Groundwater

Estimating Groundwater Pumping for Irrigation: A Method Comparison

by Andrea E. Brookfield[1,2], Samuel Zipper[3], Anthony D. Kendall[4], Hoori Ajami[5], and Jillian M. Deines[6]

Abstract

Effective groundwater management is critical to future environmental, ecological, and social sustainability and requires accurate estimates of groundwater withdrawals. Unfortunately, these estimates are not readily available in most areas due to physical, regulatory, and social challenges. Here, we compare four different approaches for estimating groundwater withdrawals for agricultural irrigation. We apply these methods in a groundwater-irrigated region in the state of Kansas, USA, where high-quality groundwater withdrawal data are available for evaluation. The four methods represent a broad spectrum of approaches: (1) the hydrologically-based Water Table Fluctuation method (WTFM); (2) the demand-based SALUS crop model; (3) estimates based on satellite-derived evapotranspiration (ET) data from OpenET; and (4) a landscape hydrology model which integrates hydrologic- and demand-based approaches. The applicability of each approach varies based on data availability, spatial and temporal resolution, and accuracy of predictions. In general, our results indicate that all approaches reasonably estimate groundwater withdrawals in our region, however, the type and amount of data required for accurate estimates and the computational requirements vary among approaches. For example, WTFM requires accurate groundwater levels, specific yield, and recharge data, whereas the SALUS crop model requires adequate information about crop type, land use, and weather. This variability highlights the difficulty in identifying what data, and how much, are necessary for a reasonable groundwater withdrawal estimate, and suggests that data availability should drive the choice of approach. Overall, our findings will help practitioners evaluate the strengths and weaknesses of different approaches and select the appropriate approach for their application.

Introduction

Effective groundwater management is critical to future environmental, ecological, and social security and sustainability (de Graaf et al. 2019; Jasechko and Perrone 2021). Groundwater extraction around the world provides 50% of domestic, 33% of industrial, and 40% of agricultural water uses (IGRAC 2018). Groundwater resources will become more important in many areas of the world in the 21st century as we attempt to address ongoing and emerging water security issues (Taylor et al. 2013). Shifts in the global hydrological cycle are occurring due to climate change and other anthropogenic stressors (Vörösmarty et al. 2013). Water security in many areas, including Western North America, is threatened by shifts in streamflow timing and magnitude; for example larger volumes of streamflow arriving in the winter and early spring due to earlier snowmelt (Stewart et al. 2005), increased duration and frequency of no-flow conditions due to increasing aridity and water use (Zipper et al. 2021; Zipper et al. 2022a), and increases in frequency and intensity of droughts in recent years (e.g., Mujumdar et al. 2020). These changes have increased reliance on groundwater resources and have important implications for the agricultural sector, energy security, and natural resource management.

Effective groundwater management hinges on accurate estimates of past and current groundwater extraction. Unfortunately, these measurements are not publicly available in most areas around the world due to a variety

[1]Department of Earth and Environmental Sciences, University of Waterloo, Waterloo, Ontario, Canada
[2]Corresponding author: Department of Earth and Environmental Sciences, University of Waterloo, Waterloo, ON, Canada; andrea.brookfield@uwaterloo.ca
[3]Kansas Geological Survey, University of Kansas, Lawrence, Kansas
[4]Department of Earth and Environmental Sciences, Michigan State University, East Lansing, Michigan
[5]Department of Environmental Sciences, University of California Riverside, Riverside, California
[6]Earth Systems Predictability and Resiliency Group, Pacific Northwest National Laboratory, Richland, Washington

Article impact statement: Multiple methods can accurately estimate groundwater extraction volumes if properly constrained, even the simple ones.

Received December 2022, accepted June 2023.

doi: 10.1111/gwat.13336

of reasons including physical, regulatory, and social challenges (Condon et al. 2021; Marston et al. 2022a). Physical challenges include those that stem from the spatial and temporal variability of groundwater pumping as it relates to frequency, volume, rate, and location of pumping (Russo and Lall 2017). Collecting a comprehensive dataset requires equipping each pumping well with a flowmeter and logging the data at the time interval desired. Logistical issues arise if data logging is completed manually, requiring scheduling personnel to visit and record the water level. There are also regulatory and social issues related to well ownership and reporting requirements that limit groundwater extraction data availability. For example, most irrigation wells are privately owned, and regulatory requirements often do not require reporting groundwater extraction. While well locations and permitted withdrawals are available in some countries (Perrone and Jasechko 2019), actual groundwater withdrawal data are rarely available, even in data-rich settings like the United States (Foster et al. 2020). While regulations can facilitate the collection and accessibility of groundwater extraction data, it can also create social challenges in adopting these rules. Groundwater use for irrigation is directly linked to economic viability, and often regulations governing the collection and reporting of groundwater pumping data is construed as a threat to that viability.

Reliable estimates of groundwater extraction data are critical for several disciplines and applications. Groundwater extraction estimates are commonly required for hydrological and hydrogeological studies to estimate aquifer or watershed-scale water balance, identify the drivers of hydrologic change, and develop inputs for surface water and groundwater models (Bohling et al. 2021; Zipper et al. 2022b). However, groundwater extraction is also a key process linking human actions to environmental systems, extending its utility beyond just water science. In the case of transboundary water resources, estimates of pumping volume are critical for allocating shared water resources and therefore can have strong political utility (Sanchez et al. 2020). Furthermore, accurate groundwater extraction data is essential for developing conservation strategies, for example by assessing the impact of groundwater extraction on ecosystem functioning (Marston et al. 2022b). Groundwater pumping is also necessary for understanding agricultural economics, due to both the costs associated with groundwater pumping and the importance of groundwater-sourced irrigation to farm profitability (Foster et al. 2019; Turner et al. 2019). Finally, groundwater extraction can have significant regional-scale impacts on climate and therefore is necessary for accurate climate modeling and forecasting (Keune et al. 2019). Overall, estimates of groundwater extraction are important for many applications and disciplines, and despite its importance there is little guidance on how to effectively estimate it.

The availability and quality of groundwater pumping data varies greatly between regions, from those where groundwater pumping is not monitored or regulated at all, to others that have mandated the use of flow meters and reporting withdrawals. The number of regions measuring and reporting groundwater pumping data are increasing as the importance of this data for effective water management strategies, such as California's Sustainable Groundwater Management Act, becomes more apparent (California 2014). Despite the increased availability of groundwater pumping data in some regions, indirect measures are needed to estimate groundwater pumping volumes in unmonitored basins and at spatial and temporal resolutions useful for hydrologic modeling and water management decisions. Indirect methods estimate pumping volumes from other available data through statistical relationships, water balance methods, or estimates of consumptive use (e.g., Ruud et al. 2004; Wada et al. 2014; Foster et al. 2019, 2020; Majumdar et al. 2020). In regions with pumping data, the temporal and/or spatial resolution of the data often requires further processing to inform water management decisions (e.g. downscale from yearly to seasonal pumping volumes, distribute regional-scale pumping volumes to field-scale), using methods similar to those employed in regions with no pumping data at all (e.g., Leenhardt et al. 2004; Castellazzi et al. 2016).

Despite the critical need for accurate groundwater pumping estimates, a review and comparison of methods, in addition to an assessment of their suitability to local conditions, has not been completed to our knowledge. Here, we conduct a qualitative review and quantitative comparison of four common methods of quantifying groundwater extraction for irrigation: (1) hydrologically-based Water Table Fluctuation method (WTFM); (2) demand-based crop modeling; (3) estimates based on satellite-derived evapotranspiration (ET) data; and (4) landscape hydrology modeling which integrates hydrologic- and demand-based approaches. To do so, we implement each method for the same irrigated domain in Kansas, USA, and evaluate the estimated pumping volumes across methods against a well-curated ground dataset based on extensive groundwater well monitoring in this region. While the focus of this work is on quantifying groundwater extraction for irrigation, which is the primary global use of groundwater, we acknowledge that many regions may also extract groundwater for other purposes, such as domestic, municipal, and industrial water supply. Some methods used in this work would may require modification in order to estimate groundwater extraction by these sectors.

Methods of Estimating Groundwater Extraction Volumes

Extracting groundwater for irrigation predominantly impacts physical and ecological components of the hydrologic cycle by altering the water budget and optimizing the crops' growth. Here, this distinction is used to categorize methods of estimating groundwater extraction between hydrologically-based approaches, demand-based approaches, and integrated approaches that utilize both. Hydrologically-based approaches use the response of the hydrologic system, such as variability in groundwater levels, evapotranspiration (ET), or other water balance components to estimate groundwater extraction volumes. Hydrologically-based approaches include hydrologic numerical models and water balance approaches that estimate groundwater extraction as the residual of the water balance (e.g., Döll et al. 2014; Peña-Arancibia et al. 2016; Xiao et al. 2017; Tolley et al. 2019). Demand-based approaches estimate crop water requirement to optimize or maximize crop growth based on crop models or estimates of crop coefficients, or use estimates of electrical consumption to estimate pumping volume (e.g., Frenzel 1985; Basso and Ritchie 2015; Basso et al. 2016). Integrated approaches estimate groundwater extraction using information about the hydrologic conditions and crop requirements. Examples of integrated approaches include integrated hydrologic models that simulate both hydrologic fluxes and storage and crop growth (e.g., Samaniego et al. 2010; Koch et al. 2020; Niswonger 2020).

The distinction between approaches is not discrete, but rather they occur along a spectrum of approaches. Purely hydrologically-based approaches, such as the water balance method based on groundwater level fluctuations, represent one end of the spectrum, whereas demand-based approaches, such as crop models that simulate irrigation, represent the other end (Figure 1). While these approaches have relatively small data requirements compared to more complex approaches, their ability to represent or predict other scenarios, such as changes in land use or climate, is limited. The middle of this spectrum captures the integration of the complex models from both the hydrologic- and demand-based approaches, which have the highest data requirements, but also the most flexibility for scenario analysis.

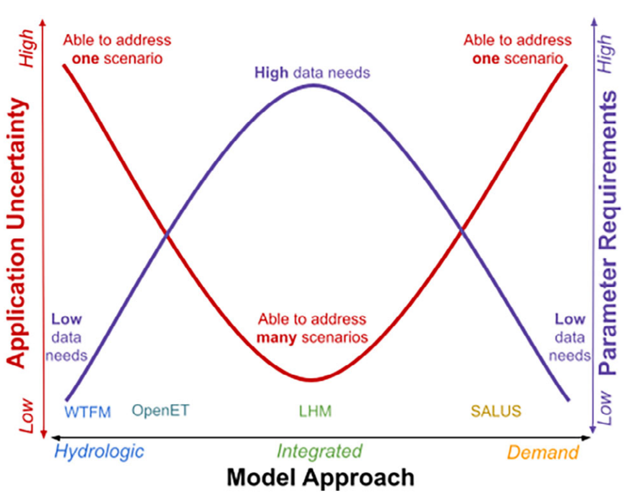

Figure 1. The spectrum of modeling approaches to quantify groundwater extraction for irrigation. Each end-member represents simple hydrologic- or demand-based approaches, with increased model complexity towards the center. Specific models indicated in this figure (WTFM, OpenET, LHM, and SALUS) represent the four approaches used in the model intercomparison. Their location along the *x*-axis is a general approximation of their parameter requirements and application uncertainty and would vary based on the specific manner in which they are being used.

Hydrologically-Based Approaches

A water balance is the foundation of hydrologically-based approaches. The quantity and timing of groundwater extraction is estimated as the residual of other inflows, outflows, and changes in storage to the system. The accuracy of the groundwater extraction estimates relies on the accuracy of individual components of the water balance estimates, and the uncertainty from these measurements or the methods. Additional problems arise when all the components of the water balance are not known, resulting in the unsolvable issue of more unknowns than equations. Fortunately, advances in both in situ and remote sensing approaches across a wide range of spatio-temporal scales have improved the availability and accuracy of individual water balance estimates. Examples include various gridded or remotely sensed products for precipitation (e.g., TRMM, Meneghini et al. 2000; GPM, Pradhan et al. 2022), evapotranspiration (e.g., OpenET, Melton et al. 2021) and soil moisture (e.g., ERS-1 and ERS-2, Wagner et al. 2003).

Hydrologically-based approaches can vary in their spatial and temporal resolution, in addition to their complexity. Simpler approaches estimate groundwater extraction by closing the water budget. These approaches, such as the WTFM, use observed changes in the hydrologic system, often through lumping processes and characteristics across large regions and timescales (e.g., basin-wide and yearly), to provide an estimate of total, cumulative groundwater extraction (Ruud et al. 2004; Xiao et al. 2017). Similarly, remotely sensed ET-based methods can infer irrigation depths through multiple approaches, including comparing total ET to precipitation within irrigated fields and comparing ET in irrigated and non-irrigated fields of the same crop type (Foster et al. 2020). Neither of these approaches is predictive; they can only be used to estimate past extraction volumes for periods in which all required datasets are available. These approaches have been used to estimate water use in data scarce basins (e.g., Ahmad et al. 2005), as the primary advantage of these simpler approaches is lower data requirements in comparison to more complex, predictive methods, such as physically-based hydrologic models.

Hydrologic models are capable of varying levels of complexity (ranging from lumped to physically based, fully distributed) and are applied extensively from local to global scales to estimate groundwater withdrawals as a function of hydroclimatic and geologic conditions (e.g., Döll et al. 2014; Peña-Arancibia et al. 2016). Groundwater extraction estimates can also be obtained through calibration of hydrologic models (e.g., Tolley et al. 2019). While the ability to represent increased levels of complexity is generally thought to increase the representativeness of the results, the increased parameterization can also increase the prediction uncertainty (Saltelli 2019). To reduce prediction uncertainty and computational cost, hydrologic models have been merged with remotely sensed data products to improve water budget estimation. For example, several remotely sensed-derived products map irrigated area (e.g., Deines et al. 2019; Xie and Lark 2021), which is an important product for parameterizing models. In recent years, satellite soil moisture products in combination with the water balance equation were used to estimate the total amount of applied irrigation. For example, Brocca et al. (2018) developed a new approach by using coarse resolution remotely sensed soil moisture products to estimate irrigation at nine pilot sites. Results showed accuracy of irrigation estimates depends on the uncertainty of soil moisture measurements, resolution of the satellite product and hydroclimatic conditions.

Demand-Based Approaches

Demand-based approaches focus on the growth patterns of the crops, providing estimates of the volume and timing of irrigation water needed to supplement precipitation to optimize crop growth, and hence crop yield. While recent research has demonstrated that estimating irrigation demand based on plant biophysical needs does not always reflect measured groundwater withdrawals (Foster et al. 2019), demand-based approaches remain a common method of determining irrigation water needs (e.g., García-Vila et al. 2009) and thus can be used to estimate groundwater withdrawals (e.g., Deines et al. 2021). Fundamental assumptions of these methods are that the irrigators apply water to their crops at the volume and timing that optimizes their growth (or through an alternate prescribed irrigation scheduling algorithm such as deficit irrigation), and that enough water is available to meet model-estimated irrigation demand. As with the hydrologically-based approaches, data availability, model parameterization, and calibration methods and targets can lead to significant uncertainty. Similar to the hydrologically-based approaches, crop-models vary in complexity ranging from deterministic approaches with significant data requirements to empirical and analytical approaches requiring relatively limited data (Mulla et al. 2020). With increased availability of remote sensing observations, the ability to use the more data-intensive approaches has also increased and has allowed application of crop models to larger areas (Kasampalis et al. 2018). Some of the more popular crop models, such as DSSAT (Jones et al. 2003) and CERES-based SALUS (Basso et al. 2006; Basso and Ritchie 2012, 2015) integrate, and often rely upon, remotely sensed data for their simulations. In addition, recent application of machine learning approaches in crop modeling provides another method of estimating groundwater withdrawals that can be adapted depending on data availability and scale of application (van Klompenburg et al. 2020).

Another demand-based approach that we do not evaluate in this study is based on the amount of energy used for groundwater withdrawals. The energy-based groundwater abstraction method estimates pumping rates as a function of pumping efficiency, total water lift from the pumping level to the land surface, and pressure head at the land surface (Frenzel 1985). Accuracy of the method depends on the pumping efficiency and accurate estimates of water lift. In some cases, this formula is simplified and the measured electricity is converted to the volume of pumped water using a fixed conversion factor. However, this approach is not very accurate as the conversion factor changes as a function of seasonal changes in groundwater levels and other hydrogeologic conditions (Wang et al. 2020) and estimates of energy used for groundwater pumping alone can be difficult to obtain.

Integrated Approaches

Integrated approaches include components from both the hydrologic- and demand-based approaches, coupling them to form a model that accounts for the hydrologic conditions that control water availability, and the crop growth dynamics that drive the demand. These approaches range in complexity and applicability similar to the hydrologic- and demand-based approaches and have the parameterization requirements of both approaches. The error and uncertainty associated with these additional parameterization requirements are often considered to be offset by the increased representativeness and applicability to a wide variety of hydrologic and vegetation-based scenarios.

Integrated approaches have increased in use over the past several years due to increases in data availability and computational ability. For example, Koch et al. (2020) setup the multiscale Hydrologic Model (mHM, Samaniego et al. 2010) over the Haihe River Basin in China and calibrated it to discharge and ET for rainfed fields. They estimated monthly net irrigation rates (evaporative loss from irrigation water) by computing the differences between the estimated ET from the PT-JPL model using remotely sensed land surface temperature and vegetation data and the mHM forced without irrigation. While irrigation data is not available for model verification, uncertainty in irrigation estimates are mostly attributed to the precipitation and ET data.

Recently, machine learning methods (e.g., random forests) have been used in conjunction with remotely sensed products such as precipitation, evapotranspiration, and land cover to predict groundwater withdrawals in the High Plains aquifer (HPA) in the USA (Majumdar et al. 2020). A new Agricultural (AG) water use package for GSFLOW, a coupled surface water model-groundwater model created by coupling MODFLOW with the precipitation-runoff modeling system (PRMS), was recently developed to simultaneously estimate groundwater pumping based on crop demand and soil water balance when surface water for irrigation is not available (Niswonger 2020). The benefit of this new package compared to the MODFLOW Farm process package (Hanson et al. 2014) is in higher temporal resolution and explicit consideration of soil water balance.

Some hydrologic models internally calculate irrigation demand based on soil moisture deficit or plant water stress, and a set of user defined rules for water supply and demand priorities. The integrated groundwater-land surface model, ParFlow.CLM, that simulates terrestrial hydrologic processes from the top of the canopy to groundwater, is coupled to a water allocation module to simulate water management operations based on supply and demand preferences and sources (Condon and Maxwell 2013). Similarly, global-scale applications of the PCR-GLOBWB hydrological model integrate water balance and demand to estimate water use (de Graaf et al. 2014, 2019). These management models use an optimization approach to determine the pumping and surface water diversion rates to satisfy agricultural water demand. The biggest challenge with these models is the increased computational demand for solving the partial differential equations representing surface water and subsurface flow systems and ensuring that enough observations exist for adequate parameterization.

Classifying by Temporal and Spatial Scale

Irrigation estimation approaches can also be classified based on the spatio-temporal scale of their application and resolutions. While some methods such as hydrologic models have greater flexibility for implementation at a range of scale and resolutions depending on the model type, groundwater levels and remote sensing approaches are limited by the support scale of measurements, number of observation wells, and spatio-temporal resolutions of sensors, respectively (Toth and Jóźków 2016). We consider the most common scales and resolutions applied using these approaches in the literature (Figure 2). Crop models are often implemented at a field scale where plant growth or ET demand are calculated at a daily time step and spatially distributed soil and land cover information are available to parameterize them (Tenreiro et al. 2020). These models typically do not incorporate surface or subsurface lateral connectivity among the modeling grid cells and cannot be easily implemented at continental scale. Most water balance methods, such as the WTFM, are based on local-scale groundwater level observations, and estimating groundwater abstraction at a larger, often watershed or aquifer, scale depends on the data spatial distribution and frequency of observations. Satellite based remotely sensed approaches can be applied at scales from an individual field to the region or continent, typically with tradeoffs between spatial resolution and scale as global products require coarser sensor resolution. Developing finer spatial resolution remotely sensed products are achieved through multi-sensor fusion and/or at the expense of reducing temporal resolution (Cammalleri et al. 2014; Melton et al. 2021). Hydrological models have greater flexibility in terms of application at multiple spatial and temporal scales but their application depends on the data availability to parameterize them and flexibility in representing irrigation types and sources (e.g., Condon and Maxwell 2013). The WTFM and hydrologic models depending on the model structure could provide estimates of total groundwater extraction. However, crop models and remote sensing approaches (e.g., Brocca et al. 2018) typically provide estimates of total consumptive water use and additional data or assumptions, for example related to irrigation efficiency, are needed to obtain total groundwater extraction volumes.

Method Comparison

To demonstrate how groundwater extraction estimates vary between some of the approaches described above, four methods are applied to one site in northwest Kansas and results are compared against each other and against reported water use. The four methods applied to this site are a demand-based approach (SALUS), two hydrologically-based approaches (WTFM and OpenET satellite-based estimates), and an integrated approach (LHM). The intention of this comparison is not to identify or demonstrate a “best” way to estimate groundwater extraction volumes, but rather to demonstrate and discuss the differences, advantages, and disadvantages of the selected methods using a well-constrained example.

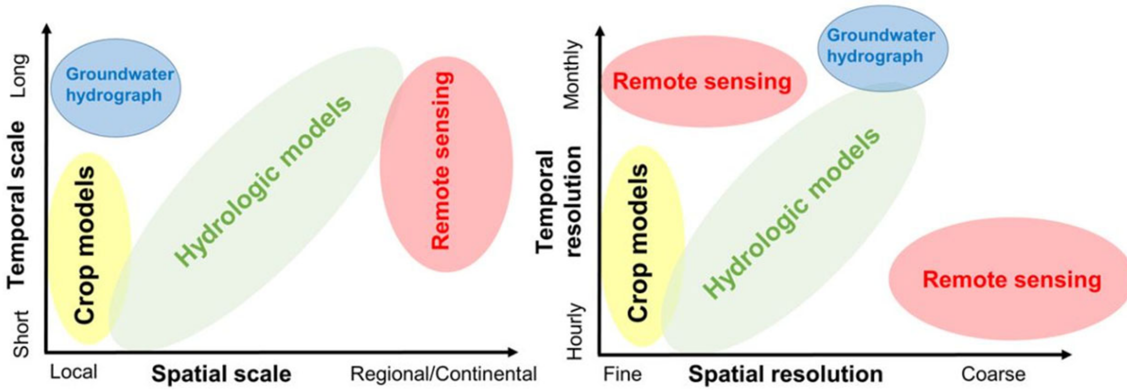

Figure 2. Commonly used irrigation estimation methods are classified based on spatio-temporal scale of their application, as well as resolutions. Spatial and temporal resolutions are limited by the inherent properties of the sensors and configurations for a particular application.

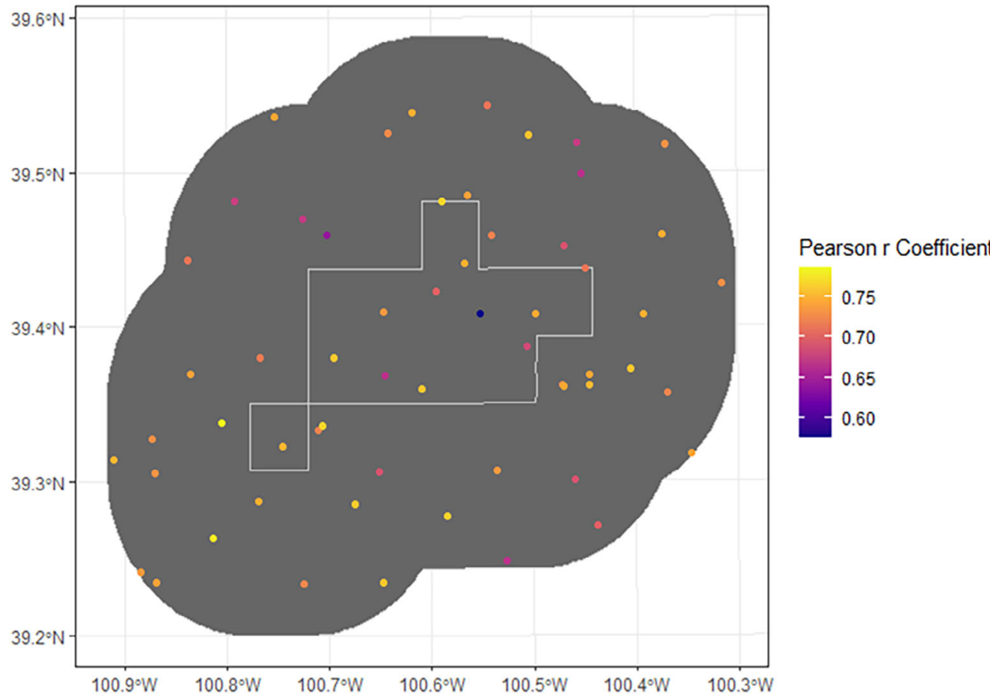

Figure 3. Water level measurement locations in the study region. Colors indicate Pearson r coefficients for the WTFM method compared to reported water use values when water level measurements from that location were removed from the analysis, so a lower value (darker color) corresponds to a greater influence of that specific well. The dark blue dot within the LEMA boundary indicates the well with the most significant influence over the performance of the method.

Site Description

The Sheridan 6 Local Enhanced Management Area (SD-6 LEMA) in northwest Kansas, USA, was selected for comparison of methods. This 255 km^2 area is located in Sheridan and Thomas counties (Figure 3) and was the first participant in Kansas' Local Enhanced Management Area (LEMA) program, a stakeholder-driven initiative designed to reduce groundwater extraction and extend the life of the High Plains Aquifer (Butler et al. 2018; Marston et al. 2022b). This area is underlain by the HPA, one of the world's largest and most productive aquifers which support agricultural production in the area, which is primarily irrigated with common crops including corn, soybeans, wheat, and sorghum. The aquifer in this region is part of the Ogallala formation, consisting of sand and gravel interbedded with silt and clay, and is generally considered to be unconfined with aquifer thickness generally ranging from 10 to 30 m (Whittemore et al. 2018; KGS 2023). This region has an arid climate, receiving approximately 55 cm of average annual precipitation per year (KGS 2023). The SD-6 LEMA received significant attention and study in recent years as a result of the LEMA program and has good data availability which allows us to test multiple approaches of estimating groundwater extraction volumes. For our purposes, annual well-specific groundwater extraction volumes are reported for all non-domestic wells in Kansas and are publicly available from the Kansas Department of Agriculture, Division of Water Resources through an online portal administered by the Kansas Geological Survey known as WIMAS. The LEMA program restricted water use by 20% relative to 2002–2012 levels over the 5-year period from 2013 to 2018 (Drysdale and Hendricks 2018). The program was highly successful, with realized water use reductions estimates at 26–31% (Drysdale and Hendricks 2018; Deines et al. 2019). Water savings were primarily attributed to improved irrigation efficiency (Deines et al. 2021). As a result of the success of the SD-6 LEMA's initial term, it was renewed for another 5 years (2019–2023) and similar local groundwater conservation programs have been developed elsewhere in Western Kansas. Further information about this site can be found in Kansas Department of Agriculture (2022).

Methods

Water Table Fluctuation Method

The WTFM is a simple water balance approach for estimating the volume of groundwater extracted from an aquifer based on the change in water levels over a designated period. WTFM has several assumptions, notably that the specific yield (for unconfined systems) and recharge of the aquifer are known, as are any other inputs or outputs to the system. Here, we simplify the SD-6 region to consider only water level fluctuations (Δh), recharge (R), and groundwater extraction (GWE; Equation 1). Recent research has indicated that the local water balance can be strongly influenced by lateral flow through the HPA, in addition to the possibility of other recharge sources, such as water movement from an aquifer below the HPA or irrigation return flows (Glose et al. 2022). These additional sources that are unaccounted for in WTFM will increase the uncertainty and error of model results in settings where they are important.

$$GWE = Sy \times A \times \Delta h - R. \quad (1)$$

Over 1500 wells in the HPA of Kansas are measured for water level yearly in late winter/early spring. These water levels are measured manually using the steel tape method, as many wells are irrigation wells that contain submerged pumps. Repeat measurements are taken in any wells with trends in water level inconsistent with other wells in the region, or with significantly different water levels from previous years (KGS 2022). Of these wells, 57 were within our study region (Figure 3), and water levels were kriged to create a continuous map of water level change. Both specific yield and recharge estimates are provided by the USGS (McGuire et al. 2012; Houston et al. 2013).

To investigate the sensitivity of the WTFM results to the quantity of water level measurements, two further analyses were conducted. To identify the importance of any one sampling point, groundwater extraction was estimated when each sampling point was removed individually. We also evaluated how random subsets of the data would perform by randomly selecting measuring points ranging from 20 to 100% of the available data. However, one data point, identified as significantly important when each sampling point was removed, was kept in all subsets. If this was not done the performance of the approach was heavily reliant on the presence or absence of that one data point in the subset.

Crop Modeling via SALUS

System Approach to Land Use Sustainability (SALUS) is a demand-based approach; a process-based crop model that simulates the interactions between soil, weather, crop genetics, and management (Basso et al. 2006; Basso and Ritchie 2012, 2015). It simulates plant growth and development, and water and nutrient fluxes in response to management at a daily time step. SALUS was developed from the CERES crop model (Ritchie and Otter 1985; Basso et al. 2016), and was previously applied to the SD-6 region to assess the sustainability of the LEMA (Deines et al. 2021). The crop water budget in SALUS includes plant transpiration, soil evaporation, irrigation water applied, precipitation and a soil water balance to simulate the top 2 m of soil in the SD-6 model (Deines et al. 2021). For more information about SALUS please see Basso and Ritchie (2012, 2015), and for the SD-6 application, please see Deines et al. (2021).

In this work, the results from the SD-6 application in Deines et al. (2021) are used without modification to compare against reported and other modeled values. Notably, unlike the other approaches used in this study, SALUS was calibrated to match observed pumping volumes by Deines et al. (2021). This is different than the Deines et al. (2021) work aimed at assessing the sustainability of the LEMA groundwater management plan in the region.

Landscape Hydrology Modeling via LHM

The Landscape Hydrology Model (LHM) is a process-based, spatially-explicit integrated ground- and surface-water model (Hyndman et al. 2007; Kendall 2009; Wiley et al. 2010). It is driven by input climate data at sub-daily intervals (here, hourly), including air temperature, wind speed, solar radiation, relative humidity, and precipitation. The landscape, including vegetation, land cover, and irrigation technology are described via remotely-sensed or other spatial data products.

Here, we simulated the SD-6 region as a "slice," or smaller model subset, from a larger model that encompasses a groundwater management district in Kansas (GMD4). The model is run hourly from 2000 to 2019 with square cells at 250-m resolution. Weather data are provided by the NLDAS-2a forcing dataset (Xia et al. 2012), a model-data fusion product incorporating observed precipitation and temperature data along with solar radiation, wind speed, and cloud cover. Satellite Leaf Area Index (LAI) data come from the MODIS sensors, specifically the MCD15A3H product, a 4-day repeat 500 m resolution fusion of both Terra (MOD) and Aqua (MYD) products. Land cover data are reclassified from the National Land Cover Dataset (NLCD), including the years 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019. Soils data are derived from the gSSURGO (Soil Survey Staff [Dataset] 2020) dataset, with hydraulic properties computed for each soil horizon, component, and unit using the ROSETTA 2 database (Schaap and Leij 2000).

For this study we apply a version of LHM with a novel irrigation module, developed since Wiley et al. (2010), documented in part in Haacker (2018), Smidt (2017), and Liu (2018). Irrigation is triggered in the module when soil moisture reaches a parameter-specified fraction of plant available water (the differences between field capacity and permanent wilting point). For more detail, please see Data S1. We have also developed this module further to simulate each of the following irrigation types: (1) high pressure center-pivot irrigation, (2) low-pressure center pivot (variable height), (3) low-pressure precision application (LEPA), (4) furrow, (5) flood, and (6) subsurface drip irrigation. These technologies are differentiated by the height of application, the width of the spray pattern (if applicable), and whether the application happens above/below the canopy, or beneath the soil surface. Furthermore, the user can specify pump flow rates, as older high-pressure irrigation systems typically require larger flow rates than new systems. Here, system flow rate was set uniformly at 135 m^3/h (~600 Gpm) for all fields.

LHM incorporates another mechanism that differentiates technologies, an empirically-driven quantification of wind drift evaporation. Wind drift evaporation is the loss of water to evaporation either before the droplets land on the leaves, or outside of the line of irrigation (i.e., not immediately below the pivot arm). Here, we compute potential wind-drift evaporation from six different empirically-derived models and take the arithmetic mean on an hourly basis. For more details on the wind-drift evaporation estimates please see Data S1.

For this study, we use two different irrigation technologies: traditional center-pivot (CP) and low-pressure low-elevation spray application (LESA). Spray heights were 4.5 and 0.5 m, and spray widths were 20 and 2 m for CP and LESA, respectively. As a result of the different spray widths, application rates differ significantly. Details on the application rate calculations and differentiation between irrigation technologies are provided in Data S1.

All of the physical aspects of irrigation described above only apply once a farmer has decided when to turn on their system, and how much water to apply. These behavioral components of irrigation water use are poorly documented in the literature, thus here we must infer them by tuning model parameters to better match total irrigated water use. This approach was taken by Deines et al. (2021) for the SD-6 region, and arrived at different parameters prior to the onset of the LEMA (i.e., 2012 and earlier). Before LEMA, Deines et al. (2021) inferred that farmers applied 3.175 cm per event, and after LEMA just 2.5 cm. For LHM, we determined that a different irrigation threshold was necessary, due to the different hydrologic descriptions within SALUS and LHM. Here, before LEMA irrigation (business-as-usual; BAU) occurred when soil moisture reached 70% of plant available water, and after LEMA just 33%. These parameters were not calibrated extensively and could be better adjusted to fit observed data, as the results show. Most importantly, the observed pumping amounts cannot be matched well by a model that does not change irrigation parameters in 2013, providing strong evidence that farmer irrigation behavior changed at that time.

Remote Sensing of Irrigation via OpenET

We estimated field-resolution irrigation depths using actual evapotranspiration (ET) estimates from the OpenET project (Melton et al. 2021), which we refer to as the "OpenET" estimates of groundwater extraction, though many other data products were also used (Figure 4). The OpenET data provided monthly, 30-m spatial resolution estimates of ET from six different satellite-based approaches: DisALEXI (Anderson et al. 2007, 2018), eeMETRIC (Allen et al. 2005, 2007, 2011), geeSEBAL (Bastiaanssen et al. 1998; Laipelt et al. 2021), PT-JPL (Fisher et al. 2008), SIMS (Melton et al. 2012; Pereira et al. 2020), and SSEBop (Senay et al. 2013; Senay 2018), as well as an ensemble mean, for the 2016–2021 period. To estimate field-resolution irrigation, we obtained the average monthly ET depth for each field using a Kansas-specific field boundary dataset (Gao et al. 2017; MardanDoost et al. 2019) and combined it with field irrigation status (Deines et al. 2019; available 1984–2020), crop type from the USDA Cropland Data Layer (USDA National Agricultural Statistics Service 2021; available 2006–2021), and precipitation from gridMET (Abatzoglou 2013; available 1979–2021).

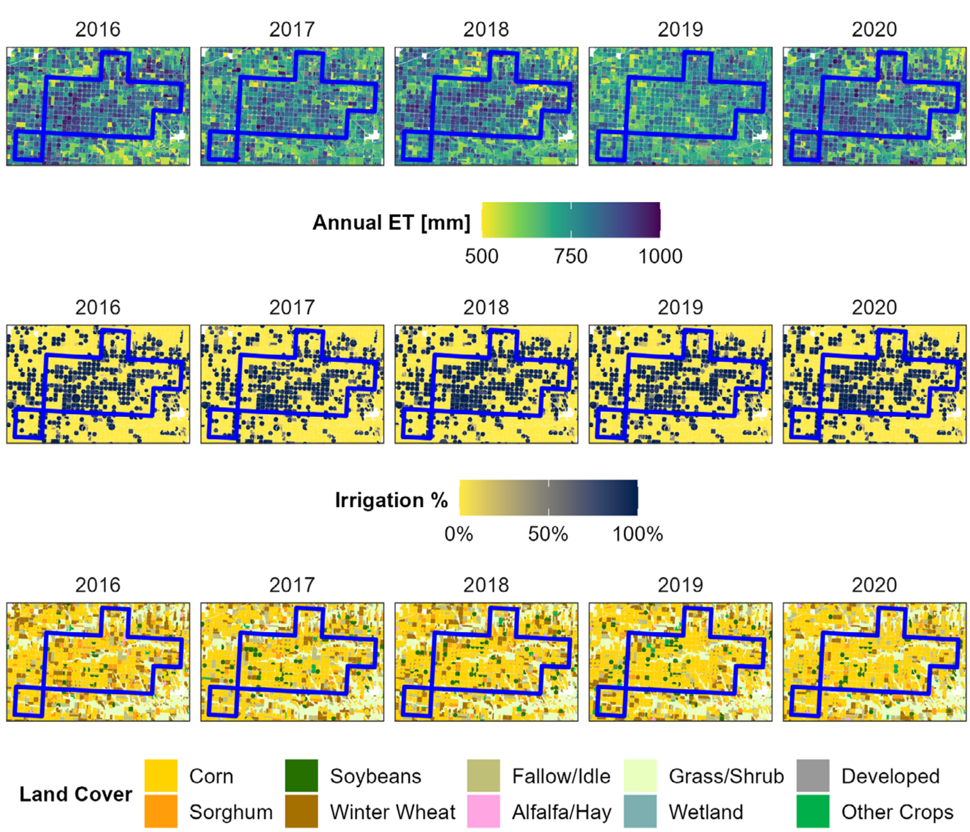

Figure 4. Data sources used to estimate annual irrigation from OpenET data include annual ET (ensemble mean), irrigation status by land parcel (modified from Deines et al. 2019), and crop type (from USDA Cropland Data Layer).

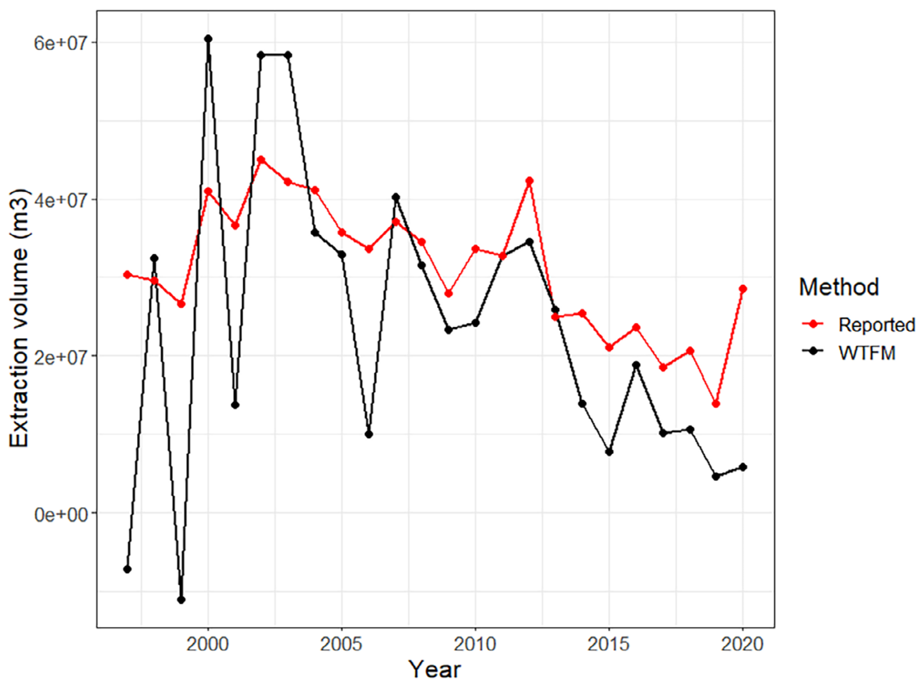

Figure 5. Reported groundwater extraction volumes vs. estimated groundwater extraction volumes using the WTFM method over the S6 region in Kansas for each year between 1998 and 2020. Interpolated lines between estimated/reported annual values demonstrate temporal trends.

Combined, this gives a common 5-year period (2016–2020) where all necessary data are available.

To estimate irrigation from these ET data, we calculated the difference between annual ET and annual precipitation (ET-P) depth for each irrigated field within the SD-6 LEMA. Irrigation for any fields that had a negative ET-P was set to 0, therefore GWE = max(0, ET-P). This approach provides a field-resolution estimates of consumptive irrigation water use, meaning that it is unable to estimate total applied irrigation because it does not account for other potential losses of irrigation water to the environment (i.e., deep percolation as irrigation return flows; Deines et al. 2021; Glose et al. 2022). We compared OpenET estimates to WIMAS estimates at the LEMA-scale. For comparison with WIMAS, we converted field-resolution irrigation depth to irrigation volume by multiplying by the field area and summing the total irrigation volume for all irrigated fields in the LEMA.

Method Comparison Results and Discussion

Water Table Fluctuation Method

Results indicate that after 2000 the WTFM was good at estimating groundwater extraction from the SD-6 region, though with a persistent underestimate over much of the study period ($r = 0.80$, $r = 0.72$ for results starting in 1997; Figure 5). This is consistent with other research that found the reliability of reported water use increased after 2000 (Butler et al. 2018). Between 1997 and 2000 the results fluctuated significantly, with negative extraction volumes for 1997 and 1999. Taken at face value, this would insinuate that water was injected into the aquifer rather than removed (e.g., greater inflows to the aquifer compared to extractions) which is unrealistic. After 2000 the estimates of groundwater extraction using the WTFM are more reasonable, and, for the most part, follow the trends and relative magnitudes of the reported values. This is likely due to the large number of high-quality annual water level data available across Kansas, including in the SD-6 region (Bohling et al. 2021). Water balance-based methods are sensitive to accurate specific yield estimates, which relate changes in water level to changes in water storage (Butler et al. 2018), and therefore will likely be most effective in areas with well-characterized hydrostratigraphy.

Water level measurements from each well location were removed from the analysis. Resulting Pearson r coefficients indicate that most measurement locations only contributed marginally to the fit of the WTFM to reported values (Figure 3). One well, located within the LEMA region, did have a significant impact on the WTFM results, reducing the fit of the entire study period from $r = 0.72$ to below 0.60 when removed. All correlation coefficients are statistically significant at $p = 0.05$. This means that, had data from this one measurement point not been available, that our results would be much less representative. Unfortunately, we were unable to identify any unique characteristics to distinguishes this well from any of the others within the LEMA region. There are several other wells within the same vicinity that are screened in the same interval of the same aquifer, yet their impact on the groundwater withdrawal estimates is lower than the most important well and similar to each other. Work continues to try to elucidate the reasons behind the importance of this measurement location. While it may be possible to relate the variability in water levels in this well to the groundwater volumes extracted, inferring the importance of this well to the estimates without the actual reported values would not be possible. The only generalized recommendation is that having more wells increases the chances of having a measurement point that significantly increases the representativeness of the estimates, which is further demonstrated when the WTFM is applied to subsets of data. A few wells, mostly located outside of the LEMA region, increased the fit slightly to a maximum of 0.78.

To understand the influence of the number of water level measurements on the WTFM results, random subsets of the measurement locations were selected, representing 20–90% of the available locations, in intervals of 10%. To remove the influence of the well identified as highly influential in the previous analysis, water level measurements from this well were always included in the subsets. As expected, results indicate that as water levels from more locations are included, the Pearson r coefficient increases linearly, from <0.10 when only 20% of data are used to 0.72 when all data are included (Figure S1).

Crop Modeling via SALUS

The SALUS model used here was calibrated to total pumping across the SD-6 region (Deines et al. 2021), and therefore it is not a surprise that it was able to match total volumes well (Figure 6). The purpose of the SD-6 SALUS model was to not only simulate historic irrigation water use, but also to evaluate the sustainability applications of the newly implemented water management program (Deines et al. 2021). Here, we include these results, unaltered from the Deines et al. (2021) to demonstrate how these demand-based models are used, how they compare to other methods, and to demonstrate the potential value of known extraction volumes.

An advantage of the SALUS method is in simulating the temporal and spatial distribution of irrigation (Figure 7). Due to the complexity of the water rights allocation and places of use, it is not possible to directly compare the field-based irrigation estimates between SALUS and WIMAS. Places of diversion, such as the groundwater supply wells, can be registered to provide water to more than one place of use, or agricultural field. In addition, each place of use can be registered to receive water from more than one point of diversion. There is no requirement by the water right holder to equally distribute the water among places of use, or to report the distribution of water to these places. As such, it is not possible to determine the exact distribution of irrigated water from wells to specific fields.

Landscape Hydrology Modeling via LHM

LHM tends to over-predict irrigation volumes (Figure 8), though the broad patterns are largely captured. Further calibration of parameters including wait time between events, soil moisture thresholds, and event volumes could allow for more accurate simulation. A key outcome of these simulations is that LHM cannot reasonably simulate irrigation both before the SD-6 LEMA went into effect (2013) and after without altered irrigation behavioral parameters. This model experiment supports other lines of evidence (Deines et al. 2021) that

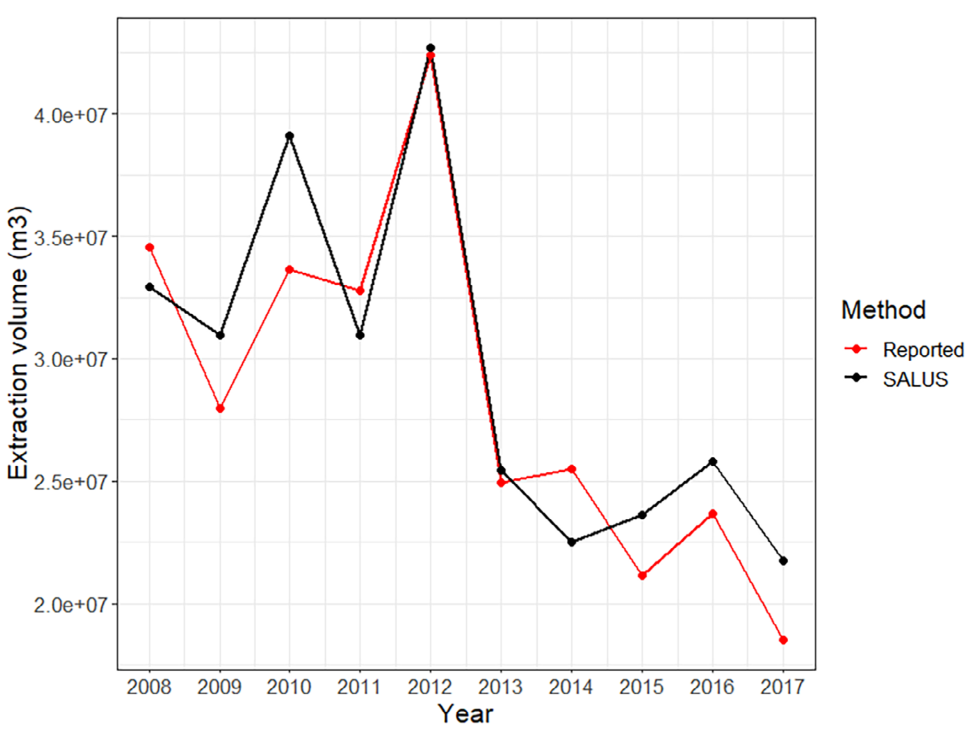

Figure 6. Comparison of SALUS estimated pumping volumes for the S6 region compared to the measured well data for each year between 2008 and 2017. Interpolated lines between estimated/reported annual values demonstrate temporal trends.

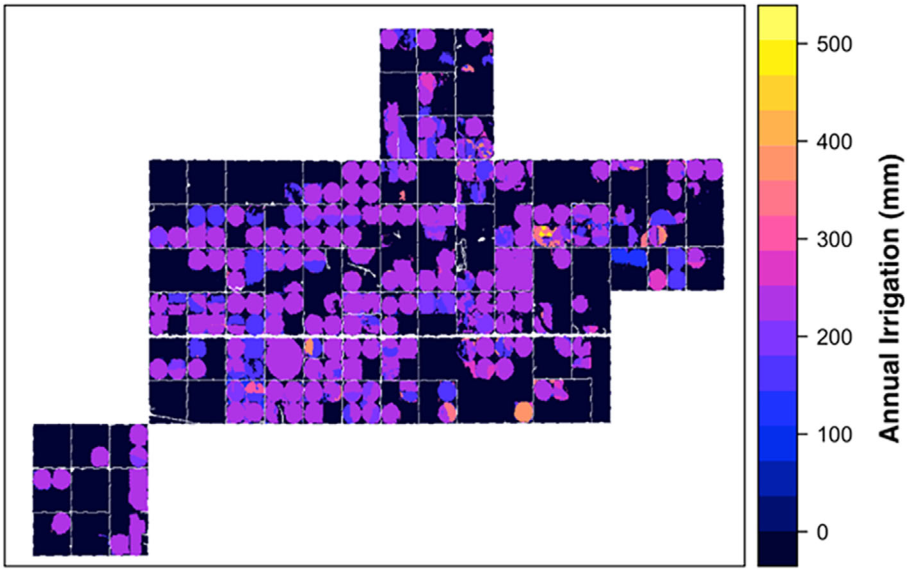

Figure 7. Spatial distribution of simulated irrigation (in mm) for the S6 region via the SALUS crop model. Note, individual pixels and fields are simulated using identical behavioral parameters, calibrated only to SD-6 totals. Thus, individual pixels are not necessarily representative of actual water use.

farmers responded to the LEMA not by altering irrigated area, but primarily by changing their water application amounts and timing (Drysdale and Hendricks 2018; Deines et al. 2019).

One notable disagreement is the decline in simulated irrigation water use by LHM during the 2012 drought. LHM predicts that water use decreased, while the observations indicate that use increased, as would be expected during deep drought. This is likely due to two factors: (1) effective irrigated area declined as farmers had to reduce irrigation, and (2) farmer behaviors changed to provide for higher supplemental water needs during the drought. In this particular simulation, the amount per application was fixed and could not respond as farmers might naturally during a drought.

Across the 20-year simulation period (2000–2019), LHM predicts roughly 350 mm of annual irrigation in most fields, with somewhat less in fields irrigated only during more recent years (Figure 9). This amount reflects the higher per-acre irrigation totals used during earlier years with CP technology dominated the region. Lower amounts are more common (typically around 250 mm, not shown separately) with newer LESA technology and following the SD-6 LEMA implementation.

Remote Sensing of Evapotranspiration via OpenET

Overall, the OpenET-based estimates of irrigation agreed with the WIMAS reported groundwater extraction volumes in magnitude. However, we found that there was more interannual variability in the OpenET-based estimates of irrigation volumes compared to the reported volumes from WIMAS (Figure 10). The different algorithms varied widely, with the lowest irrigation estimates typically provided by DisALEXI, the highest from SSE-Bop, and the Ensemble mean most closely matching the reported water use data (Figure 10a). The algorithms best agreed with the WIMAS data in 2018, a year with near-average precipitation, and had the worst agreement with a persistent overestimate across all algorithms in 2020, which was the driest year of the comparison. Since the LEMA allocated a specific amount of water to each field, we also compared WIMAS to allocation-shifted OpenET irrigation estimates, in which we shifted OpenET estimates of irrigation so that the mean total irrigation depth for fields irrigated in all 5 years was equal to 1397 mm (55″), which is the 5-year water allocation prescribed by the LEMA. This substantially reduced the variability among algorithms and brought the low- and high-estimating algorithms closer to the reported groundwater extraction (Figure 10c), though there was still more interannual variability in OpenET-based estimates than WIMAS (Figure 10c and 10d). The overestimation of irrigation during a dry year (2020) following a particularly wet year (2019) is likely caused by high antecedent soil moisture in 2020 that was depleted throughout the growing season, representing an additional source of water beyond precipitation and irrigation that is not accounted for when assessing irrigation at the annual resolution, and could be improved through more complex multi-year water accounting approaches. Additional potential sources of the difference between the two approaches include fields incorrectly classified as irrigated or non-irrigated, inaccuracies in the precipitation dataset used for irrigation estimation, and errors within the algorithms themselves.

Method Intercomparison

The four methods applied in this work have varying spatial and temporal resolution and extent. To compare between the methods all results were summarized annually

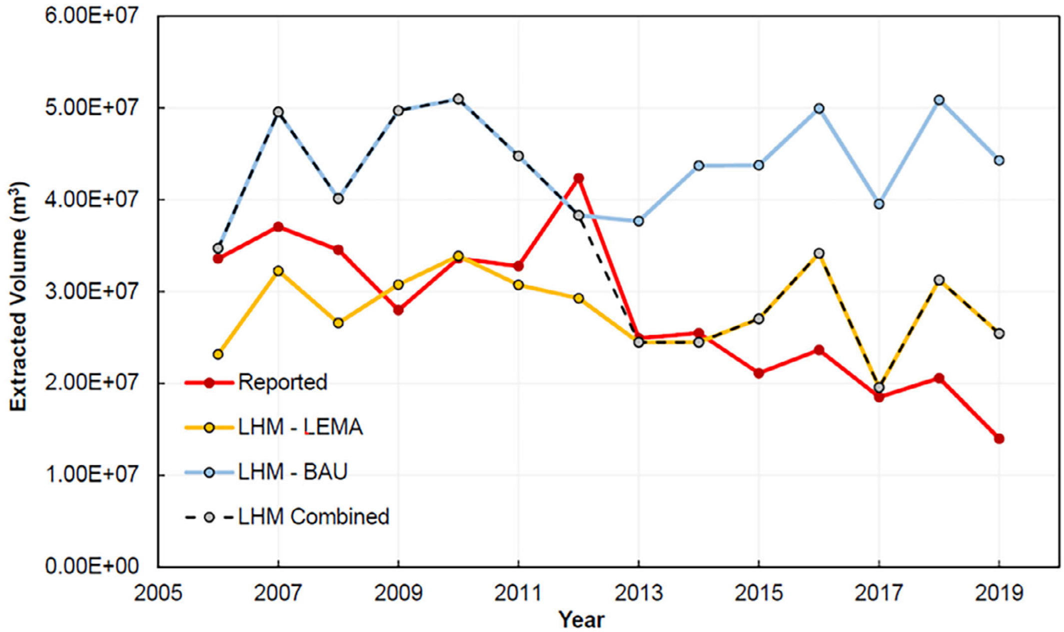

Figure 8. LHM results for business as usual scenario (LHM-BAU), LEMA management enforced (LHM-LEMA), and the combination, enforcing LEMA when regulation passed for study site (LHM-Combined). Interpolated lines between estimated/reported annual values demonstrate temporal trends.

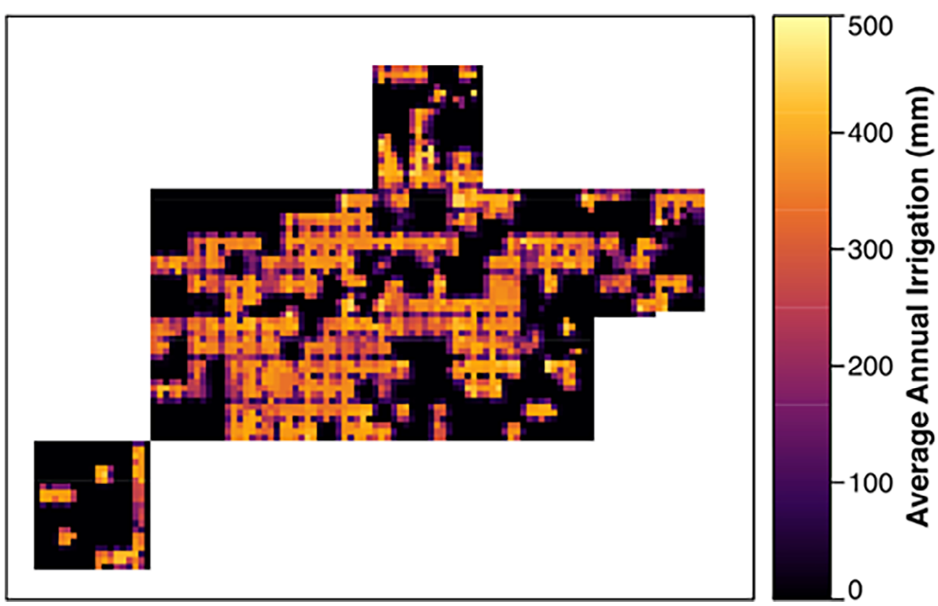

Figure 9. Map of spatially-averaged irrigation water use over the 2000–2019 period simulated by LHM. Note, individual pixels and fields are simulated using identical behavioral parameters, calibrated only to SD-6 totals. Thus, individual pixels are not necessarily representative of actual water use.

from 2006 to 2019, and at the extent of the LEMA (Figure 11). All four results provide similar estimates, with the LHM approach most often overestimating, and WTFM most often underestimating extraction volumes. These patterns were expected as LHM overestimated irrigated area, resulting in an overestimation of extracted groundwater, whereas WTFM assumes no lateral groundwater contributions which may underestimate the volume of water extracted if the net flux of groundwater is into the region, and constant groundwater recharge volumes. These assumptions may lead to consistent underestimation of groundwater extraction.

Pearson *r* correlation coefficients for WTFM, SALUS, LHM, and OpenET for this time period were 0.76, 0.72, 0.49, and 0.92 respectively. The OpenET method only produces results for four of our study years due to current data availability, but the variability in results is consistent with reported values although

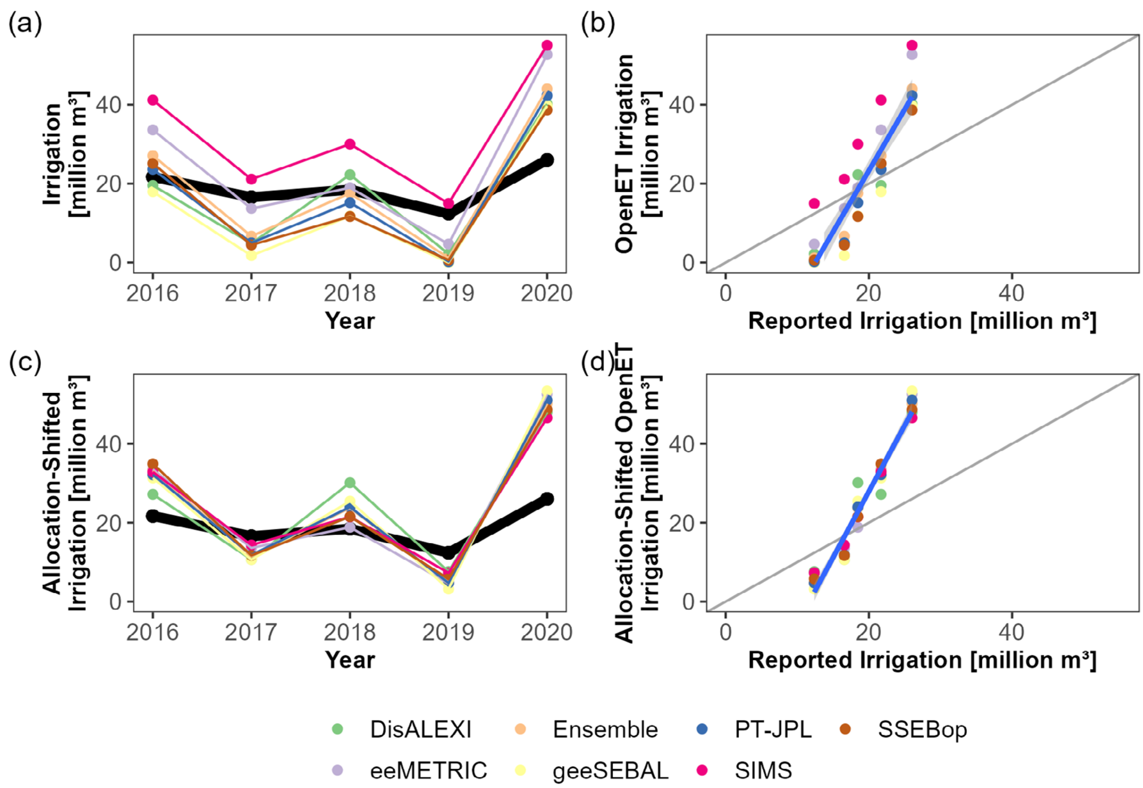

Figure 10. Comparison of OpenET irrigation estimates and reported estimates from WIMAS for the entire SD-6 LEMA area. In (c) and (d), field-resolution OpenET estimates were shifted so that the mean field-resolution irrigation depth for fields irrigated in all 5 years was equal to 1397 mm (55″), which is the 5-year water allocation prescribed by the LEMA. In (a) and (c), the black line shows WIMAS estimates. In (b) and (d), the gray line shows a 1:1 relationship and the blue line shows a linear best-fit. Interpolated lines between estimated/reported annual values demonstrate temporal trends.

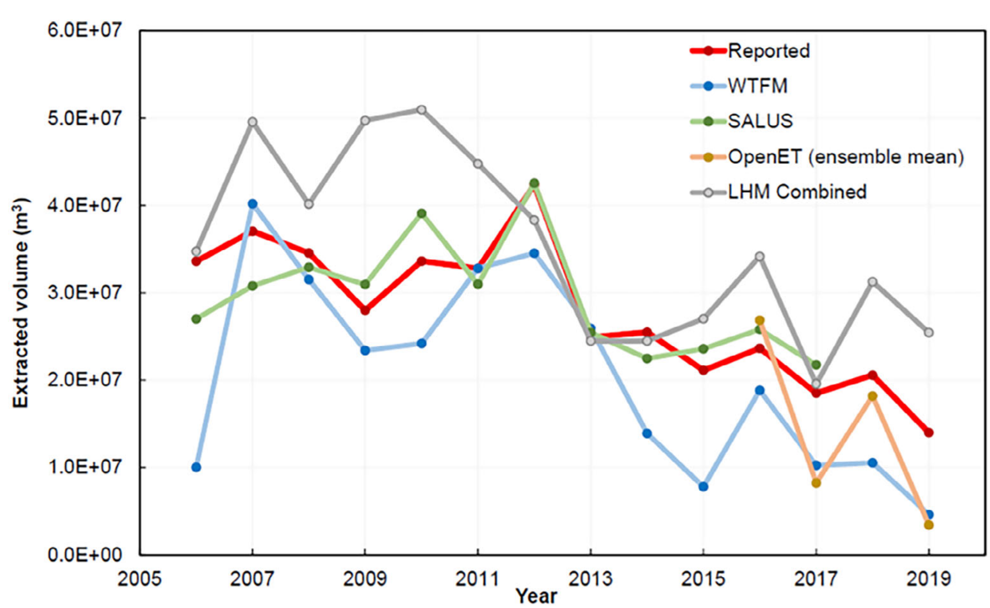

Figure 11. Comparison of annual groundwater extraction volumes for all four methods and the reported water use for the LEMA region. LHM, Landscape Hydrology Model; OpenET, remote sensing of evaporation via OpenET product; SALUS, SALUS crop model; WTFM, Water Table Fluctuation Method. Interpolated lines between estimated/reported annual values demonstrate temporal trends.

the magnitudes differ. SALUS predictions were the most accurate compared to the reported volumes, which is expected as SALUS was calibrated to match the SD-6 WIMAS water use data (Deines et al. 2021). An objective of the SALUS model was to predict water use at field-resolution as opposed to over the entire LEMA region. While previous research has compared different approaches of estimating crop water demand and irrigation scheduling (e.g., Gu et al. 2020; Wanniarachchi and Sarukkalige 2022), or remotely-sensed methods of agricultural water use (e.g., Massari et al. 2021), these methods compare within model types (e.g., crop demand; remotely-sensed). Our results provide a comparison between different model types, and the similar estimates between types demonstrate that, if adequately constrained, they all provide a method of reasonably estimating groundwater extraction.

Visually inspecting the magnitude of temporal variability in the estimated volumes, all approaches have higher year-to-year variability compared to the reported volumes. As SALUS was calibrated to groundwater extraction data, it is not surprising that it also most closely matched the temporal variability of the reported volumes. While WTFM and LHM had similar variability until 2015, LHM's variability significantly increased afterwards, becoming consistent with the high variability observed in the OpenET-based product. The inherent uncertainty and errors involved in each method could account for the differences in extracted volumes and variability. The SALUS model is informed by reported total water use in the area, and WTFM is informed by the response of the aquifer to groundwater pumping. This connects both models to the actual volume of water extracted and its variability, which represents the physical response of the aquifer to pumping and the irrigator's decision to pump the volume of water that caused the physical response. Conversely, both the LHM and OpenET-based methods are dependent on quantifying the estimated volumes required to meet crop demand or match ET estimates once precipitation is accounted for, and they are not connected to the irrigation volumes. As such, these methods would need to capture year-to-year variability in irrigator behavior to estimate irrigation volumes. For example, the LHM approach used pre-LEMA (BAU) and post-LEMA parameters to approximate those changes in irrigator behavior due to the LEMA, but other factors that may change an irrigators behavior from year-to-year were not considered. In addition, for the OpenET-based approach, changes in irrigator behavior in response to potential downward (deep percolation) or lateral (runoff) fluxes of irrigation water are not taken into consideration. This result highlights the importance of capturing both physical and behavioral components of irrigation decisions.

Conclusions

Estimates of groundwater extraction volumes are critical to a wide variety of applications, including those in hydrology, hydrogeology, and climate and economic studies. Due to this importance, measurements of fluxes and volumes of groundwater extraction are becoming more common, however, the spatial and temporal resolution of data required to support these applications are not readily available. Here, we categorized methods of estimating groundwater extraction along a spectrum from hydrologic-based to demand-based approaches. The data and computational needs of the approaches vary not only across the spectrum shown in Figure 1, but also among the methods at each point along the spectrum. In our application and comparison of four methods, it was clear that no one method is the universal "best" approach, but rather, the selection of the "best" approach is determined by the data available to constrain the model in addition to the spatial and temporal resolution of the study site. In our comparison, all four methods provided reasonable estimates of annual groundwater extraction volumes as all methods had reasonable data available to constrain them. However, each method had drawbacks in their application. Table 1 summarizes the general advantages and disadvantages of each method, in addition to suggestions of criteria to consider when selecting one of these methods.

The WTFM was the simplest method applied, and while it provided good estimates of annual water use in the study site (Pearson r coefficient of 0.72 for 1997 to 2020), it is reliant on high-quality water level data taken consistently across the study region as well as accurate information about both specific yield and recharge. The OpenET method relies on remotely-sensed data products to estimate irrigation as well as ancillary products including distributed meteorological data and irrigation status mapping. These data products are becoming more widely available and accessible, however, our results indicate that irrigation estimates from remotely-sensed data can vary depending on the ET algorithm used.

Both the SALUS and LHM approaches require more input data compared to WTFM and OpenET, however they provide representations of the physical processes that would contribute to groundwater extraction (e.g., crop-water demand, hydrologic conditions). This enables both methods to predict groundwater extraction into the future, under different conditions (e.g., climate, crop-type, etc.), and at varying spatial and temporal scales and resolutions. As with all methods investigated here, the reliability and accuracy of SALUS and LHM are dependent on the input data and the ability to represent the real-world conditions and processes.

Another key finding is that the behavior of the irrigator is an important component of estimating groundwater extraction, consistent with Deines et al. (2021). Methods that implicitly include a parameter to reflects these behavioral changes (calibration to total water use in SALUS, and dependence on groundwater levels which respond to the decision to pump that volume of water in WTFM) better matched the magnitude and variability of groundwater extraction than other methods. Simulation

Table 1
A Summary of General Advantages, Disadvantages, and Application Conditions for the Methods Compared in This Work.

Method	Advantages	Disadvantages	Application Conditions
WTFM	• Low data needs • Low computational needs • Simple implementation • Can be used in other sectors aside from irrigation	• Sensitive to specific yield and recharge estimates • Hard to discern when there is enough or appropriate data • Cannot predict future extraction estimates • Accuracy depends on the spatial and temporal resolution of groundwater levels • Able to resolve regional scales only	• Inputs and outputs to hydrogeologic system are well constrained • Availability of numerous high-quality groundwater level measurements • Availability of accurate estimates of specific yield • Goal is to estimate historic extraction at regional (rather than well) resolution
SALUS	• Can predict future irrigation extraction estimates • Allows for scenario testing • Provides additional information such as crop yield • Flexible resolution parameterization, including sub-field scales	• High data needs • Moderate computational needs and high learning curve • Not applicable for other sectors aside from irrigation	• Availability of accurate data for crop types, soil, irrigation strategy, and weather • Goal is to estimate extraction for irrigation or evaluate irrigation under different scenarios
LHM	• Can predict future extraction estimates • Allows for scenario testing • Can be used for other sectors aside from irrigation • Flexible resolution parameterization, including field scales	• High data needs • High computational needs and learning curve • Resolution limited by grid cell size • Needs extensive calibration and evaluation	• Availability of accurate for plant growth, soil, climate, irrigation strategy and hydrogeology • Goal is to estimate extraction or evaluate extraction under different scenarios
OpenET	• Low data needs • Low computational needs • Simple implementation • High spatial resolution (30 m)	• Sensitive to variability in actual ET estimates from various models and precipitation measurements • Cannot be used for other sectors aside from irrigation • Challenges in linking irrigation application location to location of extraction	• Availability of accurate estimates of AET • Goal is to estimate historic extraction for irrigation at sub-field or larger scales

results from LHM were significantly more accurate when response to the LEMA was considered, further demonstrating this point.

As the development and use of sensors to measure groundwater extraction improves and more policies requiring the collection of groundwater extraction volumes are created, the need for these approaches will decrease. Depending on how this data is collected, temporal and/or spatial downscaling may still be necessary, but ultimately, collecting direct measurements of groundwater extraction is ideal. It is our hope that given the importance of groundwater extraction data to hydrologic sciences that these direct measurements will become so prevalent that the results of this research will become obsolete, except to estimate historic groundwater extraction volumes.

Acknowledgments

The authors would like to thank Brownie Wilson, Dr. Jude Kastens, and Dr. Tim Foster for their assistance and discussions. The authors would also like to thank two anonymous reviewers and the editors for their suggestions that greatly improved this manuscript. This work was conducted as a part of the Streamflow Depletion Working Group supported by the John Wesley Powell Center for Analysis and Synthesis funded by the U.S. Geological Survey, a National Sciences and Engineering Research Council of Canada Discovery Grant awarded to Dr. Brookfield, and National Science Foundation grant no. RISE-2108916 and NASA grant no. 80NSSC22K1276 awarded to Dr. Zipper. Final results from this work are available at https://github.com/aebrookfield/IrrigationEstimates.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article. Supporting Information is generally *not* peer reviewed.

Figure S1. Pearson *r* coefficients for subsets of measurement locations for the WTFM.

Data S1. LHM Irrigation Module Details. This section includes information on Triggering Irrigation, Wind-Drift Evaporation Estimation, Application Rate, and Differentiating Irrigation Technologies.

References

Abatzoglou, J.T. 2013. Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology* 33, no. 1: 121–131. https://doi.org/10.1002/joc.3413

Ahmad, M.-D., W.G.M. Bastiaanssen, and R.A. Feddes. 2005. A new technique to estimate net groundwater use across large irrigated areas by combining remote sensing and water balance approaches, Rechna Doab, Pakistan. *Hydrogeology Journal* 13, no. 5: 653–664. https://doi.org/10.1007/s10040-004-0394-5

Allen, R.G., L.S. Pereira, T.A. Howell, and M.E. Jensen. 2011. Evapotranspiration information reporting: I. factors governing measurement accuracy. *Agricultural Water Management* 98, no. 6: 899–920. https://doi.org/10.1016/j.agwat.2010.12.015

Allen, R.G., M. Tasumi, and R. Trezza. 2007. Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC)—model. *Journal of Irrigation and Drainage Engineering* 133, no. 4: 380–394. https://doi.org/10.1061/(ASCE)0733-9437(2007)133:4(380)

Allen, R.G., M. Tasumi, A. Morse, and R. Trezza. 2005. A Landsat-based energy balance and evapotranspiration model in Western US water rights regulation and planning. *Irrigation and Drainage Systems* 19, no. 3: 251–268. https://doi.org/10.1007/s10795-005-5187-z

Anderson, M.C., F. Gao, K. Knipper, C. Hain, W. Dulaney, D. Baldocchi, E. Eichelmann, K. Hemes, Y. Yang, J. Medellin-Azuara, and W. Kustas. 2018. Field-scale assessment of land and water use change over the California Delta using remote sensing. *Remote Sensing* 10, no. 6: 889. https://doi.org/10.3390/rs10060889

Anderson, M.C., J.M. Norman, J.R. Mecikalski, J.A. Otkin, and W.P. Kustas. 2007. A climatological study of evapotranspiration and moisture stress across the continental United States based on thermal remote sensing: 1. model formulation. *Journal of Geophysical Research: Atmospheres* 112: 1–17. https://doi.org/10.1029/2006JD007506

Basso, B., and J.T. Ritchie. 2015. Simulating crop growth and biogeochemical fluxes in response to land management using the SALUS model. In *The Ecology of Agricultural Landscapes: Long-Term Research on the Path to Sustainability*, ed. Stephen K. Hamilton, Julie E. Doll, and G. Philip Robertson, 252–274. New York, NY: Oxford University Press.

Basso, B., and J.T. Ritchie. 2012. Assessing the impact of management strategies on water use efficiency using soil–plant–atmosphere models. *Vadose Zone Journal* 11: 1–14. https://doi.org/10.2136/vzj2011.0173

Basso, B., L. Liu, and J.T. Ritchie. 2016. A comprehensive review of the CERES-Wheat, -maize and -Rice Models' performances. In *Advances in Agronomy*, Vol. 136, ed. D.L. Sparks, 27–132. New York, NY: Academic Press. https://doi.org/10.1016/bs.agron.2015.11.004

Basso, B., J.T. Ritchie, P.R. Grace, and L. Sartori. 2006. Simulation of tillage systems impact on soil biophysical properties using the SALUS model. *Italian Journal of Agronomy* 1, no. 4: 677. https://doi.org/10.4081/ija.2006.677

Bastiaanssen, W.G.M., M. Menenti, R.A. Feddes, and A.A.M. Holtslag. 1998. A remote sensing surface energy balance algorithm for land (SEBAL). 1. formulation. *Journal of Hydrology* 212-213: 198–212. https://doi.org/10.1016/S0022-1694(98)00253-4

Bohling, G.C., J.J. Butler, D.O. Whittemore, and B.B. Wilson. 2021. Evaluation of data needs for assessments of aquifers supporting irrigated agriculture. *Water Resources Research* 57, no. 4: WR028320. https://doi.org/10.1029/2020WR028320

Brocca, L., A. Tarpanelli, P. Filippucci, W. Dorigo, F. Zaussinger, A. Gruber, and D. Fernández-Prieto. 2018. How much water is used for irrigation? A new approach exploiting coarse resolution satellite soil moisture products. *International Journal of Applied Earth Observation and Geoinformation* 73: 752–766. https://doi.org/10.1016/j.jag.2018.08.023

Butler, J.J., D.O. Whittemore, B.B. Wilson, and G.C. Bohling. 2018. Sustainability of aquifers supporting irrigated agriculture: A case study of the High Plains aquifer in Kansas. *Water International* 43, no. 6: 815–828. https://doi.org/10.1080/02508060.2018.1515566

Cammalleri, C., M.C. Anderson, F. Gao, C.R. Hain, and W.P. Kustas. 2014. Mapping daily evapotranspiration at field scales over rainfed and irrigated agricultural areas using remote sensing data fusion. *Agricultural and Forest Meteorology* 186: 1–11. https://doi.org/10.1016/j.agrformet.2013.11.001

Castellazzi, P., R. Martel, D.L. Galloway, L. Longuevergne, and A. Rivera. 2016. Assessing groundwater depletion and dynamics using GRACE and InSAR: Potential and limitations. *Groundwater* 54, no. 6: 768–780. https://doi.org/10.1111/gwat.12453

Condon, L.E., and R.M. Maxwell. 2013. Implementation of a linear optimization water allocation algorithm into a fully integrated physical hydrology model. *Advances in Water Resources* 60: 135–147. https://doi.org/10.1016/j.advwatres.2013.07.012

Condon, L.E., S. Kollet, M.F.P. Bierkens, G.E. Fogg, R.M. Maxwell, M.C. Hill, H.-J.H. Fransen, A. Verhoef, A.F. Van Loon, M. Sulis, and C. Abesser. 2021. Global groundwater modeling and monitoring: Opportunities and challenges. *Water Resources Research* 57, no. 12: WR029500. https://doi.org/10.1029/2020WR029500

de Graaf, I.E.M., T. Gleeson, L.P.H. van Beek, E.H. Sutanudjaja, and M.F.P. Bierkens. 2019. Environmental flow limits to global groundwater pumping. *Nature* 574: 90–94. https://doi.org/10.1038/s41586-019-1594-4

de Graaf, I.E.M., L.P.H. van Beek, Y. Wada, and M.F.P. Bierkens. 2014. Dynamic attribution of global water demand to surface water and groundwater resources: Effects of abstractions and return flows on river discharges. *Advances in Water Resources* 64: 21–33. https://doi.org/10.1016/j.advwatres.2013.12.002

Deines, J.M., A.D. Kendall, J.J. Butler, B. Basso, and D.W. Hyndman. 2021. Combining remote sensing and crop models to assess the sustainability of stakeholder-driven groundwater management in the US High Plains aquifer. *Water Resources Research* 57: WR027756. https://doi.org/10.1029/2020WR027756

Deines, J.M., A.D. Kendall, M.A. Crowley, J. Rapp, J.A. Cardille, and D.W. Hyndman. 2019. Mapping three decades of annual irrigation across the US High Plains aquifer using landsat and Google earth engine. *Remote Sensing* of Environment 233: 111400. https://doi.org/10.1016/j.rse.2019.111400

Döll, P., H. Müller Schmied, C. Schuh, F.T. Portmann, and A. Eicker. 2014. Global-scale assessment of groundwater depletion and related groundwater abstractions: Combining hydrological modeling with information from well observations and GRACE satellites. *Water Resources Research* 50, no. 7: 5698–5720. https://doi.org/10.1002/2014WR015595

Drysdale, K.M., and N.P. Hendricks. 2018. Adaptation to an irrigation water restriction imposed through local governance. *Journal of Environmental Economics and Management* 91: 150–165. https://doi.org/10.1016/j.jeem.2018.08.002

Fisher, J.B., K.P. Tu, and D.D. Baldocchi. 2008. Global estimates of the land–atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites. *Remote Sensing of Environment* 112, no. 3: 901–919. https://doi.org/10.1016/j.rse.2007.06.025

Foster, T., T. Mieno, and N. Brozović. 2020. Satellite-based monitoring of irrigation water use: Assessing measurement errors and their implications for agricultural water management policy. *Water Resources Research* 56: WR028378. https://doi.org/10.1029/2020WR028378

Foster, T., I.Z. Gonçalves, I. Campos, C.M.U. Neale, and N. Brozović. 2019. Assessing landscape scale heterogeneity in irrigation water use with remote sensing and in situ monitoring. *Environmental Research Letters* 14, no. 2: 024004. https://doi.org/10.1088/1748-9326/aaf2be

Frenzel, S.A. 1985. Comparison of methods for estimating ground-water pumpage for irrigation. *Groundwater* 23, no. 2: 220–226. https://doi.org/10.1111/j.1745-6584.1985.tb02795.x

Gao, J., A.Y. Sheshukov, H. Yen, J.H. Kastens, and D.L. Peterson. 2017. Impacts of incorporating dominant crop rotation patterns as primary land use change on hydrologic model performance. *Agriculture, Ecosystems and Environment* 247: 33–42. https://doi.org/10.1016/j.agee.2017.06.019

García-Vila, M., E. Fereres, L. Mateos, F. Orgaz, and P. Steduto. 2009. Deficit irrigation optimization of cotton with AquaCrop. *Agronomy Journal* 101, no. 3: 477–487. https://doi.org/10.2134/agronj2008.0179s

Glose, T.J., S. Zipper, D.W. Hyndman, A.D. Kendall, J.M. Deines, and J.J. Butler. 2022. Quantifying the impact of lagged hydrological responses on the effectiveness of groundwater conservation. *Water Resources Research* 58: WR032295. https://doi.org/10.1029/2022WR032295

Gu, Z., Z. Qi, R. Burghate, S. Yuan, X. Jiao, and J. Xu. 2020. Irrigation scheduling approaches and applications: A review. *Journal of Irrigation and Drainage Engineering* 146, no. 6: 04020007. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001464

Haacker, E. M. K. (2018). Sustainability of the high plains aquifer: From deliberate impacts to unintended consequences. PhD Dissertation, Michigan State University. https://www.proquest.com/openview/76bd5e99187357c34a8f6799df7e84db/1?pq-origsite=gscholarandcbl=18750

Hanson, R. T., S. E. Boyce, W. Schmid, J. D. Hughes, S. W. Mehl, S. A. Leake, T. Maddock III, and R. G. Niswonger. 2014. One-water hydrologic flow model (MODFLOW-OWHM). USGS Numbered Series No. 6-A51; Techniques and Methods.

Houston, N. A., S. L. Gonzales-Bradford, A. T. Flynn, S. L. Qi, S. M. Peterson, J. S. Stanton, D. W. Ryter, T. L. Sohl, and G. B. Senay. 2013. Geodatabase compilation of hydrogeologic, remote sensing, and water-budget-component data for the High Plains Aquifer, 2011 (USGS Data Series No. 777). https://pubs.usgs.gov/ds/777/

Hyndman, D.W., A.D. Kendall, and N.R.H. Welty. 2007. Evaluating temporal and spatial variations in recharge and streamflow using the integrated landscape hydrology model (ILHM). In *Subsurface Hydrology: Data Integration for Properties and Processes*, ed. David W. Hyndman, Frederick D. Day-Lewis, and Kamini Singha, 121–141. Washington, DC: American Geophysical Union (AGU). https://doi.org/10.1029/171GM11

International Groundwater Resources Assessment Center (IGRAC). 2018. Groundwater overview—Making the invisible visible. https://www.un-igrac.org/sites/default/files/resources/files/Groundwateroverview-Makingtheinvisiblevisible_Print.pdf

Jasechko, S., and D. Perrone. 2021. Global groundwater wells at risk of running dry. *Science* 372, no. 6540: 418–421. https://doi.org/10.1126/science.abc2755

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. 2003. The DSSAT cropping system model. *European Journal of Agronomy* 18, no. 3: 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kansas Department of Agriculture. 2022. Local enhanced management area. https://agriculture.ks.gov/divisions-programs/dwr/managing-kansas-water-resources/local-enhanced-management-areas

Kansas Geological Survey (KGS). 2023. *Kansas high plains aquifer atlas*. Lawrence, Kansas: Kansas Geological Survey. https://www.kgs.ku.edu/HighPlains/HPA_Atlas/index.html

Kansas Geological Survey (KGS). 2022. KGS—Geophysics and exploration services—Water Well Project. https://www.kgs.ku.edu/Geophysics/well.html

Kasampalis, D.A., T.K. Alexandridis, C. Deva, A. Challinor, D. Moshou, and G. Zalidis. 2018. Contribution of remote sensing on crop models: A review. *Journal of Imaging* 4, no. 4: 52. https://doi.org/10.3390/jimaging4040052

Kendall, A. D. 2009. Predicting the impacts of land use and climate on regional-scale hydrologic fluxes. PhD Dissertation, Michigan State University. https://www.proquest.com/docview/304942111/abstract/8A376CC9D8854787PQ/1

Keune, J., M. Sulis, and S.J. Kollet. 2019. Potential added value of incorporating human water use on the simulation of evapotranspiration and precipitation in a continental-scale bedrock-to-atmosphere modeling system: A validation study considering observational uncertainty. *Journal of Advances in Modeling Earth Systems* 11, no. 7: 1959–1980. https://doi.org/10.1029/2019MS001657

Koch, J., W. Zhang, G. Martinsen, X. He, and S. Stisen. 2020. Estimating net irrigation across the North China plain through dual modeling of evapotranspiration. *Water Resources Research* 56, no. 12: WR027413. https://doi.org/10.1029/2020WR027413

Laipelt, L., R.H.B. Kayser, A.S. Fleischmann, A. Ruhoff, W. Bastiaanssen, T.A. Erickson, and F. Melton. 2021. Long-term monitoring of evapotranspiration using the SEBAL algorithm and Google earth engine cloud computing. *ISPRS Journal of Photogrammetry and Remote Sensing* 178: 81–96. https://doi.org/10.1016/j.isprsjprs.2021.05.018

Leenhardt, D., J.-L. Trouvat, G. Gonzalès, V. Pérarnaud, S. Prats, and J.-E. Bergez. 2004. Estimating irrigation demand for water management on a regional scale: I. ADEAUMIS, a simulation platform based on bio-decisional modelling and spatial information. *Agricultural Water Management* 68, no. 3: 207–232. https://doi.org/10.1016/j.agwat.2004.04.004

Liu, X. 2018. Evaluating the hydrologic response to irrigation and aquifer storage and recovery in the republican river basin. MSc Thesis, Michigan State University. https://www.proquest.com/openview/84a9094911dc9a943927fa2a86be0c25/1?pq-origsite=gscholarandcbl=18750

Majumdar, S., R. Smith, J.J. Butler, and V. Lakshmi. 2020. Groundwater withdrawal prediction using integrated

multitemporal remote sensing data sets and machine learning. *Water Resources Research* 56, no. 11: WR028059. https://doi.org/10.1029/2020WR028059
MardanDoost, B., A.E. Brookfield, J. Feddema, B. Sturm, J. Kastens, D. Peterson, and C. Bishop. 2019. Estimating irrigation demand with geospatial and in-situ data: Application to the high plains aquifer, Kansas, USA. *Agricultural Water Management* 223: 105675. https://doi.org/10.1016/j.agwat.2019.06.010
Marston, L.T., A.M. Abdallah, K.J. Bagstad, K. Dickson, P. Glynn, S.G. Larsen, F.S. Melton, K. Onda, J.A. Painter, J. Praire, B.A. Ruddell, R.R. Rushforth, G.B. Senay, and K. Shaffer. 2022a. Water-use data in the United States: Challenges and future directions. *JAWRA Journal of the American Water Resources Association* 58, no. 4: 485–495. https://doi.org/10.1111/1752-1688.13004
Marston, L.T., S. Zipper, S.M. Smith, J.J. Allen, J.J. Butler, S. Gautam, and D.J. Yu. 2022b. The importance of fit in groundwater self-governance. *Environmental Research Letters* 17, no. 11: 111001. https://doi.org/10.1088/1748-9326/ac9a5e
Massari, C., S. Modanesi, J. Dari, A. Gruber, G.J.M. De Lannoy, M. Girotto, P. Quintana-Seguí, M. Le Page, L. Jarlan, M. Zribi, N. Ouaadi, M. Vreugdenhil, L. Zappa, W. Dorigo, W. Wagner, J. Brombacher, H. Pelgrum, P. Jaquot, V. Freeman, E. Volden, D.F. Prieto, A. Tarpanelli, S. Barbetta, and L. Brocca. 2021. A review of irrigation information retrievals from space and their utility for users. *Remote Sensing* 13, no. 20: 4112. https://doi.org/10.3390/rs13204112
McGuire, V. L., K. D. Lund, and B. K. Densmore. 2012. Saturated thickness and water in storage in the high plains aquifer, 2009, and water-level changes and changes in water in storage in the High Plains Aquifer, 1980 to 1995, 1995 to 2000, 2000 to 2005, and 2005 to 2009. U.S. Geological Survey Scientific Investigations Report No. 2012-5177. https://pubs.usgs.gov/sir/2012/5177/
Melton, F.S., J. Huntington, R. Grimm, J. Herring, M. Hall, D. Rollison, T. Erickson, R. Allen, M. Anderson, J. Fisher, A. Kilic, G. Senay, J. Volk, C. Hain, L. Johnson, A. Ruhoff, P. Blankenau, M. Bromley, W. Carrara, and R. Anderson. 2021. OpenET: Filling a critical data gap in water management for the Western United States. *JAWRA Journal of the American Water Resources Association* 58, no. 6: 971–994. https://doi.org/10.1111/1752-1688.12956
Melton, F.S., L.F. Johnson, C.P. Lund, L.L. Pierce, A.R. Michaelis, S.H. Hiatt, A. Guzman, D.D. Adhikari, A.J. Purdy, C. Rosevelt, P. Votava, T.J. Trout, B. Temesgen, K. Frame, E.J. Sheffner, and R.R. Nemani. 2012. Satellite irrigation management support with the terrestrial observation and prediction system: A framework for integration of satellite and surface observations to support improvements in agricultural water resource management. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 5, no. 6: 1709–1721. https://doi.org/10.1109/JSTARS.2012.2214474
Meneghini, R., T. Iguchi, T. Kozu, L. Liao, K. Okamoto, J.A. Jones, and J. Kwiatkowski. 2000. Use of the surface reference technique for path attenuation estimates from the TRMM precipitation radar. *Journal of Applied Meteorology and Climatology* 39, no. 12: 2053–2070. https://doi.org/10.1175/1520-0450(2001)040<2053:UOTSRT>2.0.CO;2
Mujumdar, M., P. Bhaskar, M.V.S. Ramarao, U. Uppara, M. Goswami, H. Borgaonkar, S. Chakraborty, S. Ram, V. Mishra, M. Rajeevan, and D. Niyogi. 2020. Droughts and floods. In *Assessment of Climate Change over the Indian Region: A Report of the Ministry of Earth Sciences (MoES), Government of India*, ed. R. Krishnan, J. Sanjay, C. Gnanaseelan, M. Mujumdar, A. Kulkarni, and S. Chakraborty, 117–141. Singapore: Springer. https://doi.org/10.1007/978-981-15-4327-2_6
Mulla, S., S.K. Singh, K.K. Singh, and B. Praveen. 2020. Climate change and agriculture: A review of crop models. In *Global Climate Change and Environmental Policy: Agriculture Perspectives*, ed. V. Venkatramanan, S. Shah, and R. Prasad, 423–435. Singapore: Springer. https://doi.org/10.1007/978-981-13-9570-3_15
Niswonger, R.G. 2020. An agricultural water use package for MODFLOW and GSFLOW. *Environmental Modelling and Software* 125: 104617. https://doi.org/10.1016/j.envsoft.2019.104617
Peña-Arancibia, J.L., M. Mainuddin, J.M. Kirby, F.H.S. Chiew, T.R. McVicar, and J. Vaze. 2016. Assessing irrigated agriculture's surface water and groundwater consumption by combining satellite remote sensing and hydrologic modelling. *Science of the Total Environment* 542: 372–382. https://doi.org/10.1016/j.scitotenv.2015.10.086
Pereira, L.S., P. Paredes, F. Melton, L. Johnson, T. Wang, R. López-Urrea, J.J. Cancela, and R.G. Allen. 2020. Prediction of crop coefficients from fraction of ground cover and height. Background and validation using ground and remote sensing data. *Agricultural Water Management* 241: 106197. https://doi.org/10.1016/j.agwat.2020.106197
Perrone, D., and S. Jasechko. 2019. Deeper well drilling an unsustainable stopgap to groundwater depletion. *Nature Sustainability* 2, no. 8: 773–782. https://doi.org/10.1038/s41893-019-0325-z
Pradhan, R.K., Y. Markonis, M.R. Vargas Godoy, A. Villalba-Pradas, K.M. Andreadis, E.I. Nikolopoulos, S.M. Papalexiou, A. Rahim, F.J. Tapiador, and M. Hanel. 2022. Review of GPM IMERG performance: A global perspective. *Remote Sensing of Environment* 268: 112754. https://doi.org/10.1016/j.rse.2021.112754
Ritchie, J.T., and S. Otter. 1985. Description and performance of CERES-wheat: A user oriented wheat yield model. In *ARS-38: 159-1*, ed. ARS Wheat Yield Project, 159–175. Spring-Field: Natl Tech Info Serv.
Russo, T.A., and U. Lall. 2017. Depletion and response of deep groundwater to climate-induced pumping variability. *Nature Geoscience* 10: 105–108. https://doi.org/10.1038/ngeo2883
Ruud, N., T. Harter, and A. Naugle. 2004. Estimation of groundwater pumping as closure to the water balance of a semi-arid, irrigated agricultural basin. *Journal of Hydrology* 297, no. 1: 51–73. https://doi.org/10.1016/j.jhydrol.2004.04.014
Saltelli, A. 2019. A short comment on statistical versus mathematical modelling. *Nature Communications* 10: 3870. https://doi.org/10.1038/s41467-019-11865-8
Samaniego, L., R. Kumar, and S. Attinger. 2010. Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *Water Resources Research* 46: 1–25. https://doi.org/10.1029/2008WR007327
Sanchez, R., L. Rodriguez, and C. Tortajada. 2020. Effective transboundary aquifer areas: An approach for transboundary groundwater management. *JAWRA Journal of the American Water Resources Association* 56, no. 3: 360–378. https://doi.org/10.1111/1752-1688.12836
Schaap, M.G., and F.J. Leij. 2000. Improved prediction of unsaturated hydraulic conductivity with the Mualem-van Genuchten model. *Soil Science Society of America Journal* 64, no. 3: 843–851. https://doi.org/10.2136/sssaj2000.643843x
Senay, G.B. 2018. Satellite psychrometric formulation of the operational simplified surface energy balance (SSEBop) model for quantifying and mapping evapotranspiration. *Applied Engineering in Agriculture* 34, no. 3: 555–556.
Senay, G.B., S. Bohms, R.K. Singh, P.H. Gowda, N.M. Velpuri, H. Alemu, and J.P. Verdin. 2013. Operational evapotranspiration mapping using remote sensing and

weather datasets: A new parameterization for the SSEB approach. *JAWRA Journal of the American Water Resources Association* 49, no. 3: 577–591. https://doi.org/10.1111/jawr.12057

Smidt, S. J. 2017. Redefining water and land management strategies for the early 21st century. PhD Dissertation, Michigan State University. https://d.lib.msu.edu/etd/4651?q=Redefiningwaterandlandmanagementstrategiesfortheearly21stcentury

Soil Survey Staff. 2020. *Gridded Soil Survey Geographic (gSSURGO) Database for The United States of America and the Territories, Commonwealths, and Island Nations Served by the USDA NRCS*. Natural Resources Conservation Service: United States Department of Agriculture.

State of California. 2014. Sustainable Groundwater Management Act (SGMA). https://water.ca.gov/Programs/Groundwater-Management/SGMA-Groundwater-Management

Stewart, I.T., D.R. Cayan, and M.D. Dettinger. 2005. Changes toward earlier streamflow timing across Western North America. *Journal of Climate* 18, no. 8: 1136–1155. https://doi.org/10.1175/JCLI3321.1

Taylor, R.G., B. Scanlon, P. Döll, M. Rodell, R. van Beek, Y. Wada, L. Longuevergne, M. Leblanc, J.S. Famiglietti, M. Edmunds, L. Konikow, T.R. Green, J. Chen, M. Taniguchi, M.F.P. Bierkens, A. MacDonald, Y. Fan, R.M. Maxwell, Y. Yechieli, J.J. Gurdak, D.M. Allen, M. Shamsudduha, K. Hiscock, P.J.F. Yeh, I. Holman, and H. Treidel. 2013. Ground water and climate change. *Nature Climate Change* 3: 322–329. https://doi.org/10.1038/nclimate1744

Tenreiro, T.R., M. García-Vila, J.A. Gómez, J.A. Jimenez-Berni, and E. Fereres. 2020. Water modelling approaches and opportunities to simulate spatial water variations at crop field level. *Agricultural Water Management* 240: 106254. https://doi.org/10.1016/j.agwat.2020.106254

Tolley, D., L. Foglia, and T. Harter. 2019. Sensitivity analysis and calibration of an integrated hydrologic model in an irrigated agricultural basin with a groundwater-dependent ecosystem. *Water Resources Research* 55, no. 9: 7876–7901. https://doi.org/10.1029/2018WR024209

Toth, C., and G. Jóźków. 2016. Remote sensing platforms and sensors: A survey. *ISPRS Journal of Photogrammetry and Remote Sensing* 115: 22–36. https://doi.org/10.1016/j.isprsjprs.2015.10.004

Turner, S.W.D., M. Hejazi, C. Yonkofski, S.H. Kim, and P. Kyle. 2019. Influence of groundwater extraction costs and resource depletion limits on simulated global nonrenewable water withdrawals over the twenty-first century. *Earth's Future* 7, no. 2: 123–135. https://doi.org/10.1029/2018EF001105

USDA National Agricultural Statistics Service. 2021. CropScape—Cropland data layer [data set].

van Klompenburg, T., A. Kassahun, and C. Catal. 2020. Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture* 177: 105709. https://doi.org/10.1016/j.compag.2020.105709

Vörösmarty, C.J., C. Pahl-Wostl, S.E. Bunn, and R. Lawford. 2013. Global water, the anthropocene and the transformation of a science. *Current Opinion in Environmental Sustainability* 5, no. 6: 539–550. https://doi.org/10.1016/j.cosust.2013.10.005

Wada, Y., D. Wisser, and M.F.P. Bierkens. 2014. Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. *Earth System Dynamics* 5, no. 1: 15–40. https://doi.org/10.5194/esd-5-15-2014

Wagner, W., K. Scipal, C. Pathe, D. Gerten, W. Lucht, and B. Rudolf. 2003. Evaluation of the agreement between the first global remotely sensed soil moisture data with model and precipitation data. *Journal of Geophysical Research: Atmospheres* 108: 1–17. https://doi.org/10.1029/2003JD003663

Wang, L., W. Kinzelbach, H. Yao, J. Steiner, and H. Wang. 2020. How to meter agricultural pumping at numerous small-scale wells?—An indirect monitoring method using electric energy as proxy. *Water* 12: 2477. https://doi.org/10.3390/w12092477

Wanniarachchi, S., and R. Sarukkalige. 2022. A review on evapotranspiration estimation in agricultural water management: Past, present, and future. *Hydrology* 9: 123. https://doi.org/10.3390/hydrology9070123

Whittemore, D.O., J.J. Butler, and B.B. Wilson. 2018. Status of the high plains aquifer in Kansas. *Kansas Geological Survey Technical Series* 22: 20.

Wiley, M.J., D.W. Hyndman, B.C. Pijanowski, A.D. Kendall, C. Riseng, E.S. Rutherford, S.T. Cheng, M.L. Carlson, J.A. Tyler, R.J. Stevenson, P.J. Steen, P.L. Richards, P.W. Seelbach, J.M. Koches, and R.R. Rediske. 2010. A multi-modeling approach to evaluating climate and land use change impacts in a Great Lakes River basin. *Hydrobiologia* 657, no. 1: 243–262. https://doi.org/10.1007/s10750-010-0239-2

Xia, Y., K. Mitchell, M. Ek, J. Sheffield, B. Cosgrove, E. Wood, L. Luo, C. Alonge, H. Wei, J. Meng, B. Livneh, D. Lettenmaier, V. Koren, Q. Duan, K. Mo, Y. Fan, and D. Mocko. 2012. Continental-scale water and energy flux analysis and validation for the north American land data assimilation system project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. *Journal of Geophysical Research: Atmospheres* 117: 1–27. https://doi.org/10.1029/2011JD016048

Xiao, M., A. Koppa, Z. Mekonnen, B.R. Pagán, S. Zhan, Q. Cao, A. Aierken, H. Lee, and D.P. Lettenmaier. 2017. How much groundwater did California's Central Valley lose during the 2012–2016 drought? *Geophysical Research Letters* 44, no. 10: 4872–4879. https://doi.org/10.1002/2017GL073333

Xie, Y., and T.J. Lark. 2021. Mapping annual irrigation from Landsat imagery and environmental variables across the conterminous United States. *Remote Sensing of Environment* 260: 112445. https://doi.org/10.1016/j.rse.2021.112445

Zipper, S.C., I. Popescu, K. Compare, C. Zhang, and E.C. Seybold. 2022a. Alternative stable states and hydrological regime shifts in a large intermittent river. *Environmental Research Letters* 17, no. 7: 074005. https://doi.org/10.1088/1748-9326/ac7539

Zipper, S.C., W.H. Farmer, A. Brookfield, H. Ajami, H.W. Reeves, C. Wardropper, J.C. Hammond, T. Gleeson, and J.M. Deines. 2022b. Quantifying streamflow depletion from groundwater pumping: A practical review of past and emerging approaches for water management. *JAWRA Journal of the American Water Resources Association* 58, no. 2: 289–312. https://doi.org/10.1111/1752-1688.12998

Zipper, S.C., J.C. Hammond, M. Shanafield, M. Zimmer, T. Datry, C.N. Jones, K.E. Kaiser, S.E. Godsey, R.M. Burrows, J.R. Blaszczak, M.H. Busch, A.N. Price, K.S. Boersma, A.S. Ward, K. Costigan, G.H. Allen, C.A. Krabbenhoft, W.K. Dodds, M.C. Mims, J.D. Olden, S.K. Kampf, A.J. Burgin, and D.C. Allen. 2021. Pervasive changes in stream intermittency across the United States. *Environmental Research Letters* 16, no. 8: 084033. https://doi.org/10.1088/1748-9326/ac14ec