Deines, Kendall, Butler, et al., 2019).

2. Methods

2.1. Remotely-sensed agricultural land use data

The USDA's NASS Cropland Data Layers (CDL) (Boryan et al., 2011; USDA-NASS, 2017) provide annual maps of crop types for 2006-2017 at 56 m resolution for 2006-2007 and 30 m resolution since 2008. This data is derived from a suite of satellite imagery and has reasonable accuracy in Kansas for the crops considered in this study, with accuracies of 70 – 95% for the study period depending on year and crop type (USDA-NASS, 2017). To minimize spurious crop classification and "salt-and-pepper" effects for small groups of pixels within fields, we first resampled all years to 30 m and smoothed annual CDL images in Google Earth Engine (Gorelick et al., 2017), which hosts the CDL product in its cloud-based data catalog (Text S1, Supporting Information). Analysis of the resulting CDL maps indicated that from 2008-2017, corn area dominated within SD-6, followed by grassland, winter wheat, fallowed land, sorghum, soybeans, developed land, and alfalfa. Together, these classes covered 98.7% of the SD-6 study area (2008-2017 average); the main crops covered 81% (Figure 2).

The LEMA program led to changes in proportional crop area compared with the previous five years (Deines, Kendall, Butler, et al., 2019), including a decrease in corn and soy area with a corresponding increase in sorghum and wheat areas (Figure 2). Developed land covered 3.8% of the study region, largely as roads, and was not included in model simulations. In reality, roads and other impervious surfaces can serve as points of enhanced recharge due to concentration of runoff along the edges of these surfaces. However, because we are focused on water balance differences in agricultural lands resulting from the LEMA program, we do not account for changes in recharge along these impervious surfaces here for simplicity.

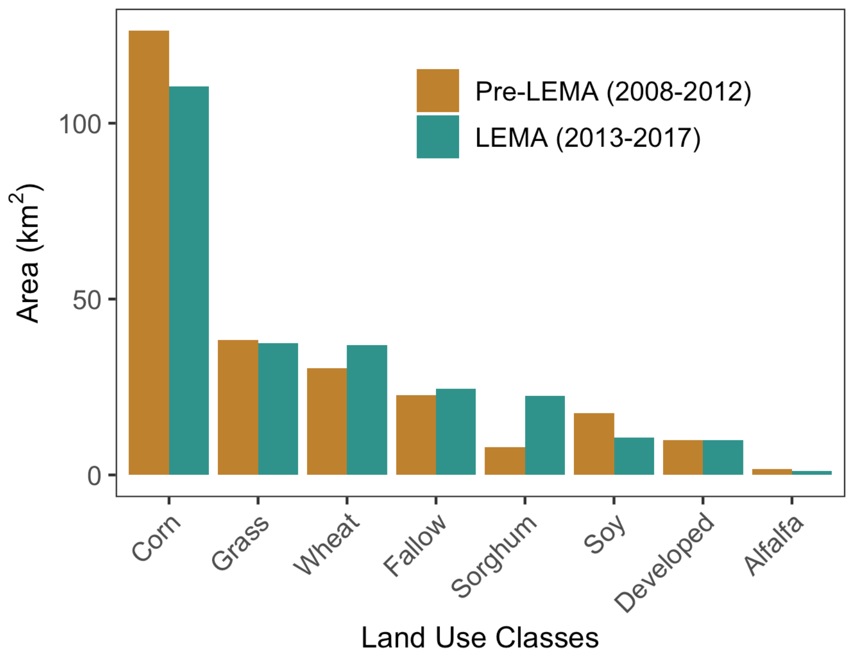

Figure 2. Dominant land cover in the Sheridan-6 Local Enhanced Management Area. Mean area for the eight predominant land cover classes based on NASS Cropland Data Layers (USDA-NASS, 2017) for the five years prior to the LEMA (2008-2012) and the initial 5-year LEMA period (2013-2017).

Irrigation status was obtained annually at 30 m resolution based on the satellite-derived Annual Irrigation Maps – High Plains Aquifer (AIM-HPA) dataset (Deines, Kendall, Crowley, et al., 2019). AIM-HPA provides annual irrigation status at Landsat resolution (30 m) from 1984-2017, allowing us to specify historic irrigation occurrence during our study. AIM-HPA is estimated to have a 91.4% overall accuracy, leading to occasional misclassified pixels. To minimize these effects, we filtered AIM-HPA with allowable irrigation place-of-use tracts maintained by the Kansas Division of Water Resources (KS DWR, 2017), removing any irrigated pixels that occurred outside of these tracts (Figure 1b). On average between 2008-2017, 39% of the total land area in SD-6 was irrigated.

2.2. Weather, soil, and water use data

Daily weather data for crop simulations were obtained from GRIDMET, a daily 4 km gridded surface meteorological dataset that includes precipitation, maximum daily temperature, minimum daily temperature, and shortwave radiation (Abatzoglou, 2013). Data was accessed through Google Earth Engine, where we combined daily observations with mean elevation per grid cell derived from the USGS National Elevation Dataset (USGS, 2012). The resulting data was formatted for the SALUS model using R (R Core Team, 2014). Soil data was obtained from gSSURGO, which provides soil classes at 30 m resolution and extensive soil properties for the United States (NRCS, 2016). There are 16 gSSURGO soil types (map units) in SD-6, texturally dominated by silty loam.

Annual data on groundwater pumping for irrigation were obtained from the Water Information Management & Analysis System (WIMAS) database maintained by the Kansas Department of Agriculture's Division of Water Resources (KDA DWR, 2017). In Kansas, flow meters are required by law on all agricultural wells. WIMAS is a publicly available dataset that provides annual water use by point of diversion, including 195 active wells within SD-6 during the study period (Figure 1b). From this, we calculated total annual groundwater pumping for the SD-6 LEMA from 2006 through 2017.

2.3. SALUS crop model and irrigation management scenarios

We used the SALUS model to simulate crop yield and crop water budget components. SALUS is a process-based crop model that simulates interactions between soil, weather, crop genetics, and management on a daily time step. The model simulates changes in plant growth, development, and water and nutrient fluxes in response to management. SALUS evolved from the widely tested CERES crop model (Basso et al., 2016; Ritchie & Otter, 1985) and has been extensively validated under diverse conditions and management scenarios (Basso & Ritchie, 2018; Dzotsi et al., 2015; Hoang et al., 2014; Liu & Basso, 2020a, 2020b; Partridge et al., 2019), including for the central High Plains Aquifer (Cotterman et al., 2018). Crop water budget components include plant transpiration, soil evaporation, irrigation water applied, precipitation, and the soil water balance, which we simulated for the top two meters of soil. Text S2 provides a description of how SALUS simulates crop growth and crop response to water stress. SALUS has been validated relative to cumulative soil drainage from soil lysimeters at two sites in Michigan (mean values of 1901 vs 1904 mm and 1862 vs 1857 mm, RMSE = 24.4 and 54.5 mm, respectively) (Basso & Ritchie, 2015). Field validations across space and time in Argentinian maize fields found good performance for soil water content (r^2 = 0.86, RMSE = 26 mm) and growing season evapotranspiration (r^2 = 0.79, RMSE = 34 mm) (Albarenque et al., 2016). SALUS estimates of nitrate leaching have also compared well against field measurements, demonstrating fidelity for soil water redistribution and deep percolation (Giola et al., 2012). SALUS was recently used to evaluate the impact of evapotranspiration on crop yield across the US Midwest (Basso et al., 2021).

We consider all water that percolates below the modeled root zone to be irrigation return flow (deep percolation, Figure 1c). We note that due to the thick unsaturated zone in this system (average depth to water = 55 m under irrigated fields), we are unable to fully track how this water recharges the aquifer without a detailed groundwater model. An analysis in southwestern Kansas with similar unsaturated zone thicknesses found persistent downward hydraulic gradients under irrigated areas, indicating that drainage below the root zone would continue downward and eventually recharge the water table (McMahon et al., 2003). Across the High Plains Aquifer, lag times for deep percolation to reach the aquifer range from ~5 years in the Nebraska Sand Hills (Rossman et al., 2014) to ~50 - 375 years under cropland sites across the aquifer, although chemical signals finding modern water in the aquifer indicate there are also likely fast paths for water movement (McMahon et al., 2006). According to the estimates from Zell and Sanford (2020), unsaturated zone travel times average approximately 230 years under our study domain. Note also that the arrival of a recharge pulse may be significantly faster than that of the recharged water, as pressure waves move more quickly through the subsurface than water and solutes. Moreover, lag times likely vary based on deep percolation rates and soil moisture conditions prior to the growing season, as seen in other systems (Nazarieh et al., 2018). Here, we focus on the net aquifer balance between water extracted for pumping and drainage below the root zone, or deep percolation, assuming it will eventually reach the water table.

SALUS is a point-based model that runs continuously (versus being annually reinitialized), accumulating year-to-year changes to properly track components such as soil moisture across years (Basso et al., 2015, 2018) and simulating both the actively-cropped and dormant periods of the year. Therefore, we developed a set of real-world, spatially explicit experiments that captured both the year-to-year sequences of crop choice and irrigation status along with the soil and climate variability across the study area. We discretized the study area into 30 m grid cells based on the resolution of the remotely sensed inputs (see section 2.1) and simulated individual experiments for each grid cell based on cell-specific soil properties, observed climate, and annual crop types and irrigation status between 2006-2017 from remote sensing products (Figure 3a). The absence of spatially explicit crop type data prior to 2006 limited an earlier start of the study period, thus 2006-2007 provided our model spin-up period.

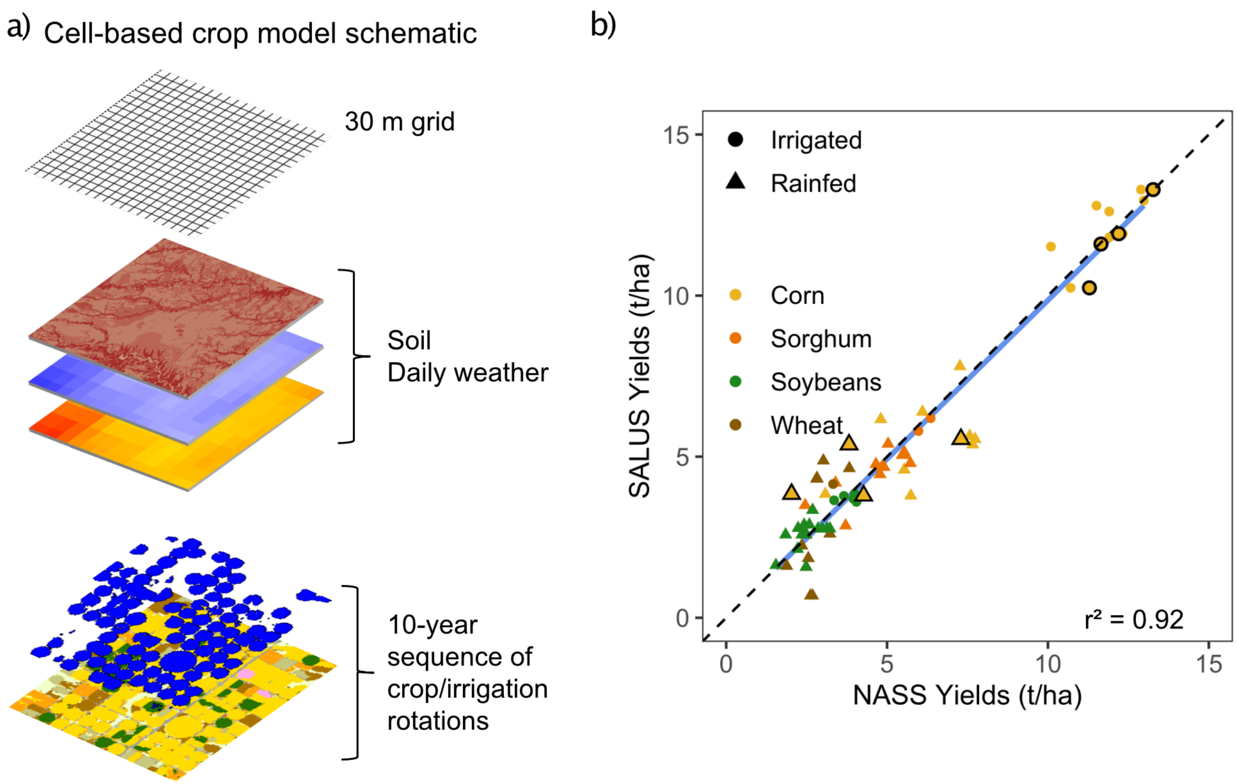

Figure 3. Modeling framework and performance of yield estimation. (a) Modeling approach using the SALUS crop model. Models were run for each 30 x 30 m grid cell based on cell-specific soil, climate, and 10-year crop/irrigation rotation sequences. Results were then aggregated for SD-6. b) SALUS simulated yield validation. SALUS calibrated yields for the four primary crops in the Sheridan-6 LEMA by irrigation status compared with USDA NASS annual statewide crop yield statistics for years 2008-2017. NASS data for Sheridan County are outlined in black when available by irrigation status.

We defined SALUS crop management and water use parameters in a two-step process. First, crop cultivar and management parameters were validated against observed annual yields between 2008-2017 obtained from the USDA's National Agricultural Statistics Service (NASS, 2019). Rainfed and irrigated crops were calibrated separately using state yield data reported by irrigation status from NASS, since county-level yields by irrigation status were available only for maize and only for four years prior to 2014. Overall agreement between SALUS simulated yields and NASS yields for the four primary crops in the study area was strong (r^2 = 0.92; see Results section 3.1, Figure 3b). Text S3 and Table S1 provide a detailed description of model calibration and model parameters. Annual planting date in the model was based on the observed median planting date from NASS. All other crop-specific parameters were uniformly applied for the entire study period.

Second, we used this calibrated yield model to develop two model scenarios for analysis with SALUS irrigation application parameters adjusted to approximate aggregate irrigation behavior in SD-6: 1) a business-as-usual model (BAU) calibrated to pre-LEMA irrigation described by WIMAS water use data from 2008-2012, which we used to estimate BAU pumping and irrigation that would have occurred during the LEMA period in the absence of groundwater restrictions, and (2) a LEMA model calibrated to observed irrigation behavior. This second scenario used BAU parameters for the pre-LEMA period that were then adjusted to match the reduced irrigation pumping observed during the LEMA from 2013 through 2016 (2017 data was unavailable at the time of model development). To identify SALUS irrigation parameters for each period, we iteratively varied the soil moisture threshold, which triggers SALUS's automatic irrigation application, between 45 and 90% of soil plant available water in steps of 5% for each of three application depths: 19.1, 25, and 31.8 mm (roughly 0.75, 1, and 1.25 in.). These irrigation application depths fall within observed practices in the region, where medium and fine-textured soils provide adequate field capacity for 19.1 – 33 mm (0.75 – 1.3 in) water applications for corn (Kranz et al., 2008), the dominant crop in SD-6. We then simulated all possible combinations of these two parameters (soil moisture threshold and application depth), resulting in 30 candidate possibilities. To account for water extracted from the aquifer but lost in delivery through wind-drift evaporation and other efficiency factors, we adjusted SALUS modeled irrigation volumes for each run by a 90% efficiency penalty based on typical values for well-maintained center pivot sprinkler irrigation systems (Kranz et al., 2008). Finally, we used WIMAS water use data to select the irrigation parameter set (soil moisture threshold and application depth) that best estimated actual pumped water use during the target periods for each scenario based on the mean absolute error for the 30 candidates. We also conducted a sensitivity analysis to see how the chosen parameters affected our estimates of reduced pumping during LEMA by evaluating all combinations of the three top performing candidates for each scenario, which generates nine estimates of pumping reductions between BAU and LEMA scenarios.

To estimate deep percolation in grid cells with grassland or fallow land, we used 1% of annual precipitation based on available literature estimates (Hansen, 1991). To assess changes from the LEMA program, modeled crop-specific yields and water budget components from the BAU and LEMA scenarios were compared during the LEMA period. We note that our analysis focuses on aggregate changes for the SD-6 region as a whole to allow us to effectively calibrate a parsimonious model. In reality, changes in irrigation decision making and their impacts will vary among producers. Future studies designed to collect fine-scale data and sociological variables would improve understanding of this variation.

2.4. Economic analysis

To assess the economic sustainability of the LEMA program, we estimated changes to farmer net income based on differences in regional crop yields and water use between the BAU and LEMA model scenarios. To estimate income from crop production, we obtained national annual crop prices from NASS and adjusted those to 2017 equivalent dollars per kilogram of yield. We then summed simulated annual crop-specific yields for the full SD-6 region for each scenario (total kg of production for each crop). We converted this to monetary regional totals based on crop price data. For this analysis, we assume that other costs associated with production such as fertilizer, seed, equipment, land, and labor are fixed across scenarios to focus only on yield and crop prices.

To estimate monetary savings from reduced pumping costs, we first quantified the pumping volumes for the BAU and LEMA models for 2013-2017. We then translated the volume of water extracted into required energy to operate groundwater pumps based on estimates from McCarthy et al. (2020). Briefly, their method calculated energy use annually for each well in the WIMAS database based on three quantities: 1) annual water volume extracted; 2) annual depth to water derived from groundwater level maps and estimates of each well's cone of depression from aquifer saturated thickness and hydraulic conductivity, and 3) energy efficiencies based on each well's pump type and energy source. Using their results, we calculated the average energy intensity for all wells in our study area from 2008 to 2017, which was 3.65 megajoules per cubic meter. Because a linear model of energy intensity over time revealed no significant trend ($p = 0.99$), we applied the mean energy intensity uniformly to the pumping volumes in our model scenarios to get total energy use for each scenario (MJ). We then converted this energy required for pumping into dollars based on a typical cost for industrial energy in Kansas of 1.97 cents per megajoule (www.electricitylocal.com/states/kansas/) and calculated the difference in total pumping costs between the BAU and LEMA scenarios.

3. Results and Discussion

3.1. Model calibration

To assess the impact of the LEMA program, we calibrated the SALUS model to represent historic yield and water use conditions in the SD-6 LEMA. SALUS simulated yields generally showed good agreement with NASS state statistics by irrigation status (Figure 3b). Overall agreement across irrigated and rainfed simulations for the four major crop types for years 2008-2017 had an $r^2 = 0.92$. NASS state yield statistics for irrigated corn were available in all years of the calibration period (2008-2017) and were within 14% of median simulated yields in all years (range: 0.85 to 14%). NASS corn yield data for Sheridan County by irrigation status for the four available years shows similar agreement (within 0.15 to 9% of median simulated yields; Figure 3b). NASS state yields by irrigation status were less frequently available for sorghum (two years), soybeans (five years), and wheat (one year). For available years, simulated irrigated yields were within 3%, 11%, and 24% for sorghum, soybeans, and wheat, respectively.

For simulated water use, we used the mean absolute error to select the irrigation parameters that best agreed with WIMAS well pumping data from among the 30 model runs (section 2.3; Figures 4a, 4d). For the BAU scenario, the model that best captured 2008-2012 groundwater use delivered 31.8 mm (1.25 in) irrigation applications when soil moisture dropped below 85% of plant available water. For the LEMA scenario, the model that best captured 2013-2017 groundwater use delivered 25 mm (1 in) irrigation applications when soil moisture dropped below 80% of maximum capacity (Figure 4d). Typical ranges for soil moisture thresholds triggering irrigation for this region were not available to corroborate parameter estimates. If the assumed 90% irrigation efficiency was too high, it is possible that soil moisture thresholds are artificially inflated; lower efficiencies would require more water extracted from the aquifer to meet simulated water demand by SALUS, resulting in models parameterized with lower soil moisture thresholds better matching the WIMAS well data. Similarly, by modeling SD-6 as a region and calibrating to total annual water use, it is not possible to provide detailed differences that may exist by crop type, crop growth stages, or individual water managers. More information such as the timing of individual water deliveries and management units would be needed for this type of analysis.

Regardless of the uncertainty around the absolute values, the better performing models for the LEMA applied less water at lower soil moisture thresholds compared to the best BAU models (Figure 4a). Although the selected parameters do not represent a unique solution, the two scenarios indicate that producers on aggregate likely achieved the observed water savings by irrigating less often and at reduced application irrigation depths for each irrigation event. This shift is consistent with on-the-ground observations based on soil moisture sensors that SD-6 farmers are becoming better groundwater managers through increased awareness of irrigation scheduling and soil moisture monitoring, leading to less overwatering (Lauer & Sanderson, 2017; NW KS GMD 4, 2017, Butler et al. 2018). The sensitivity analysis of estimated pumping reductions indicates that these best performing models generates an intermediate estimate within the range of the nine top performing scenarios (Figure 4b).

Opportunities to evaluate SALUS's ability to estimate hydrologic fluxes in the study area are limited due to the lack of surface water features and long lag times for deep percolation to reach the water table (Figure 1, section 2.3). Comparisons of SALUS modeled evapotranspiration (ET, the sum of plant transpiration and soil evaporation) for the LEMA scenario with ET estimates derived from MODIS satellite data (Zhang et al., 2019) for all irrigated pixels indicate adequate agreement ($r^2 = 0.15$, RMSE = 38.8 mm year^{-1}) given inherent uncertainties in satellite-based estimates, with SALUS estimates of mean ET over SD-6 ranging from 659 to 738 mm year^{-1} and satellite-derived estimates ranging from 618 to 774 mm year^{-1} (Text S4, Figure S1). This suggests that SALUS is able to reasonably simulate key soil water fluxes, effectively allocating water to plant transpiration, soil evaporation, and deep percolation.

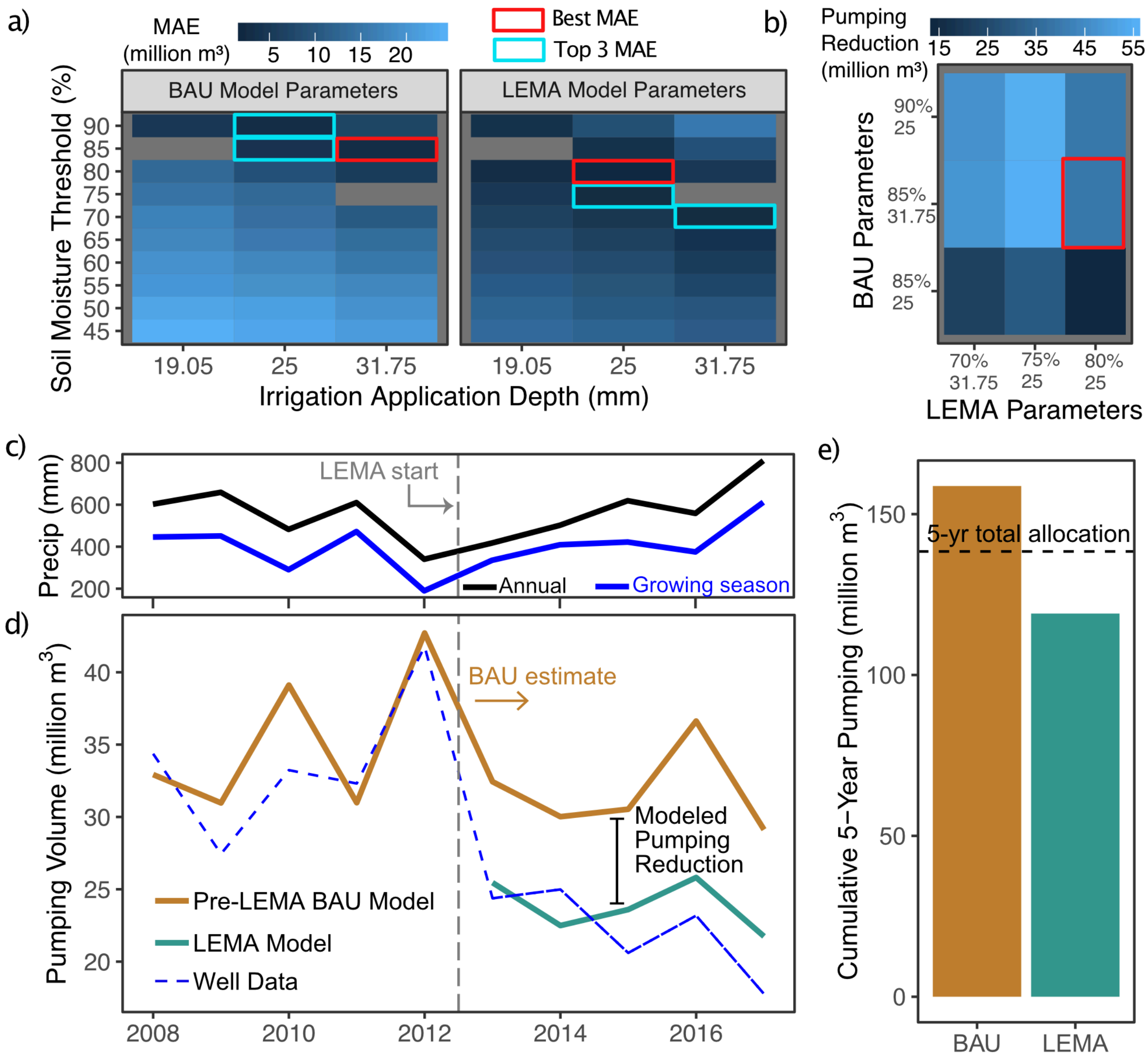
a)
MAE (million m³)
5 10 15 20
Best MAE
Top 3 MAE
BAU Model Parameters
LEMA Model Parameters
Soil Moisture Threshold (%)
90 85 80 75 70 65 60 55 50 45
19.05 25 31.75
Irrigation Application Depth (mm)
b)
Pumping Reduction (million m³)
15 25 35 45 55
BAU Parameters
90% 25
85% 31.75
85% 25
70% 31.75
75% 25
80% 25
LEMA Parameters
c)
Precip (mm)
800 600 400 200
LEMA start
Annual
Growing season
d)
Pumping Volume (million m³)
40 35 30 25 20
BAU estimate
Modeled Pumping Reduction
Pre-LEMA BAU Model
LEMA Model
Well Data
2008 2010 2012 2014 2016
e)
Cumulative 5-Year Pumping (million m³)
150 100 50 0
5-yr total allocation
BAU
LEMA

Figure 4. SALUS crop model water use for the business-as-usual (BAU) and Local Enhanced Management Area (LEMA) scenarios. (a) Performance of SALUS irrigation parameter combinations based on Mean Absolute Error (MAE) when compared with WIMAS well data for that period. The combination with the lowest MAE was selected for each scenario (red box). Teal boxes indicate the 2nd and 3rd lowest MAE, used in the sensitivity analysis. (b) Sensitivity analysis for estimated pumping reductions based on best performing irrigation parameters. The three best performing parameters for the LEMA and BAU scenarios are on the x and y axis, respectively. The color scale indicates the model-estimated reductions in pumping for each parameter combination. The red box highlights the selected model. (c) Mean annual precipitation (black) and growing season precipitation (May 1 – Oct. 15, blue) for the Sheridan-6 (SD-6) study region. (d) Total pumping volume estimated for SD-6 via SALUS for the BAU scenario based on pre-LEMA groundwater use (2008-2012, brown) and the LEMA scenario, based on LEMA groundwater use (2013-2017, green). Actual irrigation pumping volumes extracted from WIMAS well data (KDA DWR, 2017) is indicated with the blue dashed line. Following the start of the LEMA program in 2013, the pre-LEMA model served as a business-as-usual (BAU) estimate of water use had the LEMA not been implemented. Differences between the BAU and LEMA scenario models from 2013-2017 represent reductions in pumping volumes estimated due to the LEMA program. (e) Total 2013-2017 pumping volume based on the BAU and LEMA scenarios. Dashed line shows the total water allocation for the five-year LEMA period, based on 20% of 2002-2012 water use.

3.2. LEMA program impacts on the regional water budget and crop yields

3.2.1 Changes in groundwater extraction

We compared model scenarios to quantify LEMA-induced changes in water use, aquifer net balance, and crop yields. Based on modeled water use, we found that the LEMA program reduced total 5-year groundwater extraction by 25% to 119 million m^3 compared to BAU estimates of 159 million m^3 (Figure 4e). This translates to average annual savings of 7.9 million m^3. The resulting 39.6 million m^3 saved over the 5-year LEMA was greater than BAU estimates for mean annual pumping (31.8 km^3), suggesting groundwater extraction was reduced by over a year's worth of historical groundwater use. The region surpassed the 20% water reduction goal, which would not have been met under BAU irrigation behavior (Figure 4e).

The approach presented here modeled water savings from changes in irrigation depth and frequency while keeping the spatial distribution of annual crop types and irrigated area the same in both scenarios. Previous work based on statistical modeling found that such changes in overall irrigation efficiency accounted for 72% of water savings in the SD-6 LEMA (Deines, Kendall, Butler, et al., 2019). Thus, modeled estimates from SALUS were similar to previous findings based on statistical analysis, while providing further insight into how water savings impact yields and irrigation return flow. The previous statistical analysis estimated that in total, the SD-6 LEMA reduced water use by 31% at an average rate of 10.2 million m^3 per year across three adaptation strategies (irrigation efficiency, crop choice, and irrigated area). Improvements in irrigation efficiency, therefore, reduced water use by approximately 7.3 million m^3 per year (Deines, Kendall, Butler, et al., 2019), similar to our simulated estimate of 7.9 million m^3 here. The close agreement from these two complementary approaches based on statistical and process-based modeling indicates that the SALUS scenarios developed here reasonably captured observed changes due to the LEMA program, lending confidence in using the SALUS model for water budget evaluation, yield assessment, and economic analysis.

3.2.2 Changes in the overall water balance

When comparing the overall water balance between scenarios, we found that the LEMA scenario had a more favorable net balance (deep percolation – groundwater extraction) than BAU in all years (Figure 5a, b). Over the five-year period, this amounted to 8.6 million m^3 of water conserved through the LEMA program compared to BAU estimates. Given that SD-6 covers 256 km^2, this translates to an average relative increase in aquifer recharge of 34 mm, assuming water in deep percolation reaches the water table. Although the precise time lag for this region is uncertain and warrants further study (Butler et al., 2020), drainage below the root zone is generally assumed to reach the water table and recharge the aquifer in this system (Crosbie et al., 2013; McMahon et al., 2003; Scanlon et al., 2010).

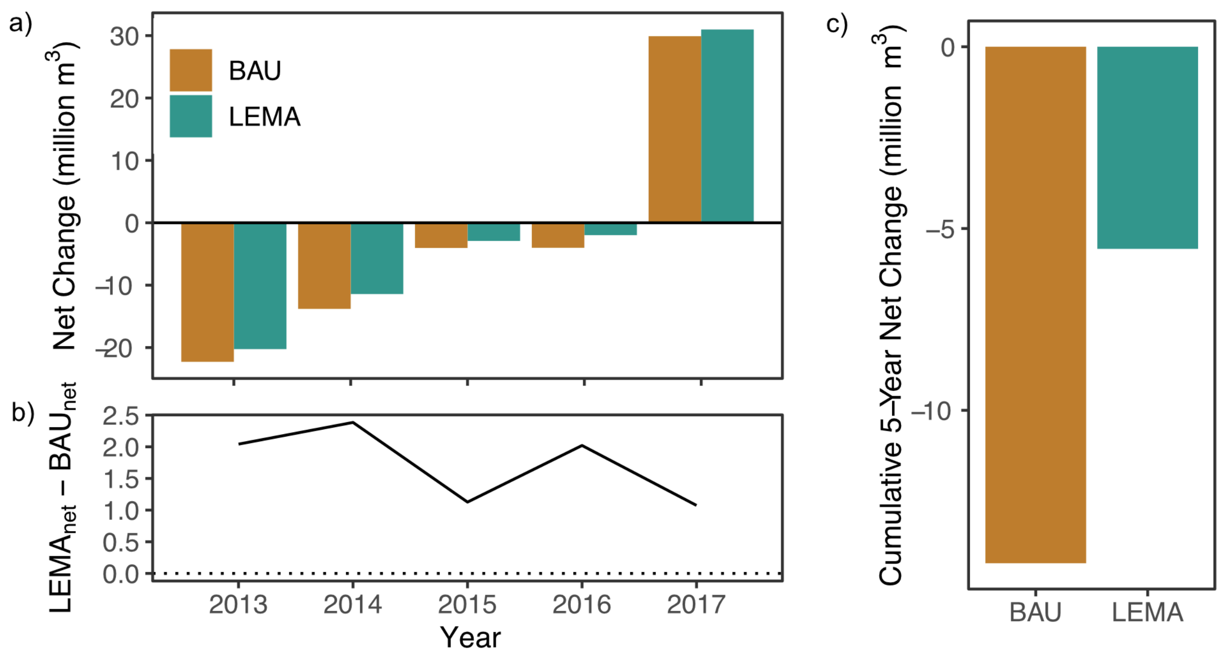

Figure 5. Net groundwater savings estimates. Aquifer balance indicated by net change calculated from the SALUS crop model (deep percolation – groundwater extraction). (a) Annual net change by model scenario. (b) Annual difference in net change between the LEMA and BAU model scenarios. Positive values indicate years where the LEMA model scenario conserved more water. (c) Cumulative net change for the 5-year LEMA management period (2013-2017).

Despite this net improvement, the overall system balance was still negative for 2013-2017 (Figure 5c); for sustainability to be achieved, the water extracted from the system through pumping needs to be less than or equal to the volume of water added to the system through deep percolation, which combines rainfall infiltration and irrigation return flow. We found that although the amount of deep percolation now accounts for 96% of extracted volume compared with 91% in the BAU scenario, the system may still be short of achieving groundwater sustainability. When looking at the net change by year, we found that the balance was negative for all years with the exception of 2017, where high precipitation totals contributed to a positive net change (Figure 4c, Figure 5a). This suggests that in addition to irrigation behavior, the net balance is influenced by annual precipitation patterns and more stringent pumping reductions may be needed in the event of recurrent dry years.

Notably, we found that the amount of water conserved when analyzing the overall water balance is only 21.7% of the pumping reductions we estimated (8.6 vs 39.6 million m^3, respectively). Once irrigation water is applied, SALUS simulates whether the water transpired through the plant, evaporated from the soil, became runoff, or infiltrated the ground past the root zone as irrigation return flow (deep percolation). From this, we found that the discrepancy in overall versus pumping water reductions arises from a reduction in irrigation return flow under LEMA irrigation behavior (114 million m^3) compared to BAU (145 million m^3, Figure 6), demonstrating the paradox of irrigation efficiency (Grafton et al., 2018). Because efficient irrigation more closely meets crop water needs, there is less excess to re-infiltrate the soil. The characteristic circular shape of reduced percolation seen in Figure 6 is due to the dominance of center pivot irrigation technology in the region and also demonstrates how our method can capture sub-field level variability based on annual crop type, soil properties, and irrigated area, although it should be noted that the crop model output is based on aggregate irrigation behavior for the study area and not tailored to individual farm-level decisions on irrigation scheduling. The overall impact on the aquifer depends on the other components of the net inflow to the LEMA area and, as mentioned earlier, the lag time for the irrigation return flow to transit the vadose zone (Butler et al., 2018, 2020).

Net water savings, therefore, come from reductions in other components of the water budget. Over the five-year LEMA period, we found a small decrease of 0.64%, 0.61%, and 1.5% for total SD-6 plant transpiration, soil evaporation, and run off, respectively, in the LEMA scenario, totaling a net water savings of 4.62 million m^3 compared to BAU (Figure S2). The soil evaporation ratio between BAU and LEMA was nearly constant across years, whereas differences in plant transpiration were larger in dry years such as 2013 and nearly identical in wet years such as 2017, likely accounting for the differences in yield (see section 3.2.3). Remaining net water conservation comes from reductions in water losses to factors such as wind drift evaporation during irrigation application, which we assumed to be 10% of water applied (section 2.3).

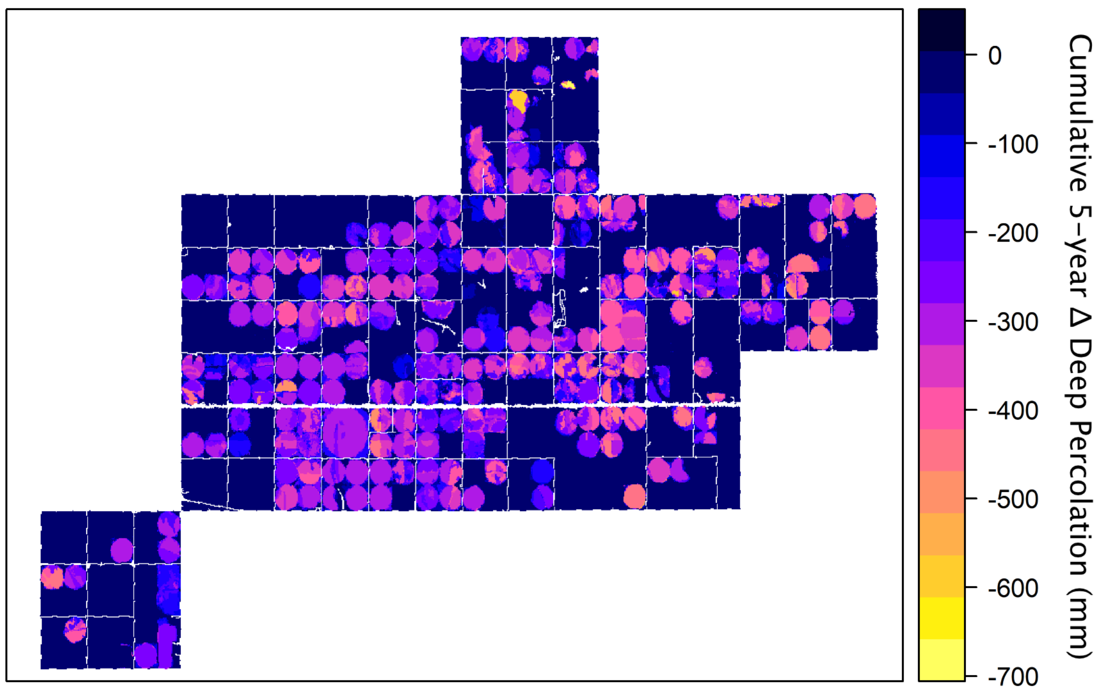

Figure 6. Cumulative change in deep percolation in Sheridan-6 from the LEMA program compared to business-as-usual, 2013-2017. The comparison is based on SALUS crop model output for each scenario. LEMA-induced reductions in irrigation applications resulted in reduced irrigation return flow across agricultural fields, leading to a 21.4% decrease compared to BAU. Circular shapes are due to center pivot irrigation technology, which dominates SD-6. White lines represent “no data” for roads, which were omitted from the model.

3.2.3 Changes in crop yields

The yield penalty from LEMA-induced irrigation reductions was small. By comparing the LEMA and BAU scenarios, we found that the 5-year mean decrease in median yield was 0.67%, 1.21%, 1.41%, and 0.07% for corn, sorghum, soybeans, and wheat, respectively (Figure 7). For all crops, interannual differences in median yield for the SD-6 region were larger than differences between modeled scenarios.

The ability to track yield effects of different irrigation regimes is a key metric needed to evaluate the LEMA program, but to date, data on crop yields for the region have been collected only from voluntary reporting on a limited number of fields and disconnected from soil and rainfall attributes, inhibiting robust statistical conclusions (Golden, 2018). Preliminary conclusions from this data for corn, for which the most data was available with 20 observations within SD-6 to compare with 11 observations in neighboring fields, suggest there was a 1.2% yield decline due to the LEMA water restrictions (Golden, 2018). Given the uncertainties involved, this provides some support that yield declines estimated by SALUS are reasonable.

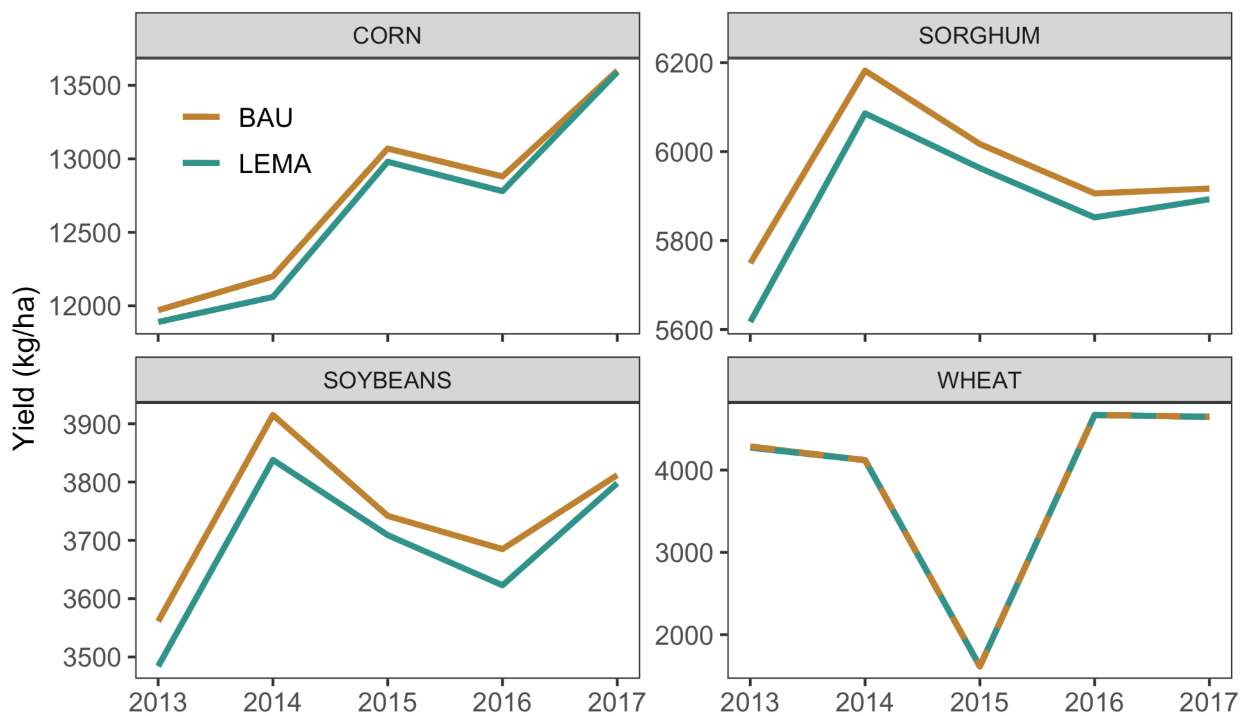

Figure 7. Yield penalty due to reduced irrigation water use, 2013-2017. Annual median yield by crop estimated from the SALUS crop model for the Sheridan-6 Local Enhanced Management Area (LEMA). The LEMA scenario (teal) slightly underperformed the business-as-usual (BAU) scenario (brown) for all crops except wheat, which were highly similar between the two model scenarios (here, the two lines are nearly identical).

3.3. LEMA program impacts on regional economics

Based on crop yields and pumping reductions, we found that the SD-6 LEMA generated an overall 5-year net benefit of $2,244,400 across the region compared to the BAU scenario (Table 1). By combining annual national commodity prices with crop-specific yields, we estimated that total crop gross income for the LEMA ranged from $14.7 million in 2015 to $21.2 million in 2013. Over the 5-year period, the irrigation regime under the LEMA program resulted in a $604,380 loss in gross income compared to the BAU irrigation regime. This was a 0.75% reduction in crop income for irrigated fields. Differences were worse in dry years ($194,144 in 2013) and smallest in wet years ($18,019 in 2017, Table 1), likely mirroring differences in plant transpiration. Estimated energy costs based on pumping volume, energy needs to lift water from the ground, and Kansas energy prices ranged from $1.56 million in 2017 to $1.86 million in 2016 for the LEMA. Compared to the BAU scenario pumping costs, the LEMA saved a total of $2.85 million over 2013-2017, a 25% reduction in energy costs for the 5 years, scaling linearly from the reduced water volume due to our uniform application of energy intensity (3.65 MJ m^{-3}, section 2.4).

Table 1. Estimated gross crop income and groundwater pumping costs in the Sheridan-6 Local Enhanced Management Area (LEMA). Estimated amounts are given for the LEMA scenario, as well as changes from business-as-usual. Amounts are in U.S. dollars, adjusted to 2017 dollars.

Year	LEMA Crop Income ($)	Δ Crop Income ($)	LEMA Pumping Costs ($)	Δ Pumping costs ($)
2013	21,183,697	-194,144	-1,830,073	501,535
2014	15,003,266	-179,193	-1,616,862	541,029
2015	14,737,243	-98,098	-1,696,380	498,586
2016	14,793,577	-114,926	-1,855,748	777,331
2017	15,004,331	-18,019	-1,563,137	530,299
Total		**-604,380**		**2,848,780**

Combined, these calculations indicate that the LEMA program provided a net profit for SD-6 farmers. Our estimate of lost crop income is likely low, since we held annual crop types and irrigation extents constant between the BAU and LEMA scenario. In reality, under full BAU conditions producers likely would have irrigated approximately 2-4% more crop area as well as planted more corn (Deines, Kendall, Butler, et al., 2019), presumably resulting in a higher total crop income for the SD-6 region. Despite this, overall losses are likely fully recovered by the \$2.85 million saved in energy costs.

4. Conclusions

We used the process-based SALUS crop model to assess water and economic sustainability from stakeholder driven groundwater management in the Sheridan-6 Local Enhanced Management Area (SD-6 LEMA). Our approach leveraged annual agricultural land use maps derived from remote sensing to simulate crop yields and the agricultural water budget within the SD-6 region from 2008-2017. With this approach, we estimated that groundwater extraction volumes decreased by ~25% (39.6 million m^3) due to reductions in irrigation application depths and frequency, which is consistent with previous statistical modeling efforts (Deines, Kendall, Butler, et al., 2019; Drysdale & Hendricks, 2018; Golden, 2018). Critically, however, SALUS was able to translate this reduced pumping volume into corresponding changes in the simulated water balance due to diminished irrigation return flow when irrigation becomes more efficient. We estimated that although LEMA-induced changes in irrigation behavior reduced groundwater pumping by 25% or 39.6 million m^3, the net water balance increased by only 8.6 million m^3, indicating that only approximately 22% of pumping reductions translated into net water conservation in this system.

Our results suggest that the SD-6 LEMA program improves both the economic and hydrologic sustainability of the region, increasing net profits while improving the aquifer water balance compared to business-as-usual conditions. SALUS's ability to model yield at sub-field resolution across SD-6 allowed us to assess how the LEMA program affected regional income. Overall, we estimated that changes in irrigation behavior in the LEMA scenario substantially increased aggregate net profits by $2.24 million when both yield penalties and energy savings were included. In this way, SD-6 is at the forefront of a shift from traditional approaches focused on yield maximization and risk reduction, to a more targeted approach focused on profit maximization and efficient use of water. SD-6's outcomes have spurred the formation of additional LEMAs in the larger Groundwater Management District 4 (Figure 1a) as well as the Wichita County LEMA in Groundwater Management District 1. Furthermore, extending the aquifer lifespan can generate long-term benefits to the system given expected future higher yielding varieties and by preserving the ability to mitigate future droughts (Foster et al., 2017; Quintana Ashwell et al., 2018; Zipper et al., 2016).

Despite improvements compared to BAU, our results indicate that LEMA-era levels of irrigated agriculture in the SD-6 region are still not fully sustainable. Our analysis of net aquifer change indicated that the aquifer balance was positive only in abnormally wet years (Figure 5). The initial LEMA cycle from 2013-2017 was 26.7% wetter than the 2002-2012 period upon which reduction targets are based. This suggests that aquifer sustainability may be difficult to achieve under typical to drought conditions. Given the region's intermediate drought frequency and expected increases in water stress due to climate change (Dai, 2013), LEMA effectiveness and yield implications in drought conditions need to be better understood to inform future planning efforts. It is plausible that larger yield penalties would be observed in drought conditions if irrigation water was unable to meet crop water needs, potentially with nonlinearities if insufficient water leads to crop failures. A better understanding of the drought resilience of such conservation programs would help inform management plans going forward. As aquifer depletion threatens crop production in many parts of the world, approaches that integrate models with in-situ and remotely sensed data can estimate critical system components that are difficult to directly measure, thus informing economically and hydrologically sustainable management strategies.

DATA AVAILABILITY STATEMENT

All model output and data used to produce manuscript figures are available on Zenodo at https://doi.org/10.5281/zenodo.4271209. Raw input can be obtained at the sources listed in the manuscript. SALUS model files and implementations scripts for the chosen models are also available in the repository.

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Water Resources Research

Supporting Information for

Combining remote sensing and crop models to assess the sustainability of stakeholder-driven groundwater management in the High Plains Aquifer

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Contents of this file

Introduction

This supplement contains supporting information for the methodology used in Deines et al. This includes descriptions for processing crop type maps and calibrating SALUS crop model simulations. Associated model files, processing codes, and data can be found in the accompanying repository hosted on Github for the review stage (https://github.com/jdeines/Deines_etal_LEMA_SALUS); the repository will be permanently hosted at Zenodo with an issued DOI upon acceptance.

Text S1: Cropland Data Layer Smoothing

The USDA's NASS Cropland Data Layers (CDL) (USDA-NASS 2017) contain some misclassified pixels, including small groups of pixels within larger fields. To minimize these spurious crop classifications, we smoothed annual CDL images with a two-step process in Google Earth Engine (GEE) (Gorelick et al., 2017), which hosts the CDL product in its cloud-based data catalog. First, we resampled all CDL years to 30 m where needed and ran a connected pixel counter that identifies the number of connected pixels by class type. We flagged patches with < 25 pixels (2.25 ha) as potentially spurious classifications given the typical field size ~60 ha in this region. Second, we updated values at these flagged patches with the most common crop class within a circular moving window with radius of 120 m. The effect of this "despeckling" process is to re-classify small patches with the most common class type within a moving local window, thus reducing the "salt and pepper" effect often produced from per-pixel classifications. We then used the 2016 TIGER road vector dataset to update underlying pixels as roads. This provided consistent location of roads across CDL years and protected them from the implemented despeckling technique, since roads are often small patches due to imagery resolution and their long, narrow shape. Raster crop type maps at 30 m resolution were then exported from GEE at geotiffs for analysis.

Text S2: Description of the SALUS crop growth module and crop response to water stress

The SALUS crop growth module is based on a sink-source relationship for almost every process during the plant growth ontogeny. The sink provides a constraint on growth related to the maximum cell division and expansion. Supply and demand are calculated daily for soil water and nutrient balance. For each daily time step, SALUS uses the law of the minimum to determine the quantity of water or nutrients that is limiting crop growth. Crop development is based on the calculation of thermal time accumulation. During vegetative growth, SALUS quantifies the sink size as function of leaf area index (LAI) and intercepted photosynthetic active radiation (PAR) to provide an estimate of daily growth, and the source of assimilate for the canopy based on the species radiation use efficiency (RUE Kg/MJ). The carbon assimilates are partitioned into roots, stems, and leaves during vegetative growth, into ear growth during ear formation, and into grain growth during grain filling. The organ partitioning amounts are retrieved from the SALUS species table, which changes during plant ontogeny. In the event that the sink is smaller than the source, the plant grows according to the sink, but the roots are given the difference between the source and the sink in addition to their normal allocated biomass. When the source is smaller than the sink, the individual organs receive only the source limited growth amount. Deficiencies of water and nutrients decrease the sink in proportion to the water or nitrogen sufficiency factor. Plant water use can be limited by energy available for transpiration or by the ability of the root system to take up water. The potential transpiration depends on the potential soil evaporation and the wetness of the soil surface. For partially covered surfaces, plant transpiration is highly dependent on the soil evaporation occurring that day. SALUS first calculates soil evaporation and then by difference with total potential evapotranspiration, plant transpiration is calculated. When the soil surface is wet, plants are surrounded by a humid environment and transpire considerably less (Basso and Ritchie, 2012; Basso and Ritchie, 2018).

If soil water is not limited, the root system will use water to satisfy the potential evapotranspiration demand. As the soil dries, the conductivity of the soil water decreases and the potential root water uptake decreases, due to soil water deficit. SALUS has two water deficits factors. The first soil water deficit factor reduces transpiration and biomass production, and it is calculated as the ratio between the actual over the potential transpiration. The second water deficit factor is calculated to account for water deficit effects on plant physiological processes that are more sensitive than the stomata-controlled processes of transpiration and biomass production. This second factor allows for a greater proportion of biomass partitioned to roots during water deficit conditions. The changing of root-shoot partitioning during soil drying is an important feature of the SALUS crop model. SALUS was recently used to evaluate the impact of evapotranspiration on crop yield across the US Midwest (Basso et al., 2021).

Text S3: SALUS modeling framework

Our modeling approach aimed to simulate real-world crop production in the Sheridan-6 (SD-6) study area from 2006-2017. To do so, we ran individual SALUS crop simulations for each 30-m grid cell in the study area. Because SALUS is a continuously run model and not annually reinitialized, we simulated rainfed crops and fallowed fields in addition to irrigated crops in order to generate continuous estimates of soil drainage based on annual land use decisions. Each simulation followed the annual sequence of observed crop type and irrigation status from the remote sensing data (section 2.1). To extract the full set of simulations to run, we extracted all unique combinations of soil type, GRIDMET climate cell, and 12-year crop/irrigation rotations including fallow classifications. For crop types, we simulated the seven most prevalent land cover during the study period (corn, wheat, sorghum, soy, alfalfa, grassland, and fallow; Figure 2). Crop rotation sequences had missing crop values in 4.0% of cells due to less common crop choices, such as sunflowers, omitted from this study. For cells with crop sequences missing two years or less due to these uncommon crop types, we assigned the alfalfa class in the missing years as a reasonable proxy to maintain model output for these locations across years. Sequences with more than two years of alternative crops were not simulated (0.4% of non-developed area in the study region). This resulted in 48,279 unique combinations from 270,814 active SALUS grid cells not covered by roads or other developed lands, repeated rare crops, or small water bodies, covering 95.5% of the total study area.

Crop cultivar and management parameters were calibrated to observed annual yields obtained from the USDA's National Agricultural Statistics Service (NASS, 2019). For baseline parameters, we gathered information from available agronomic resources related to crop growth in northwest Kansas to set base model parameter conditions. Management parameters including annual state median planting dates were obtained through the USDA's National Agricultural Statistics Service (NASS, 2019). Typical planting densities and regional offsets from state planting dates were obtained from the Kansas Crop Planting Guide (Shroyer et al., 1996). Initial cultivar selection for corn and wheat were taken from a previously published SALUS model in the adjacent Central High Plains portion of the HPA, including large parts of Kansas (Cotterman et al., 2018). Corn and wheat were run in "complex" mode within SALUS, while soybeans, sorghum, and alfalfa were run in "simple" mode within SALUS since "complex" mode with specific cultivars are not available for these crops. All crops were set to harvest at maturity as determined by the model. For this study, nitrogen was assumed to be non-limiting. We therefore ran SALUS with the nitrogen module off. All fields were set to no-till for parsimony, based on Cotterman et al. (2018). Finally, although we planted pasture grass to mimic grassland and fallow land use types within the SALUS runs, we had difficulty simulating reasonable recharge values for perennial grasses. To get an improved overall deep percolation estimate while ultimately not affecting estimation of the relative impact of LEMA water reductions, we manually overrode recharge estimates for these cells using 1% of annual precipitation based on available literature (Hansen, 1991).

We then calibrated these reference-informed starting parameters for cultivar type and planting density to better match state yield data from NASS. County-level annual statistics were also considered when available but were infrequent for the study area. Rainfed and irrigated crops were calibrated separately. During yield calibration, irrigation parameters were set to be non-limiting by delivering 25 mm (~1 in) of irrigation via sprinklers when soil moisture content dropped below 75% of plant available water (defined as the difference between the drained upper limit and lower limit of the soil). Initial parameters for soybeans and sorghum performed well, so these were not modified. The medium-high yielding wheat variety and planting density from Cotterman et al. (2018) matched yield data better than other available cultivars and was thus selected for both rainfed and irrigated wheat. For corn, we found good agreement with NASS statistics by using a low yielding cultivar for rainfed fields, and a moderate yielding cultivar for irrigated fields. We did not calibrate alfalfa parameters due to its small proportional representation on the landscape.

Table S1 provides model parameters for the irrigation and rainfed simulations for each crop. The full set of model parameters and script to produce SALUS run files for each grid cell can be found in the code repository.

Crop Type	Irrigation Status	Cultivar	Row Spacing (cm)	Planting density (plants/m^2)
Alfalfa	Irrigated	Simple	50.8	733.5
	Rainfed	Simple	76	488.7
Corn	Irrigated	SD6_2	76.2	8.4
	Rainfed	IB0072	76.2	4.4
Sorghum	Irrigated	Simple	50.8	14
	Rainfed	Simple	50.8	9
Soybeans	Irrigated	Simple	54	39.54
	Rainfed	Simple	54	39.54
Wheat	Irrigated	IB1099	17.78	295
	Rainfed	IB1099	17.78	295

Table S1. Summary of SALUS crop parameters. All crop simulations were run with the SALUS nitrogen module off, assuming fertilizer applications met crop nutrient needs. Planting dates varied by year according to the state median planting date from NASS and northwest Kansas regional offsets. Cultivar SD6_2 is based on a Pioneer medium yielding cultivar. Cultivar IB0072 is based on a Pioneer low yielding cultivar. Cultivar IB1099 is a higher yielding wheat cultivar. Full parameters for each crop cultivar can be found in the Crop database input file (.cdb.xml) for SALUS in the code repository associated with this manuscript.

Text S4: Comparison of SALUS Evapotranspiration (ET) estimates with satellite data

Text S4.1: Methods

To evaluate SALUS's ability to estimate components of the water budget, we compared SALUS ET estimates with satellite-derived estimates. We used the Penman-Monteith-Leuning Evapotranspiration V2 product (PML-V2; Zhang et al. 2019). PML-V2 uses a coupled diagnostic biophysical model to incorporate MODIS satellite data (leaf area index, albedo, and emissivity) with GLDAS weather data. Because of the dependance on MODIS, PML-V2 provides ET estimates at 500 m resolution every 8 days starting in 2002. PML-V2 outperforms most similar ET products (Zhang et al. 2019).

We performed two comparisons, one point-based and one based on the mean annual ET for irrigated pixels in the study area. For the point comparison, we manually placed sample points near field centers identified from Google basemap imagery in Google Earth Engine. We targeted field centers in an attempt to minimize mixed-pixel contamination, since the 500 m resolution of the satellite data means that pixels often encompass multiple fields or field borders (Figure S1a). We placed 200 manual points and then sampled the annual ET at each point from PML-V2 and our SALUS simulations for 2008-2017. For each point, we also extracted that year's crop type and irrigation status based on CDL crop type maps and AIM irrigation maps. We focused on analysis on corn and soy fields, since they are the most abundant in the study area. For the comparison of study area mean ET over irrigated areas, we first resampled PML-V2 to 30 m and then used AIM to mask non-irrigated pixels. We then calculated annual mean ET volume for SD-6 irrigated area from each data source (SALUS and PML-V2).

Text S4.2: Results

Overall, we found that SALUS ET estimates performed adequately, but the satellite product lacked spatial resolution for a robust location-specific comparison. SALUS estimates of mean annual ET were moderately correlated with PML-V2 estimates (r^2 = 0.15, RMSE = 38.8 mm year^{-1}, Figure S1b). Annual estimates ranged from 659 to 738 mm year^{-1} for SALUS and 618 to 774 mm year^{-1} for PML-V2. Given the uncertainty inherent in ET estimation and satellite-based ET products, the similarity in ET ranges between methods lends confidence to SALUS's ability to represent ET in the study region.

For the point-based comparison, we found marginal agreement between SALUS and PML-V2. This appears to be driven by the low resolution of PML-V2 and possible spatial averaging due to the coarser resolution input GLDAS weather data (Figure S1a). Notably, PML-V2 is unable to distinguish ET rate between irrigated and rainfed fields (Figure S1c), further indicating that satellite data at this resolution is not sufficient for evaluating point-based estimates.

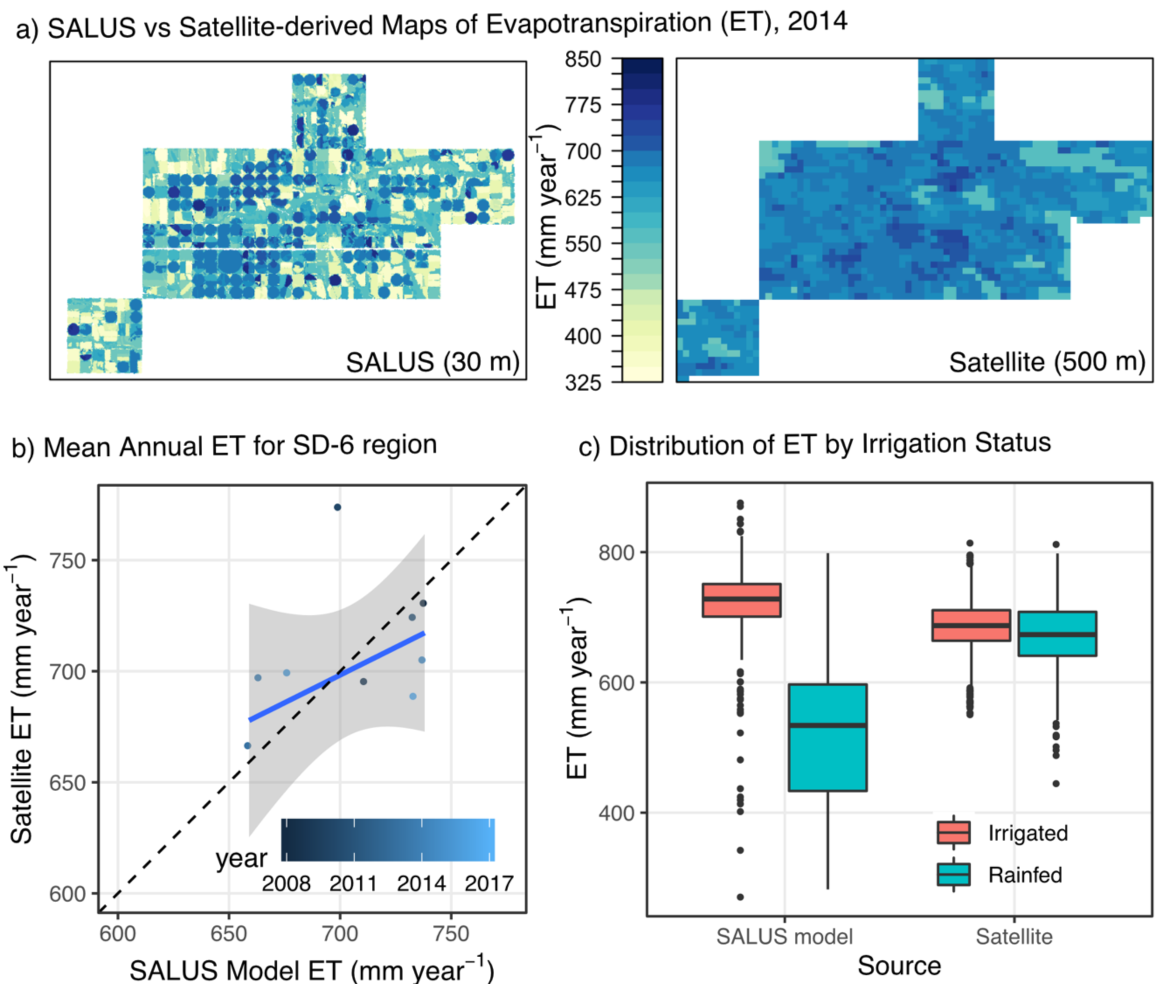

Figure S1. SALUS estimated evapotranspiration (ET) vs. satellite data.

a) Maps of ET for the Sheridan-6 study area in 2014 derived from SALUS crop simulations at 30 m resolution (left) and a MODIS satellite-based dataset produced at 500 m resolution (PML_V2, Zhang et al. 2019). b) Comparison of total annual ET in million m^3 for irrigated areas within Sheridan-6 for 2008-2017 derived from SALUS crop simulations and PML_V2 satellite estimates. Agreement from the squared Pearson's correlation coefficient is $r^2 = 0.15$ with RMSE = 38.8 mm year^{-1}. c) Distribution of ET values for 2000 point samples by data source and irrigation status. Two-hundred points were manually placed near field centers to minimize mixed pixel contamination from the 500 m resolution PML_V2 product. ET values were sampled for each year from 2008-2017, providing 2000 samples. The satellite product is unable to distinguish between irrigated and rainfed fields due to low resolution.

Figure S2. Annual water budget components by scenario.