Lagged streamflow depletion due to pumping-induced stream drying: Incorporation into analytical streamflow depletion estimation methods

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Highlights

- Analytical depletion functions (ADFs) estimate streamflow depletion caused by pumping
- Stream drying shifts timing of streamflow depletion due to hydrologic disconnection
- ADFs incorporating stream drying had strong agreement with observed streamflow
- Modeling stream drying requires accurate estimates of non-depleted streamflow
- Strong ADF performance suggests potential use as a low-cost decision-support tool

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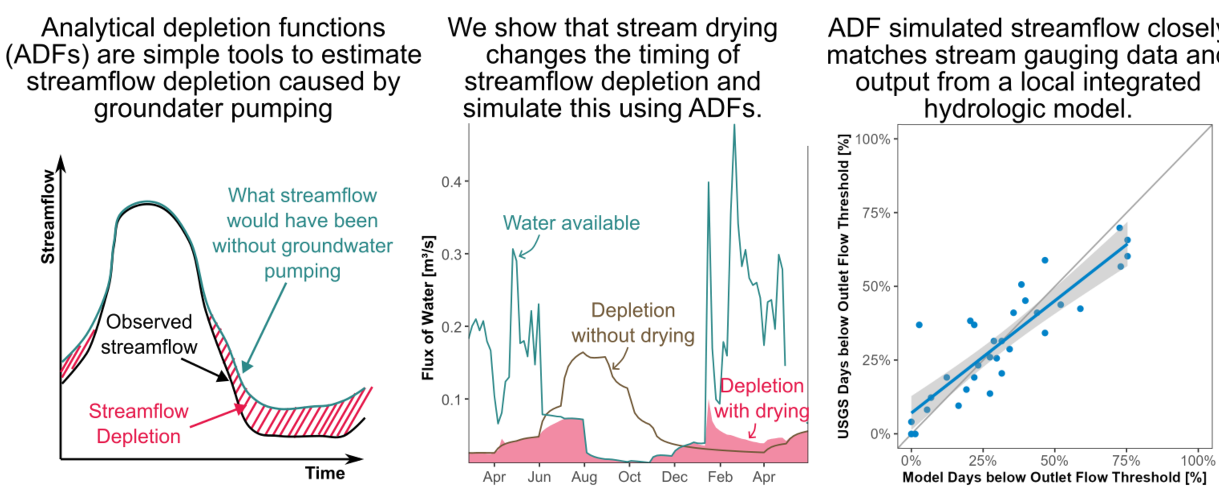
Abstract

Water management often requires accounting for reductions in streamflow caused by groundwater pumping (‘streamflow depletion’). Since streamflow depletion cannot be quantified from observational data, it is typically modeled. Analytical depletion functions (ADFs) are a low-cost, low-complexity approach for estimating streamflow depletion with utility for decision support, but ADFs adopt several simplifying assumptions, including an infinite supply of water within the stream. Here, we develop an approach to incorporate stream drying into ADFs to improve their estimation of streamflow and streamflow depletion. Using Scott Valley (California) as an example, we compare ADF results to observed streamflow data and the Scott Valley Integrated Hydrologic Model (SVIHM), a process-based numerical model. ADFs incorporating stream drying have strong agreement with observed streamflow and SVIHM results. Critically, ADFs with drying can simulate a temporal shift in streamflow depletion that occurs when summer stream drying causes stream network disconnections and a substantial fraction of streamflow depletion is lagged until the fall/winter, when the stream network rewets. Estimates of what streamflow would have been without groundwater pumping are required to incorporate stream drying into ADFs, and we evaluate the ability of a statewide statistical model of unimpaired monthly streamflow (the California Natural Flows Database [CNFD]) to meet this need. ADFs using CNFD data simulate appropriate temporal dynamics but overestimate streamflow. This suggests that regional unimpaired flow estimates combined with local bias-correction could provide a mechanism to apply ADFs in watersheds without local numerical models.

Graphical Abstract



Keywords: streamflow depletion, groundwater pumping, non-perennial streams, groundwater-surface water interactions, California, SGMA, integrated water resources management

1. Introduction

While surface water and groundwater resources have historically been managed and regulated separately (Gage & Milman, 2020), in many settings they are a single interconnected resource (Winter et al., 1998). Reductions in streamflow caused by groundwater pumping, known as 'streamflow depletion' (Barlow et al., 2018; Barlow & Leake, 2012), are a primary mechanism by which groundwater use can affect surface water resources and groundwater-dependent ecosystems (Rohde et al., 2017). In recent decades, water management frameworks have emerged which require quantifying and accounting for interconnections between groundwater and surface water, such as streamflow depletion, when developing water management plans. For example, the European Water Framework Directive and the Australian National Water Initiative both specify that groundwater use cannot impair interconnected surface water resources (Kallis & Butler, 2001; Rohde et al., 2017; Ross, 2018; Vázquez-Suñé et al., 2006). In the United States, California's Sustainable Groundwater Management Act (SGMA) was passed in 2014, requiring specific priority groundwater subbasins to achieve groundwater sustainability by 2040. SGMA defines sustainability as long-term groundwater management which prevents significant and unreasonable undesirable results, including the depletion of interconnected surface waters (Harter, 2020; Leahy, 2016; Owen et al., 2019). Under SGMA, groundwater managers are expected to estimate the location, timing, and quantity of streamflow depletion occurring due to groundwater pumping (California Department of Water Resources, 2024).

Quantifying streamflow depletion is challenging because pumping impacts are frequently obscured by other causes of variability such as weather/precipitation dynamics, surface water impoundments/diversions, and lags between groundwater pumping and streamflow impacts (Barlow & Leake, 2012). Streamflow depletion can only be directly measured using observational data at the scale of a stream reach over short timescales (Flores et al., 2020; Hunt et al., 2001; Kollet & Zlotnik, 2003; Malama et al., 2024; Nyholm et al., 2002). However, due to the intensity of data requirements, streamflow depletion cannot be quantified using solely observational data at management-relevant scales such as aquifers or watersheds, and is instead modeled using a variety of approaches (Zipper et al., 2022a). Numerical models, such as MODFLOW, MIKE-SHE, and HydroGeoSphere, simulate stores and fluxes of water in groundwater and surface water systems using physical governing equations (Falke et al., 2011; Fienen et al., 2018; RRCA, 2003; Tolley et al., 2019). Numerical models are generally considered the most reliable tools for assessing streamflow depletion due to their process-based foundation and opportunity for site-specific calibration. Due to their complexity they also have high development costs in terms of data, effort, and expertise (Barlow & Leake, 2012; Zipper et al., 2022a).

Analytical depletion functions (ADFs) have been proposed as a low-cost and scalable approach for estimating streamflow depletion (Zipper et al., 2019). ADFs are based on analytical models for streamflow depletion, which mathematically simplify physical governing equations by adopting assumptions, commonly including a well pumping in a homogeneous subsurface connected to a single stream partially or fully penetrating into the aquifer system (Glover &

Balmer, 1954; Hantush, 1965; Huang et al., 2018; Hunt, 1999). Simplifications in analytical models can introduce uncertainty, for example by neglecting spatial heterogeneity in the hydrologic response to pumping. ADFs extend analytical models by using empirical approaches to address some of these assumptions, for example by identifying multiple potentially affected stream segments by each well and distributing depletion among stream segments using geometric approaches known as depletion apportionment equations (Zipper et al., 2018; additional details in Section 2). However, a key simplifying assumption that remains is the assumption of an infinite supply of water in the stream. Non-perennial (intermittent or ephemeral) streams are common, estimated to make up more the half the global river network (Messager et al., 2021), and are becoming increasingly widespread due to climate change and human activities (Sauquet et al., 2021; Tramblay et al., 2021; Zipper et al., 2021a). Furthermore, in settings where pumping is a substantial fraction of the water balance, streamflow depletion itself can lead to reductions in stream storage and stream drying (Datry et al., 2022; Malama et al., 2024; Zipper et al., 2022b), which violates the assumption of infinite water.

To advance integrated groundwater-surface water decision-making capabilities in watersheds affected by groundwater pumping, this study asks, how does the incorporation of stream drying and the downstream accumulation of streamflow depletion affect the timing of streamflow depletion and the ability of ADFs to simulate spatiotemporal patterns of streamflow and streamflow depletion? To accomplish this, we compare ADF simulations of streamflow and streamflow depletion to observed streamflow data and output from the process-based Scott Valley Integrated Hydrologic Model (SVIHM; Foglia et al., 2013, 2018; Tolley et al., 2019) in the Scott River Valley (California, USA). We develop a novel and simple water budget-based approach to represent stream drying when coupled with ADFs. We thus account for temporal shifts in streamflow depletion caused by stream network drying and can propagate both pumping and drying impacts through the river network. We also demonstrate how a regional statistical model of unimpaired streamflow provides a potential approach for ADF implementation in ungauged and unmodeled watersheds.

2. Analytical depletion function (ADF) theory and development

Analytical depletion functions have three primary steps to estimate the impacts of groundwater pumping on streamflow (Figure 1a), which are described in Zipper et al. (2019). First, 'stream proximity criteria' are used to identify the stream segments that could be affected by a well based on stream network geometry (Zipper et al., 2019). Second, 'depletion apportionment equations' distribute depletion among the affected segments using stream network geometry (Huggins et al., 2018; Reeves et al., 2009; Zipper et al., 2018). Third, streamflow depletion is calculated separately for each affected stream segment using an analytical model (Glover & Balmer, 1954; Hantush, 1965; Hunt, 1999) and scaled based on the apportioned depletion from step two. The resulting output is a three-dimensional streamflow depletion response matrix (White et al., 2021) that quantifies the individual response of each stream segment to each pumping well at each simulated timestep. The impacts of multiple wells are assumed to be linearly additive. Each step can be carried out using different algorithms, and the specific methods used for each of these steps in this study are described in Section 3.4.

Past work has evaluated multiple different approaches for each of these steps via comparison to numerical models in a variety of hydrogeological settings including coastal California, coastal and interior British Columbia, and the U.S. High Plains aquifer region (Li et al., 2020; Zipper et al., 2018, 2019, 2021b). This work has shown that ADF and numerical model simulations largely agree for several aspects of pumping impacts on stream networks, including identifying the segment with the greatest streamflow depletion by a given well, the magnitude of depletion in that segment, and the overall spatial distribution and magnitude of depletion across all affected stream segments (Li et al., 2022; Zipper et al., 2019). However, this past work has only used intermodel comparisons for accuracy assessment and has not included any direct comparison to observational data, such as streamflow from gauging stations. Additionally, these evaluations focused on segment-resolution changes in stream-aquifer flux rather than the accumulated streamflow depletion within the stream network and do not account for limited surface water supply (stream drying).

In this study, we advance the development of ADFs through two interlinked process representations: (i) the routing of streamflow and streamflow depletion through the stream network, and (ii) stream drying, which leads to a redistribution of depletion in time and space (Figure 1b). To accomplish this, we defined the stream network as a directed graph, with each stream segment represented by a node. To account for potential drying at a given segment, we incorporated an estimate of the streamflow that would have occurred in a segment if there were no groundwater irrigation, which we refer to as “water available”.

Combining the two steps, for each timestep, the resulting streamflow is calculated as the difference between water available and ADF depletion if and only if the calculated cumulative depletion by the ADFs in that segment and in upstream segments is less than the water available. If the depletion exceeds the amount of water available, the depletion is assumed to dry the stream and any calculated depletion exceeding water available is “banked” for a later timestep in the same stream segment.

Once additional water is available in the stream, banked streamflow depletion is added to the calculated depletion for each timestep, but only up to the water available for depletion in the segment. Thus, a timeseries of redistributed depletion is generated. For each simulated timestep, streamflow and streamflow depletion are calculated starting from headwater segments and moving downstream through the stream network so that any temporal redistributions of streamflow depletion are propagated to downstream segments. This approach to depletion routing and stream drying adopts several assumptions, including that pumping impacts can propagate from upstream to downstream in the stream network within the length of a timestep, and that accurate information about segment-resolution water available can be obtained for each timestep. Details for how these steps are specifically implemented for our study domain are provided in Section 3.

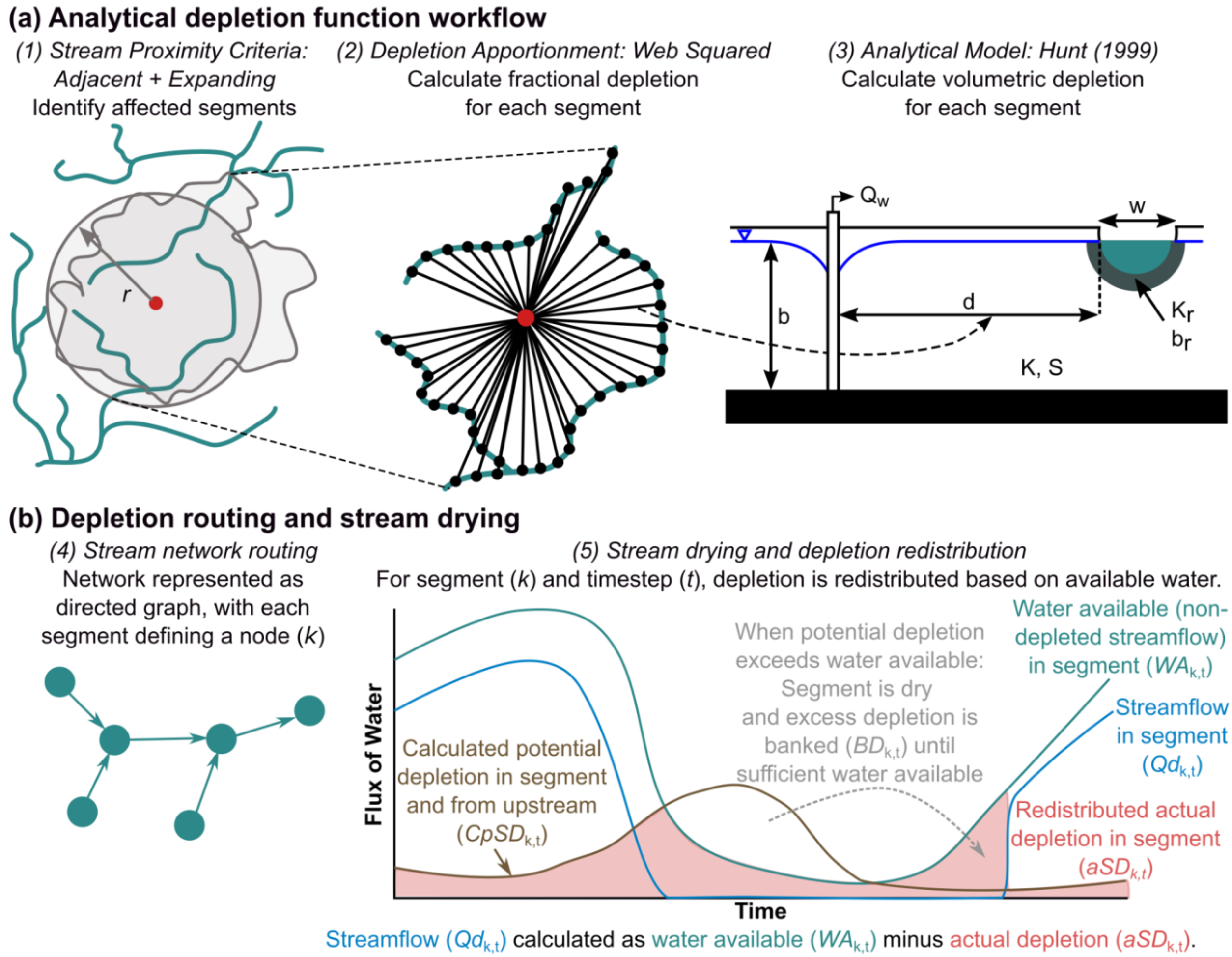


Figure 1. (a) Overview of analytical depletion functions (ADFs) and (b) methods for incorporating depletion routing and stream drying into ADFs. The specific equations and variables used in the figure are defined in Section 3.4.

3. Methods

In this study, we develop and test ADFs including stream drying and depletion routing via comparison to stream gauging data and a process-based numerical hydrologic model (SVIHM) in the Scott Valley region of California.

3.1 Study domain: Scott Valley, California

Nestled in the Siskiyou mountains in Northern California, Scott Valley is a Mediterranean-climate montane valley 800 m above sea level and approximately 200 km^2 in area (Tolley et al., 2019). The Scott River runs north through the valley (Figure 2), draining an area approximately 2100 km^2 and eventually flowing into the Klamath River. Land use in the flat portions of the valley floor is almost entirely agricultural, with alfalfa and pasture land comprising the largest proportions, while the surrounding uplands are largely managed as part of Klamath National Forest. Agricultural irrigation is the primary use of water, as the 500 mm of average precipitation that occurs in the valley falls between October-May, while the primary growing season is April-September.

The Scott River provides habitat to a variety of native aquatic fauna, including Chinook salmon and threatened coho salmon. Quantifying streamflow depletion therefore is critical to effective ecohydrological management. In an attempt to protect these aquatic populations, minimum flow requirements (details in Section 4.4.1) have been suggested for the Scott River at the Fort Jones gauge operated by the U.S. Geological Survey (USGS; gauge 11519500). The Scott River at Fort Jones gauge is located immediately downstream of the closed intermontane valley floor (41.64069017°N, 123.015037°W) at the top of a narrower bedrock canyon, and has streamflow records dating back to 1941. The valley floor is underlain by an aquifer made up of fluvial and alluvial deposits of gravels, sands, silts and clays that form a productive aquifer greater than 120 m thick in places (Mack, 1958), underlain by very low permeability, heterogeneous fractured bedrock. This aquifer system is strongly connected to the river system and stream-aquifer exchange is highly spatially and temporally heterogeneous (Tolley et al., 2019).

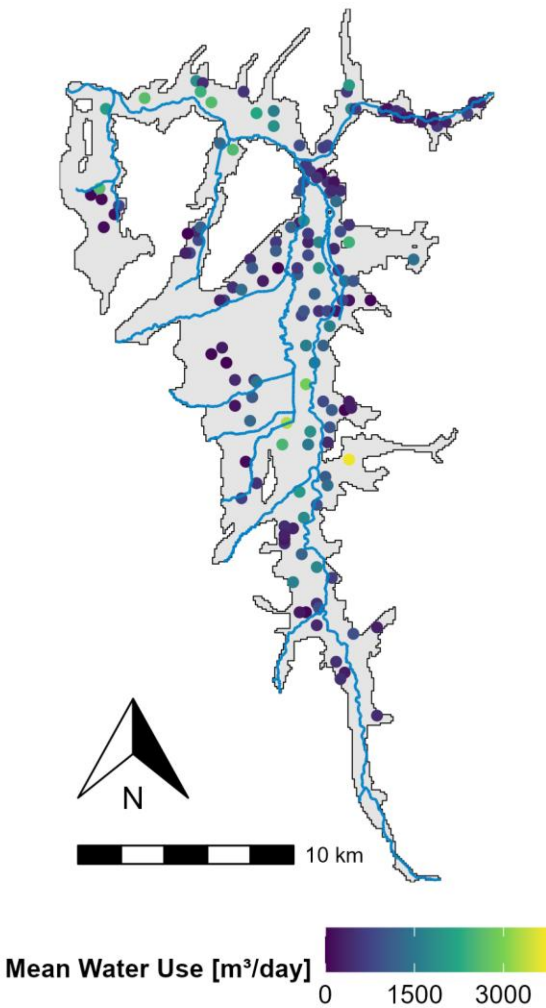


Figure 2. Scott Valley study domain. The grey shaded area is the active SVIHM model domain, which encompasses the valley bottom aquifer. Blue lines show the stream network, with the watershed outlet in the northwest corner of the domain. Pumping wells are colored by their average water use over the period of comparison.

3.2 Scott Valley Integrated Hydrologic Model (SVIHM)

SVIHM consists of three models run sequentially: an upper watershed tributary streamflow regression model, a soil-crop-water balance (agricultural water demand) model, and a numerical groundwater-surface water flow model using MODFLOW-NWT (Niswonger et al., 2011). The streamflow regression model predicts inflows into the topographically flat portion of Scott Valley overlying the aquifer system using statistical relationships estimated between the tributary gauges (dependent variable) and the Fort Jones gauge (independent variable). The soil-crop-water balance model estimates surface water and groundwater abstraction using a crop-coefficient based ET estimation and field-scale information about crops, soils, irrigation systems, their efficiency, and water sources (Foglia et al., 2013; Tolley et al., 2019). Recharge to the underlying aquifer system is estimated for each field using a tipping-bucket approach; the method and underlying equations are fully documented in Tolley et al. (2019). The MODFLOW-NWT model simulates the coupled groundwater-surface water system. The model consists of 2 layers, 440 rows and 210 columns (19,869 and 14,054 active nodes in layers 1 and 2, respectively), each 100m x 100m in size, and aquifer properties vary spatially via nine contiguous, homogenous hydrogeologic zones (Tolley et al., 2019). The model has monthly stress periods, daily time steps, and uses tab files to input the tributary inflows into the valley on a daily basis.

SVIHM has been used as a decision-support tool in Scott Valley for over a decade (Foglia et al., 2013, 2018; Kouba & Harter, 2024; Siskiyou County Water Conservation and Flood Control District, 2021; Tolley et al., 2019). Agricultural water use data are not available in the region, and thus the model serves an important purpose in estimating the valley water use and water balance. Additionally, SVIHM facilitates a wide variety of scenarios to be tested, e.g., removal/addition of pumping wells, land use changes, irrigation method changes, groundwater and surface water curtailments, droughts, etc. The specific SVIHM scenarios used in this study are described in Section 3.4.3.

3.3 California Natural Flows Database (CNFD)

The California Natural Flows Database (CNFD) is the result of a modeling approach developed in partnership between the California Environmental Flows Framework (https://ceff.ucdavis.edu/) technical team and the U.S. Geological Survey (USGS) that uses machine learning models to predict monthly unimpaired flows across the state of California. Unimpaired flows are a key water resource management consideration, particularly for the conservation of aquatic ecosystems. Modeling the natural flow regime allows for an increased understanding of existing alteration across surface water systems. Zimmerman et al. (2018) identified 250 reference stream gages with minimal flow alteration and divided them into three regions based on climate and hydrologic conditions. Using observed monthly flows, climate and run-off variables, and fixed physical watershed characteristics, they developed random forest statistical models for each region. These random forest models were then applied to predict flows for all streams in the state, estimating natural flow values from 1950 to 2015 at stream segment resolution (based on the resolution of the U.S. National Hydrography Dataset [NHD]), along with the range of uncertainty (Zimmerman et al., 2018).

Predictive accuracy of the model was assessed by comparing predicted monthly minimum, mean, and maximum flows to observed flows at randomly selected reference stream gages believed to have natural flows (locations lacking upstream hydrologic alteration). Average model performance results included the ratio of observed to predicted value of 0.94, an r-squared value of 0.80, a percent bias of -3.30 and a Nash-Sutcliffe Efficiency of 0.75 (Zimmerman et al., 2018). Studies have expanded upon this approach, utilizing modeled natural flows to propose ecologically functional flow metrics for riverine ecosystems statewide (Grantham et al., 2022). The CNFD is continuously updated, and monthly unimpaired flow estimates are available up to the present day (https://rivers.codefornature.org/). The specific CNFD data used in this study are described in Section 3.4.3.

3.4 ADF implementation to calculate depletion, streamflow, and drying in Scott Valley

3.4.1 Calculating potential streamflow depletion from ADFs

ADFs directly calculate the potential streamflow depletion, defined as the amount of streamflow depletion that would occur if the stream had an unlimited supply of water, for each stream segment at each timestep. The primary data sources for ADFs are the hydrostratigraphic parameters of transmissivity and storativity; the locations and pumping schedules for any wells; and the stream network. For our comparison, we used data from SVIHM to parameterize ADFs to maximize input data commensurability for an 'apples to apples' comparison. Therefore, our study is intended to understand the differences in simulated streamflow and streamflow depletion that can be attributed to differences in model structure and complexity, rather than differences that may be caused by model input data source or uncertainty. While we do not carry out a formal sensitivity analysis in this study, we do evaluate multiple data sources related to water available to understand the sensitivity of ADF performance to this input data. For transmissivity (*Tr*), we developed gridded maps by multiplying horizontal hydraulic conductivity (*K*) by aquifer thickness (*b*) at each SVIHM grid cell. For storativity (*S*), we summed specific yield (*Sy*) and the product of specific storage (*Ss*) and *b*. Since *Sy* is substantially larger than *Ss*b*, variation in *S* is primarily driven by *Sy* zones within SVIHM. Pumping locations were defined as the center of each SVIHM grid cell with a pumping well, and pumping schedules (*Qw*) were obtained from SVIHM as described in Section 3.2. The stream network was also defined based on the SVIHM grid. We then summarized hydrostratigraphic input parameters for each potential combination of wells and affected streams using the average *Tr* and *S* value for any grid cell along a line connecting each well to the closest point on each stream segment.

For ADF implementation, we used the 'adjacent + expanding' stream proximity criteria (Figure 1a, step 1), which allows wells to affect streams in any adjacent catchment or within a radial distance that expands with time (details in Zipper et al., 2019). The allowable radial distance at each timestep was based on the 10th percentile of *S* and 90th percentile of *Tr* for all well-stream pairs. Since low values of *S* and high values of *Tr* are generally associated with a greater fraction of pumping from streamflow depletion, these values are meant to represent an inclusive stream proximity criteria and ensure that all potentially impacted streams are identified. For the depletion apportionment equation (Figure 1a, step 2), we used the web-squared approach developed in Zipper et al. (2018) that distributes fractional depletion based on a weighted inverse distance of evenly spaced points along each affected stream segment. Compared to a simple inverse-distance approach, the web squared approach accounts for both the distance from wells to streams as well as the geometry of each stream segment. The 'adjacent + expanding' and 'web squared' approaches have generally been found to provide the best performance in past studies (Li et al., 2020; Zipper et al., 2018, 2019, 2021b), so we did not conduct additional testing of alternate stream proximity criteria and depletion apportionment equations in this study.

To estimate the amount of streamflow depletion due to pumping in each stream segment (Figure 1a, step 3), we used the analytical model developed in Hunt (1999) which simulates a partially-penetrating stream with a streambed layer that impedes flow as a function of its conductance (λ). For the conductance of the streambed layer, we used the λ values in each segment defined in SVIHM. In practice streambed conductance has tremendous fine-scale spatiotemporal variability (Abimbola et al., 2020b, 2020a; Korus et al., 2018, 2020) and is rarely known with any confidence (Christensen, 2000), and therefore this parameter is typically unknown or calibrated. To evaluate the potential impacts of the analytical model selection, we repeated our analysis using the Glover & Balmer (1954) analytical solution that assumes a fully penetrating stream with no resistance to flow and therefore does not require λ. We found that simulated depleted streamflow at the watershed outlet was insensitive to the selection of an analytical model in this domain (Figure S4), and therefore only results from the Hunt model are shown throughout the rest of the manuscript. All ADF simulations were done using a five-day timestep for the period from October 1, 1990 to September 30, 2023 and were implemented using the streamDepletr package for R (Zipper, 2023).

3.4.2 Incorporating depletion routing and stream drying

The ADF as described in Section 3.4.1 and shown in Figure 1a calculates the potential streamflow depletion, $pSD_{k,t}$ at each stream segment k and time-step t, with no regard to whether there is sufficient water in the stream to meet this demand. In this section, we describe how incorporating the water available in each segment at each timestep ($WA_{k,t}$) allows us to calculate the estimated depleted streamflow ($Qd_{k,t}$) and actual streamflow depletion ($aSD_{k,t}$) for each segment and timestep (five days) as shown in Figure 1b. To do this, we consider that each stream segment has a "memory" of the amount of potential streamflow depletion that could not actually occur due to lack of instream flow, which we define as the banked depletion (BD). Initially, BD_k for each segment is zero. BD_k increases whenever $pSD_{k,t}$ exceeds $WA_{k,t}$, which occurs when instream flows are insufficient for the streamflow depletion demand. BD_k decreases when BD_k is greater than 0 and $pSD_{k,t}$ is less than $WA_{k,t}$, which occurs when there is both banked depletion and water available in the stream beyond simulated potential depletion. Specifically, the following algorithm is used to compute streamflow depletion (aSD) and streamflow (Qd) for each segment k and time t:

- Using the directed graph stream network (Figure 1b), aSD in time-step t upgradient of segment k is summed and added to the $pSD_{k,t}$ to provide the 'cumulative potential streamflow depletion' $CpSD_{k,t}$ in a segment:

$$CpSD_{k,t} = pSD_{k,t} + \text{sum}[aSD_t \text{ for all segments upstream of } k] \qquad \{\text{Eq. 1}\}$$

- If $CpSD_{k,t} \leq WA_{k,t}$, then:
  - The actual streamflow depletion, $aSD_{k,t}$, equals the cumulative potential streamflow depletion plus any accumulated banked depletion, $BD_{k,t}$ (see below), up to the amount of water available in the stream:

$$aSD_{k,t} = \min[(CpSD_{k,t} + BD_{k,t}), WA_{k,t})] \qquad \{\text{Eq. 2}\}$$

  - For the following time-step, $BD_{k,t+1}$ is then adjusted by the amount of delayed depletion that occurred in time-step t, unless it is zeroed out:

$$BD_{k,t+1} = \max[0, (BD_{k,t} - (aSD_{k,t} - CpSD_{k,t})] \qquad \{\text{Eq. 3}\}$$

- Else, if $CpSD_{k,t} > WA_{k,t}$, then:
  - The actual streamflow depletion is equal to the amount of water available and the stream has dried:

$$aSD_{k,t} = WA_{k,t} \qquad \{\text{Eq. 4}\}$$

  - The amount of potential streamflow depletion that did not occur is added to the accumulated delayed depletion available in the next time step, $BD_{k,t+1}$:

$$BD_{k,t+1} = BD_{k,t} + (CpSD_{k,t} - WA_{k,t}) \qquad \{\text{Eq. 5}\}$$

- For each timestep, the depleted streamflow is then calculated as the difference between water available and actual streamflow depletion:

$$Qd_{k,t} = WA_{k,t} - aSD_{k,t} \qquad \{\text{Eq. 6}\}$$

- Calculations are done sequentially, starting at the headwaters (nodes in the directed graph that do not have any inflowing segments) and moving downstream so that the actual streamflow depletion following banking and redistribution ($aSD_{k,t}$) propagates downwards to influence the timing of streamflow and depletion in downstream segments.

3.4.3 Defining water available

Incorporation of depletion routing and stream drying requires input data on the amount of water available, which is the streamflow that would have occurred without pumping. For this study, we compared two different water available sources: SVIHM and CNFD. The simulations using SVIHM to simulate water availability are intended to maximize commensurability with SVIHM estimated streamflow depletion, allowing us to understand the differences between observed streamflow, SVIHM, and ADFs when the non-depleted streamflow is well-known. The use of CNFD data is intended to test the potential applicability to watersheds that do not have locally-developed estimates of non-depleted streamflow to help understand potential applications of ADFs for unmodeled regions.

From SVIHM, we used output from two specific SVIHM simulations: the calibrated basecase (#1 in Table S1), with historical land use and water withdrawals for the period from 10/1/1990 to 9/30/2023; and a no-groundwater-irrigation scenario (#3b in Table S1), in which all model parameters and inputs are the same except that there is no groundwater pumping and groundwater-irrigation-dependent crops are replaced by natural vegetation. For ADF implementation, we used the segment-scale results of the SVIHM no-groundwater-irrigation scenario as our water available input. In SVIHM, we compared differences between these two scenarios to quantify the magnitude of streamflow depletion caused by groundwater pumping (Barlow & Leake, 2012; Zipper et al., 2022a). Other factors causing streamflow variability and groundwater-surface water exchange are identical to the basecase (including weather variability, surface water diversions, land use practices associated with surface water irrigation, etc). Hence, the differences between these two scenarios provide the hydrologic response to both changes in pumping and associated differences in the water balance that occur as a result of land use reverting to natural vegetation due to the lack of groundwater irrigation (Kouba & Harter, 2024). For our segment-resolution evaluation of ADF performance, we also compared ADF output with water available defined using an additional SVIHM scenario in which there was no groundwater pumping, but land use practices stayed the same throughout the watershed (i.e., groundwater-irrigated fields reverted to rainfed agriculture; scenario #2 in Table S1). While this is not a realistic agricultural practice for the region, this comparison allowed us to isolate the direct effects of pumping on streamflow, ignoring other changes to the water balance associated with conversion of groundwater-irrigated fields to natural vegetation. To assess the overall influence of the SVIHM scenario used for defining water available, we tested nine different SVIHM model configurations (Table S1, Figure S5, Figure S6). All SVIHM simulations used the version of the model calibrated and described by Tolley et al. (2019).

Table 1. Model simulations compared in this study.

Name	Streamflow depletion model	Water available source	Consideration of stream drying
ADF + SVIHM, No Drying	ADF	SVIHM, no irrigation in groundwater-dependent cropland scenario (#3b in Table S1)	No
ADF + SVIHM + Drying	ADF	SVIHM, no irrigation in groundwater-dependent cropland scenario (#3b in Table S1)	Yes
ADF + CNFD, No Drying	ADF	CNFD v2.1.1	No
ADF + CNFD + Drying	ADF	CNFD v2.1.1	Yes
SVIHM	SVIHM basecase with historical irrigation and land use (#1 in Table S1)	SVIHM, no irrigation in groundwater-dependent cropland scenario (#3b in Table S1)	Yes

To assess the potential for ADF applications in locations without locally calibrated streamflow models, we used data from version 2.1.1 of the CNFD database as water available input for ADFs. This version of CNFD has a Nash-Sutcliffe Efficiency > 0.9 for the 2010-2021 period via comparison to reference gages around the state, though reference gages are largely not available for northern portions of the state such as the Scott Valley area. We extracted monthly CNFD predicted flow for the October 1990 to September 2023 study period at each NHD segment in the study domain. In some parts of the study domain, the NHD stream segments used in CNFD were more finely discretized than the MODFLOW stream segments used by SVIHM (i.e., < 100 m resolution). For these segments, we averaged the predicted unimpaired flow from CNFD segments to match the spatial scale of SVIHM. This produced a timeseries of monthly CNFD unimpaired flow at the same spatial resolution of SVIHM. Since CNFD does not incorporate surface water diversions (which are not simulated by ADFs), we then subtracted out estimated surface water diversions from SVIHM at each segment. Therefore, the ADF + CNFD simulations provide an evaluation of the potential for ADFs to estimate streamflow depletion in settings where non-depleted streamflow is unknown, but estimates of surface water diversions have been developed.

For each water available source, we compared ADF simulations without stream drying (i.e., only steps shown in Figure 1a and described in Section 3.4.1) and with stream drying (i.e., including steps shown in Figure 1b and described in Section 3.4.2). The full collection of scenarios is described in Table 1.

3.5 ADF model evaluation

To evaluate the performance of the ADFs and the importance of incorporating stream drying into these models, we compared a variety of variables for each model configuration in Table 1. To evaluate the ability to simulate streamflow, we compared streamflow simulated by ADFs and SVIHM with observations from the USGS streamflow gauging station at the watershed outlet. This was primarily done at the model output timestep (5-day), though we also tested fit for monthly/annual average streamflow and the number of days streamflow dropped below important management thresholds. Since low flows are of particular management interest in this domain due to their impact on salmonid habitat, we used log-transformed streamflow, referred to as log(Streamflow), for our comparison. For the calculation of fit statistics when streamflow was equal to 0, we added a small value (1% of the minimum observed streamflow) to avoid infinite log(Streamflow) values. Beyond streamflow, at the watershed outlet we compared the total depletion at each timestep between ADFs and SVIHM. To evaluate performance throughout the network, we also compared segment-resolution streamflow and streamflow depletion between the ADFs and SVIHM.

We calculated fit statistics including the Kling-Gupta Efficiency (KGE; Gupta et al., 2009), coefficient of determination (R^2), and root mean squared error as a percentage of the range of observed streamflow values (normalized RMSE). The KGE is a fit statistic that integrates bias, correlation, and relative variability between simulated and observed values , with a KGE of 1.0 indicating a perfect agreement between simulated and observed data and KGE < -0.41 indicating that using the mean of the observational data would be a better fit than the model (Knoben et al., 2019). The R^2 represents the overall degree of correlation between the model and observations. The normalized RMSE provides an indication of the degree of error in proportion to the magnitude of observed variability.

4. Results and Discussion

4.1 Simulating streamflow and streamflow depletion at the watershed outlet

The ADF + SVIHM models were able to accurately simulate both streamflow (Figure 3a, Figure S1) and streamflow depletion (Figure 3b, Figure S2) when drying was included. Across most years, ADFs without drying underestimate streamflow and overestimate streamflow depletion during summer and early fall, and as a result incorrectly predict that the stream should dry at the watershed outlet during the summer. In contrast, the ADF + SVIHM + Drying models accurately simulate the depletion of flow without drying across all years (Figure 3a). Overall, the performance of the ADF + SVIHM + Drying models for simulating for log(Streamflow), assessed via comparison to the USGS stream gauging data, is comparable to the performance of SVIHM (Figure 4). The ADF + SVIHM + Drying models have a KGE of 0.91 (compared to 0.94 for SVIHM), an R^2 of 0.92 (compared to 0.93 for SVIHM), and a normalized RMSE of 5.9% (compared to 6.5% for SVIHM). The ADF + SVIHM, No Drying models have substantially worse agreement with observations (KGE of 0.02, R^2 of 0.76, normalized RMSE of 27.2%), highlighting the strong improvements in ADF performance from the incorporation of stream drying.

Due to their lower data requirements relative to numerical models, ADFs are potentially useful for water management decision support in settings without existing integrated groundwater-surface water models (Huggins et al., 2018; Li et al., 2022). Our ADF + CNFD simulations provide one opportunity to evaluate their potential application in these settings. We found that the ADF + CNFD models, which define water available based on the statewide unimpaired flow model, effectively captured temporal patterns of streamflow and streamflow depletion, but streamflow is biased high (Figure 3). The ADF + CNFD models were parameterized using calibrated hydrostratigraphic parameters from SVIHM to maximize the commensurability of the comparison, and absent this information, may have performed differently (see Section 4.4.2 for more discussion of ADF parameterization and uncertainty). The ADF + CNFD model results also have a blockier pattern because the CNFD is a monthly model, unlike the daily SVIHM output.

The high bias in depleted streamflow in the ADF + CNFD model occurs because unimpaired flow estimates from the CNFD model tend to be higher than the SVIHM no-groundwater-irrigation scenario (Figure S5), which may result from several factors. The first is that the two models are not designed to simulate the same thing. The SVIHM no-groundwater-irrigation scenario still includes agricultural land cover in areas of the domain where irrigation is supplied by direct surface water diversions, while the CNFD is meant to represent unimpaired flow under a natural vegetation land cover and unaltered land use (though the volume of the diversions is subtracted out). Non-irrigated agricultural land and an unaltered landscape without modifications such as ditching would likely produce differences in the timing and magnitude of fluxes such as groundwater recharge and evapotranspiration that can lead to differences in streamflow, even in the absence of pumping. To assess this potential driver of differences, we compared CNFD to additional SVIHM model scenarios with a variety of different natural vegetation parameterizations. We found that the SVIHM natural vegetation scenarios still had a lower simulated streamflow than CNFD (Figure S5). A second potential reason for disagreement between these two models could be that the CNFD is trained on reference watersheds across the state (Zimmerman et al., 2018), most of which are watersheds discharging from mountain regions without upstream alluvial valleys. Therefore, it is possible that the important hydrological processes in the Scott Valley are outside the range of training watersheds and may have different dynamics that are not well-captured by CNFD. Finally, we would generally expect SVIHM to be more accurate for the Scott Valley because it is locally calibrated, while CNFD is a statewide model. It may be possible to mitigate the high bias of CNFD or other unimpaired flow models through approaches such as regional bias-correction or ADF calibration, which are not tested in this study but discussed in Section 4.4.2.

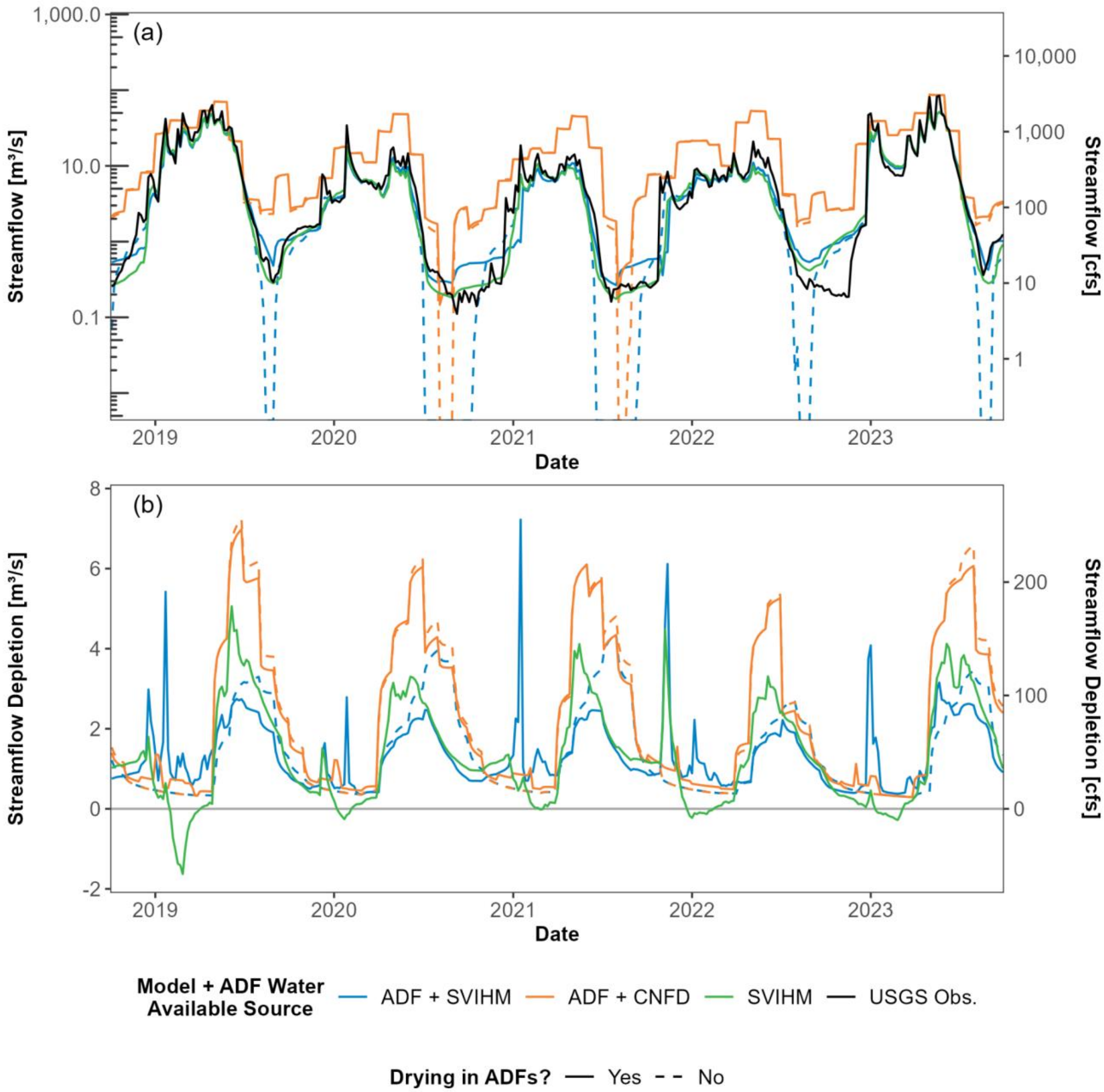


Figure 3. Comparison of ADFs to stream gauge and numerical model data at the watershed outlet over the last 5 years of the study period. (a) Streamflow. (b) Streamflow depletion. The USGS Obs. data is not included in panel (b) because streamflow depletion cannot be quantified from observational data alone. Results from all 33 study years are shown in Figure S1 and S2.

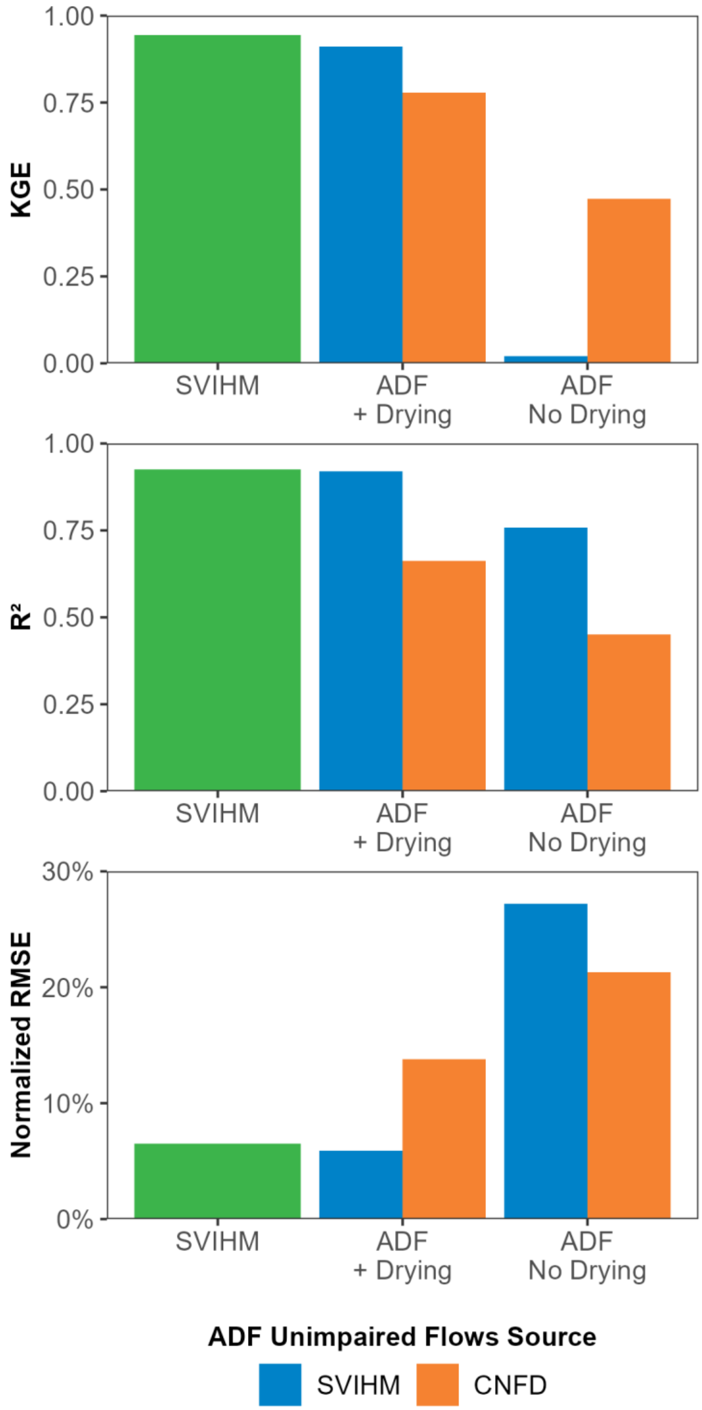


Figure 4. Model fit metrics for daily log(Streamflow), for SVIHM and ADFs with and without drying, calculated via comparison to USGS gauge at the watershed outlet. Normalized RMSE is the RMSE divided by the range of observed values. For fit statistics based on water year type, see Figure S3.

4.2 Impacts of stream drying on timing and magnitude of streamflow depletion

The ADF models including stream drying have better agreement with observations compared to the no drying models (Figure 3, Figure 4). Simulating stream drying is critical because upstream flow intermittency can lead to delays in the manifestation of streamflow depletion at the watershed outlet, even if the outlet itself does not dry, due to changing stream connectivity and storage dynamics within the stream network. This can lead to a behavior in which there are multiple peaks in streamflow depletion within a year, including outside the pumping season (Figure 3b), which has not to our knowledge been described in the literature.

Mechanistically, the multiple streamflow depletion peaks are caused by changes in hydrologic connectivity in both the longitudinal (upstream-downstream stream network disconnection) and vertical (stream-aquifer) dimensions. In the Scott Valley, the first streamflow depletion peak occurs early in the pumping season, when seasonal pumping has led to the onset of streamflow depletion in the watershed but there is still sufficient surface water available from snowmelt (Peak 1 in Figure 5). This pumping steadily depletes streamflow until drying occurs, typically first in relatively small tributaries flowing into the main stem of the river, at which points these tributaries become longitudinally disconnected from the outlet. Once the stream network starts to dry, additional pumping leads primarily to groundwater depletion, rather than streamflow depletion, and the water table drops below where it would have been in a non-pumped condition. As a result, once fall/winter rains begin and the stream network starts to rewet, there is enhanced infiltration through the streambed in order to refill groundwater storage and reconnect the stream to the aquifer (peak 2 in Figure 5). These changes in hydrologic connectivity are explicitly simulated in the process-based SVIHM and reasonably reproduced in the simple ADF water budget approach developed in this study (Figure 1b). Since the primary impacts of drying are changes in the timing (but not total volume) of streamflow depletion, incorporating these dynamics is important to accurately simulate daily and monthly average streamflow, but not influential for annual streamflow estimates (Figure 6).

The timing of stream drying and rewetting, and related changes in stream connectivity, are critically important for local aquatic ecosystems and downstream water users (Price et al., 2021, 2024). In the Scott River, the timing of the transition from the dry to wet season is a key ecohydrological process supporting local salmonid populations (Kouba & Harter, 2024). Since stream intermittency is globally widespread, particularly in semi-arid to arid regions where irrigated agriculture is common (Hammond et al., 2021; Messager et al., 2021; Shanafield et al., 2021), it suggests these lagged depletion peaks during stream rewetting may be a common phenomena that require explicit consideration when developing integrated groundwater and surface water management plans (Lapides et al., 2022). The water budget-based method we developed provides a parsimonious approach that appears to work well in seasonally dry watersheds like the Scott River Valley. In watersheds with different drying regimes (Price et al., 2021), particularly those with multi-year shifts between dry and wet regimes driven by interconnections between alluvial and regional aquifer systems (Zipper et al., 2022b), additional evaluation is needed to determine whether this approach is suitable.

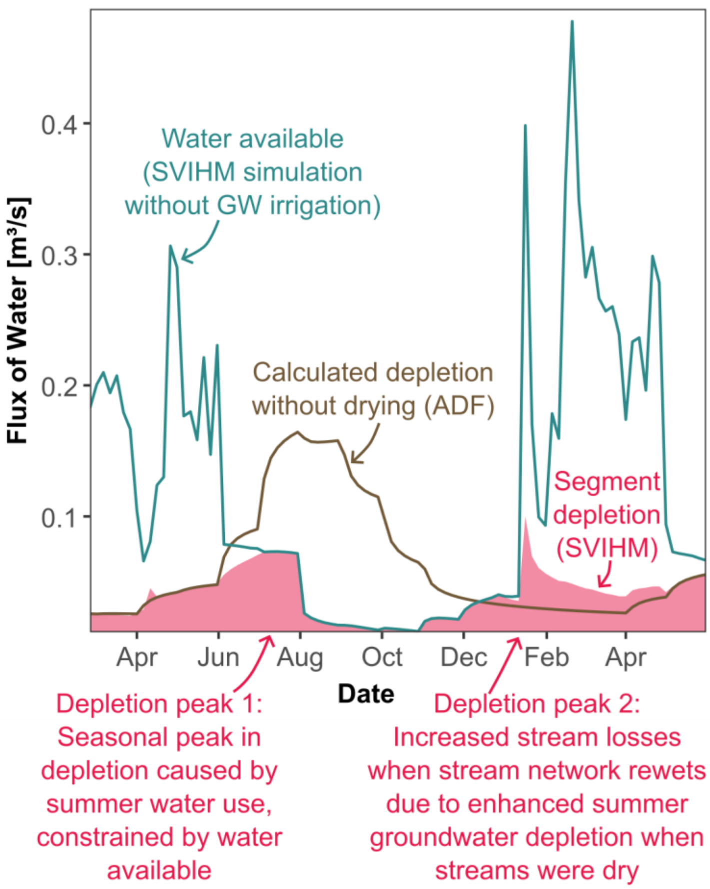


Figure 5. Example illustrating multiple streamflow depletion peaks, which forms the basis for the ADF implementation of drying in Figure 1b. The blue line shows the SVIHM no-groundwater-irrigation scenario, which defines water available, and the red shading shows the difference between the SVIHM no-groundwater-irrigation scenario and basecase scenario, illustrating the double peak dynamics in the process-based numerical model. The brown line shows ADF estimated depletion without drying to illustrate what depletion would have been in the absence of stream drying. Data shown here are for Patterson Creek, a tributary to the Scott River on the west side of the study domain, for the March 2020 to May 2021 period. SVIHM scenarios are detailed in Table S1.

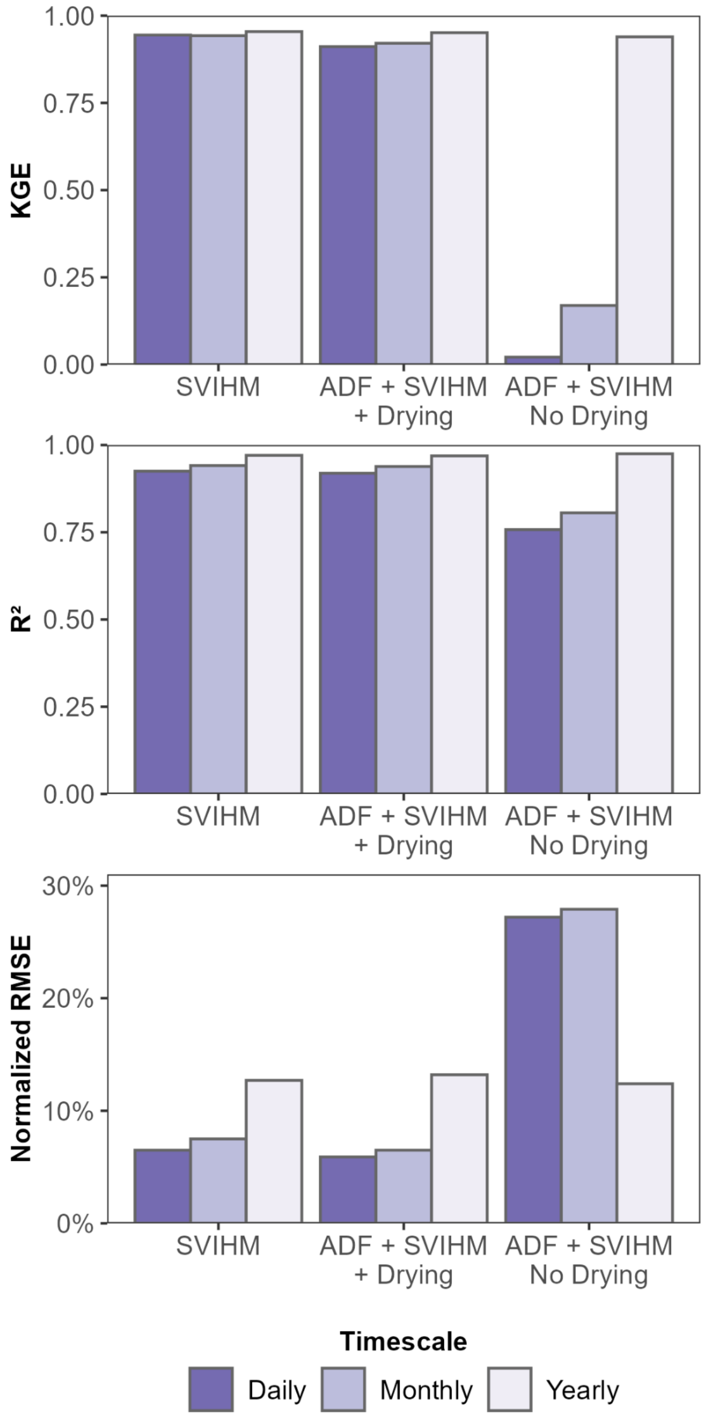


Figure 6. Model fit metrics based on timescale of comparison for log(Streamflow), for SVIHM and ADFs with and without drying, calculated via comparison to USGS gauge at the watershed outlet. ADFs shown here are using the SVIHM no-groundwater-irrigation scenario as available water. Normalized RMSE is the RMSE divided by the range of observed values. The Yearly fit is calculated as April-March average streamflow, based on the timing of the onset of seasonal pumping in the watershed.

4.3 Simulating streamflow and streamflow depletion throughout the watershed

To evaluate the accuracy and utility of ADFs throughout the Scott Valley watershed, including in settings where there was no stream gauging data available, we compared segment-resolution ADF + SVIHM + Drying output to results from SVIHM. We excluded stream segments where SVIHM results indicated depletion was < 1% of non-depleted streamflow > 90% of the time to focus only on locations with substantial pumping impacts. We found that agreement between the two modeling approaches was generally good (KGE > 0) to excellent (KGE > 0.5) for log(Streamflow) when using the SVIHM no-groundwater-irrigation scenario to define ADF water available (Figure 7a). Agreement in terms of streamflow depletion (Figure 7b) was worse than agreement for streamflow, primarily in tributary regions, but generally had KGE > 0.5 along the main stem of the Scott River.

While our primary comparisons between the ADFs and SVIHM used output from SVIHM that modified pumping and land use simultaneously (scenario #3b from Table S1), we also compared streamflow depletion using an alternate SVIHM parameterization, in which pumping was turned off but groundwater-irrigated areas remained in agricultural land cover (scenario #2 from Table S1). This is not a realistic representation of feasible land use practices in the Scott Valley, since groundwater-supported agriculture would likely revert to non-agricultural land cover if irrigation was unavailable, but rather a model experiment that allows us to isolate the impacts of groundwater pumping on streamflow in SVIHM to provide a more commensurate comparison to ADF results which directly simulate the impacts of pumping (not land use change) on streamflow. We found that agreement in simulated streamflow depletion was much stronger using scenario #2 compared to scenario #3b (Figure 7d), with only a slight degradation in simulated streamflow (Figure 7c). This comparison among SVIHM scenarios highlights the need for segment-level management decision-making to consider the full suite of hydrologic changes associated with land use and water management decisions. Since ADFs directly simulate streamflow depletion caused by changes in pumping and do not simulate other changes in the water balance associated with conversion between natural and agricultural land cover, it suggests that ADF performance could be further improved by developing complementary approaches to assess holistic changes to the water balance associated with pumping decisions, such as differences in recharge, infiltration, and runoff. If independent estimates of changes in consumptive water use could be developed (for example, through approaches like remote sensing of evapotranspiration; Asarian et al., 2025), these water balance changes could be integrated with ADF-based estimates of pumping impacts on streamflow to provide a full accounting of changes in the water balance and impacts on streamflow.

Agreement for both streamflow and streamflow depletion tends to be best for the higher-streamflow and more heavily-depleted segments along the main stem (Figure 7, Figure S7) and worst in isolated tributaries where there is little streamflow and little depletion. In tributaries, ADF estimates of streamflow depletion tended to be greater than SVIHM and therefore ADF streamflow estimates were lower than SVIHM and included more frequent drying than SVIHM. However, the strong agreement in the more heavily-depleted areas means that ADFs are capturing the majority of pumping impacts accurately. KGE is > 0.5 in ~55% of the segments for log(Streamflow) (Figure 8a), and these segments represent >80% of total streamflow depletion in the domain (Figure 8b). Similarly, KGE is > 0.5 in ~25% of segments for streamflow depletion (Figure 8a), but these represent ~70% of the total streamflow depletion in the domain (Figure 8b). This indicates that the impacts of pumping are best-simulated by ADFs in the settings where depletion is greatest and accuracy is most important. In sum, the ADF simulations including drying effectively simulate both the magnitude and spatial distribution of streamflow depletion in this domain.

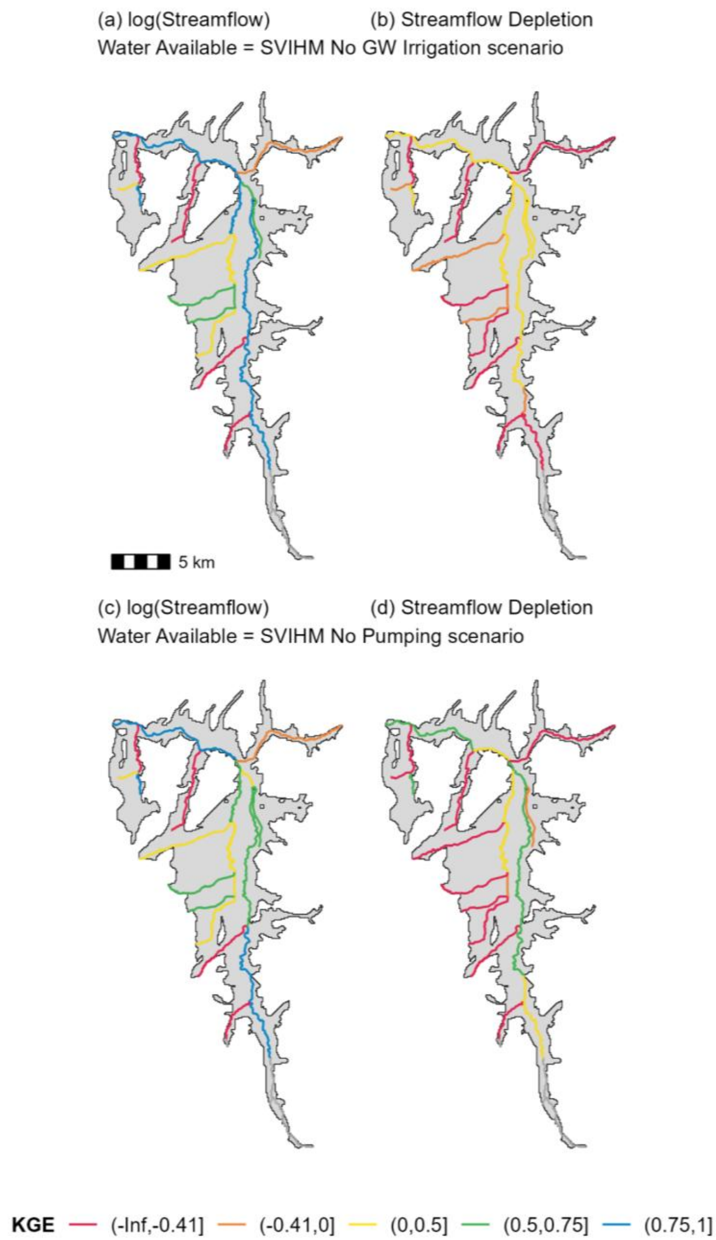


Figure 7. Distribution of segment-resolution agreement between ADFs and SVIHM for (a) streamflow and (b) streamflow depletion. ADF models shown here include drying. Panels (a) and (b) use the SVIHM no groundwater irrigation scenario (#3b from Table S1) and panels (c) and (d) use the SVIHM no pumping scenario (#2 from Table S1). A KGE < -0.41 indicates that the model performs worse than using the mean of observational data (Knoben et al., 2019).

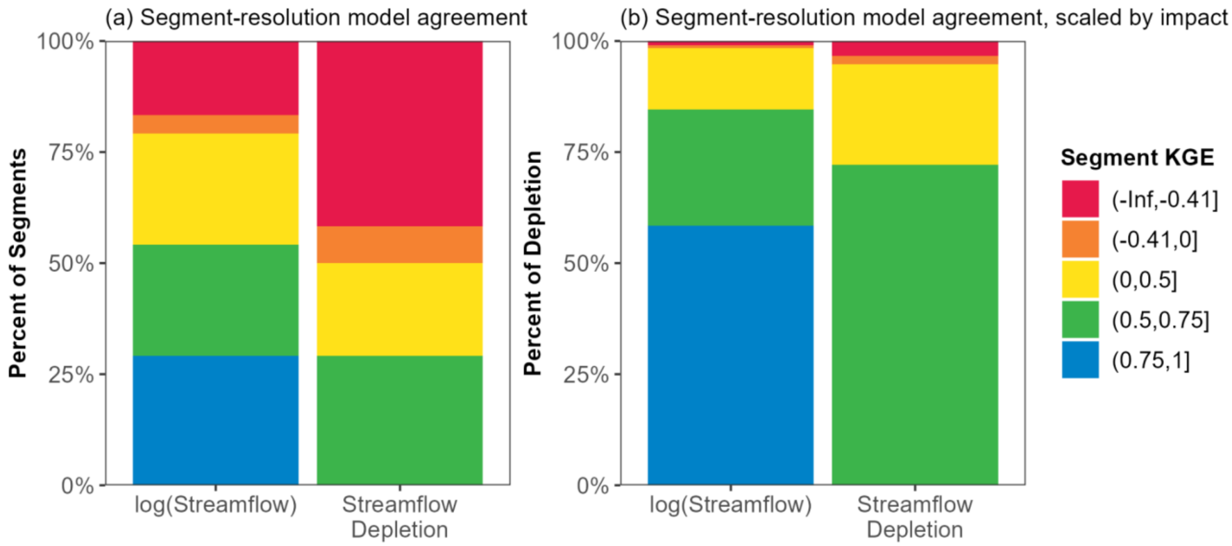


Figure 8. Segment-resolution agreement between ADFs and SVIHM, expressed as (a) the percentage of the number of segments in the model domain and (b) the percentage of mean simulated streamflow depletion (from SVIHM) in the model domain. NA values indicate segments where a KGE could not be calculated because the ADFs did not simulate any depletion, which are the two segments at the southern inlet to Scott Valley. These results show the ADF + SVIHM + Drying model configuration with water available and SVIHM streamflow depletion calculated using the SVIHM no-pumping scenario (#2 in Table S1), as visualized in Figure 7c-d.

4.4 Integration with water management decision-making

<u>4.4.1 Simulation of critical streamflow management thresholds</u>

Accurate estimates of streamflow depletion are critical to effective integrated groundwater and surface water management. To determine if ADFs have sufficient accuracy to support local ecohydrological management decisions, we evaluated their ability to simulate the duration of streamflow below monthly minimum streamflow requirements for the gauging station at the Scott Valley watershed outlet. These streamflow thresholds are designed to provide ecological flows sufficient for salmonid survival at all life stages and vary throughout the year (Figure S8), from a minimum of 0.85 m^3/sec (30 ft^3/sec) in August to a maximum of 5.7 m^3/sec (200 ft^3/sec) in January (California State Water Resources Control Board [SWRCB], 2025). The monthly minimum streamflow requirements were developed in 2021 by the SWRCB, as recommended by the California Department of Fish and Wildlife in coordination with the National Marine Fisheries Service, and were readopted in 2022, 2024, and 2025 under additional drought emergency regulations. Under emergency drought regulations, the SWRCB has the right to curtail water users if Scott River flows fall below minimum flow requirements. As of 2025, the SWRCB is in the process of pursuing the development and implementation of permanent instream minimum flow requirements for the Scott River. As a result, the ability of streamflow depletion models to accurately estimate streamflow relative to these minimum instream flow thresholds is critical to water resources management and the future development of decision-support tools.

The ADF + SVIHM + Drying models simulate the annual duration of threshold exceedance with comparable accuracy to the locally-calibrated SVIHM model (Figure 9). The duration of model-simulated threshold exceedance agrees well with observations, with a mean absolute error (MAE) of 7.3% for the ADF + SVIHM + Drying model and 9.5% for the SVIHM model. In general, the models (both SVIHM and ADF + SVIHM + Drying) tend to simulate slightly more threshold exceedance than was observed during dry years.

For basins without locally calibrated models, which are areas that ADFs can provide potentially useful and low-cost estimates of streamflow and streamflow depletion, input data of water available without pumping are necessary to convert depletion calculated by ADFs to streamflow and, if needed, redistribute in time to account for stream drying. We tested the applicability of the CNFD for this purpose and found that threshold exceedance predicted by the ADF + CNFD + Drying models was positively correlated ($r = 0.42$) with the observed threshold exceedance, but the percent of time exceeding the thresholds is underestimated by the ADF + CNFD + Drying model (MAE = 24%; Figure 9b). This occurs because the CNFD unimpaired flow estimates are higher than the SVIHM no-groundwater-irrigation scenario (Figure S5), as discussed in Section 4.1. The resulting overestimates in depleted streamflow and underestimates in threshold exceedance when using the CNFD could lead to inaccurate predictions of when and where streamflow is below critical environmental thresholds and/or streams are dry. For example, depleted streamflow in the ADF + CNFD + Drying models tends to remain above the in-stream flow thresholds for most of the year, even during dry conditions like 2015 and 2021. This indicates that, for decision-making processes, locally refined CNFD estimates may be valuable for improving ADF model predictions (see Section 4.4.2 for additional details).

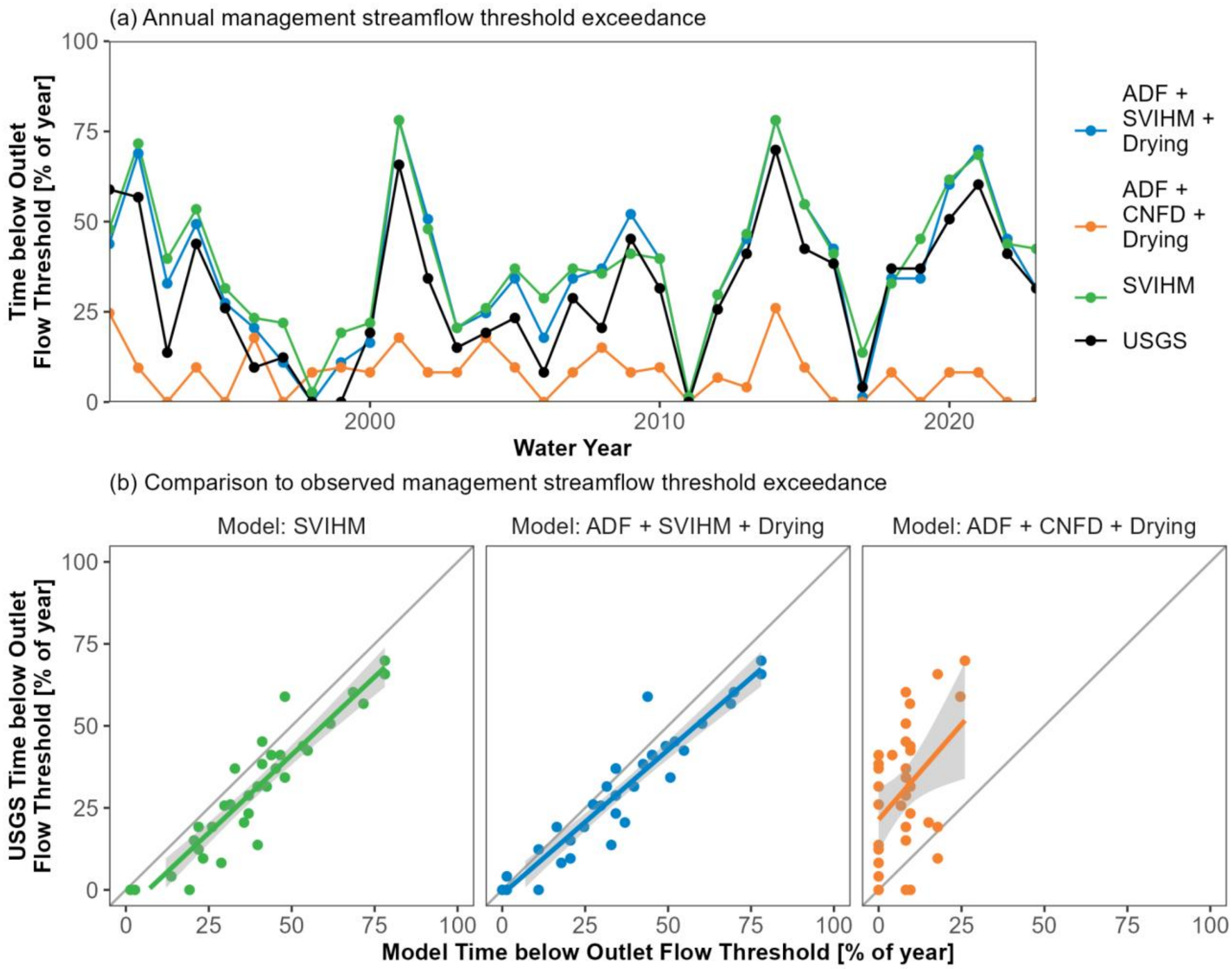


Figure 9. (a) Number of days per year with watershed outlet streamflow below California Department of Fish and Wildlife management thresholds for each modeling approach and USGS observed flow. (b) Comparison of each modeling approach to USGS observations. ADF simulations plotted here include drying.

4.4.2 Transferability to other settings

Scott Valley was an ideal setting to develop and test the methods developed in this study due to the highly transmissive aquifer that is well-connected to the stream, the availability of high-quality input datasets developed as part of the creation of SVIHM, and the presence of both SVIHM simulations and streamflow observations for evaluation. The potential applicability of ADFs in other watersheds would be dependent on the suitability of analytical models for those settings. For example, ADFs would not be expected to work well in settings where the water table is disconnected from the stream (e.g., by a confining layer) since ADFs assume a connection between the groundwater being pumped and the surface water network. Additionally, settings with a highly heterogeneous subsurface, such as where fracture flow dominates stream-aquifer interactions, may not be well-simulated by ADFs since the simplifying assumptions in analytical models are violated. These types of hydrogeologic settings are also notoriously hard to simulate with numerical models and an area where additional method development is needed.

However, where the subsurface is heterogeneous but groundwater flow is still through porous media, it is possible to incorporate some heterogeneity into ADFs by integrating multiple geological units into calculations of effective transmissivity and storativity (as described in Appendix A of Li et al., 2022) and defining different hydrostratigraphic parameters separately for each well-stream pair to account for spatial differences in subsurface properties. This averaging process, however, inherently will reduce the ability of ADFs to represent spatial heterogeneity of responses to pumping and lead to uncertainty in model output.

ADFs are also applicable only where there is sufficient input data. Groundwater pumping locations, rates, and schedules are critical inputs to both analytical and numerical models, but water use data are unavailable in many settings (Marston et al., 2022). Flowmeters on pumping wells are the most accurate approach to developing water use input datasets, but these data are rarely collected or publicly available (Foster et al., 2020). Remote sensing approaches may be a potentially valuable tool for estimating field-resolution water use (Ott et al., 2024; Zipper et al., 2024, Jalilvand et al., 2023), though these approaches can struggle to identify changes in irrigation efficiency when consumptive use does not change (Asarian et al., 2025). Other approaches to estimate groundwater use include interpretation of groundwater hydrographs (Brookfield et al., 2024) and the application of crop models (Lamsal & Marston, 2025). The SVIHM estimates water using process-based simulations of crop water requirements to estimate local water needs, and partitions these between surface water and groundwater sources (Tolley et al., 2019). Since water use is a primary control over the volume of streamflow depletion, continued refinement of techniques for estimating the timing and location of groundwater withdrawals is critical to improving analytical, numerical, or statistical models of streamflow depletion.

For incorporation of stream drying into ADFs, estimates of segment-resolution water available (i.e., the $WA_{k,t}$ term described in Section 3.4.2) are required. In settings that do not have locally-calibrated streamflow models, there are multiple approaches that could be explored to develop reliable water available estimates. In California, regional statistical models like CNFD are available, and in other domains there is an increasing abundance of data-driven models that could provide local non-depleted streamflow estimates (Kratzert et al., 2019, 2022). Since data-driven modeling, to date, has primarily focused on reference watersheds with relatively minor human impacts, predictions from these models for ungauged basins may be representative of non-depleted streamflow. However, these data-driven modeling efforts primary focus on watershed-scale predictions, rather than providing segment-resolution data that is needed for incorporation into ADFs. There are also an increasing number of regional- to national-scale process-based models, such as the National Hydrologic Model (NHM; Regan et al., 2019) or ParFlow-CONUS (Condon & Maxwell, 2019; Maxwell et al., 2015), which simulate streamflow at the resolution of individual stream segments based on governing physical equations. Since many national-scale models do not explicitly incorporate groundwater pumping (Bosompemaa et al., 2025; Towler et al., 2023), or can be run in both pumping-on and pumping-off configurations (Condon & Maxwell, 2019), their flow estimates could provide a useful segment-resolution water available input for the ADF models.

Beyond input data needs, incorporating a local calibration and bias correction approach into ADF workflows would likely improve transferability and better match observed streamflow. The ADFs used in this study are not calibrated, though they use calibrated model parameters from SVIHM as inputs. In most settings, hydrostratigraphic inputs (such as transmissivity and storativity) and ADF-specific parameters (such as the weighting factor for depletion apportionment) will need to be estimated and refined based on local data. Developing appropriate parameter estimates can add time and expense to the model development process, but could decrease model uncertainty by better constraining ADF inputs. The primary ADF uncertainty addressed in this study is the result of different water available input datasets, through our comparison of CNFD and multiple SVIHM scenarios (in Table S1), and we find that selection of an appropriate water available data source is essential to developing accurate estimates of depleted streamflow and stream drying. For use in settings without well-known input data, ADF model parameters and inputs (including water available) could be calibrated to improve agreement with observed streamflow data, as is typically done for numerical models of streamflow depletion (Barlow et al., 2018; Fienen et al., 2018; Foster et al., 2021). This process would provide an opportunity for calculating robust uncertainty estimates, which are critical to effective decision-support modeling efforts (Doherty & Moore, 2020) and enhance user confidence in model outputs (Afzal et al., 2025). There are existing open-source tools for parameter estimation and uncertainty analysis that are well-suited for integration with ADFs (Ford et al., 2024; White et al., 2021).

For ungauged areas where no streamflow data are available for calibration, additional work would be needed to identify locally-appropriate refinements. One potential pathway for this could be parameter regionalization, in which calibrated parameters are developed for locations where outputs can be compared to observations, and then these parameters are transferred to other settings with similar hydrological characteristics (Bawa et al., 2025; Beck et al., 2016; Mihret et al., 2025). Future work evaluating the feasibility of this approach, and resulting uncertainties, would be valuable to better understand the potential for transferability to other domains.

4.4.3 Integrating multiple modeling approaches to meet management needs

Streamflow depletion cannot be measured directly at the scales relevant to regional water resource management, and therefore modeling tools must be developed to support decision-making (Zipper et al., 2024). While a globally relevant issue, this technical need has recently emerged within two management contexts in California. As previously mentioned, assessing depletion of interconnected surface waters is a requirement under SGMA, and many groundwater managers across the state must develop models capable of estimating streamflow depletion. Additionally, courts in California have recently ruled that groundwater withdrawals are subject to regulation under the Public Trust Doctrine on the basis that groundwater withdrawals have the potential to harm navigable waterways (*Environmental Law Foundation v. State Water Resources Control Board*, 2018). This has resulted in county agency efforts to revise well permitting regulations and has highlighted the need for modeling tools to estimate potential impacts of streamflow depletion on public trust resources such as navigable waters or aquatic ecosystems.

In many management contexts, it is likely that a combination of analytical and numerical methods will be implemented as groundwater managers balance resource constraints (time, cost, available technical expertise, risk of significant impacts, etc., as discussed in Zipper et al., 2022a). Our analysis demonstrates that ADFs may be implemented effectively as low-complexity, low-cost techniques in hydrogeologic settings where their simplifying assumptions hold (i.e. alluvial groundwater subbasins where a high degree of interconnectivity between surface and groundwater resources exist) and ADFs can be accurately extended outside these conditions where reasonable process-representations can be developed, as we demonstrate with our simplified approach for stream drying (Figure 1b). For example, remote sensing tools could provide an opportunity to estimate consumptive water use by agriculture, which could be used to account for potential changes in the water balance associated with changes in pumping such as irrigation return flows (Asarian et al., 2025). This emerging ADF modeling framework is promising based upon its ability to be developed as a cost-effective solution to estimating streamflow depletion due to groundwater pumping and potential integration into web-based decision support tools (Huggins et al., 2018). Numerical models will continue to be key tools in complex settings where water resources management decision-making benefits from a detailed representation of water balance dynamics or necessitates complex management scenario simulations (managed aquifer recharge, phreatophytic evapotranspiration dynamics, reservoir operations, etc.). Importantly, pumping changes are often associated with changes to land use and impact other hydrological fluxes including recharge, evapotranspiration, and runoff. To avoid unintended consequences, effective water management strategies must account for the holistic impacts of pumping decisions on the water balance. A unified modeling philosophy that utilizes a suite of streamflow depletion modeling methods in varying contexts and considers integrated impacts of land use and water management changes simultaneously will provide groundwater managers with the flexibility to develop decision-support tools appropriate to the scope of their specific needs.

5. Conclusions

Analytical depletion functions (ADFs) are a low-complexity and scalable approach that provide accurate estimates of both streamflow and streamflow depletion for the Scott River Valley. This work describes pumping-induced stream drying and resulting lagged pumping impacts on streamflow, where disconnection during drying delays streamflow depletion until the seasonal rewetting period, and provides a mechanistic, water-budget-based framework for simulating these processes. We find that ADF estimates of streamflow are comparable to observed streamflow from a USGS gauging station at the watershed outlet (KGE = 0.91, R^2 = 0.92, normalized RMSE = 5.9%) and consistent with simulated streamflow by SVIHM, a process-based integrated hydrologic model developed for the watershed. ADFs also accurately predict how frequently streamflow drops below critical management thresholds (MAE = 7.3%).

However, developing accurate estimates of streamflow and streamflow depletion using ADFs requires a locally accurate estimate of non-depleted streamflow (what streamflow would have been without groundwater pumping). ADFs simulate the direct effects of pumping on streamflow, and do not explicitly account for other changes in the water balance caused by the conversion of natural vegetation to irrigated agriculture, and therefore could be enhanced by integration with estimates of other water balance changes associated with pumping practices, for example remotely sensed estimates of differences in consumptive water use. We show that using a regional statistical model, the California Natural Flows Database (CNFD), provided reasonable temporal dynamics, but estimated non-depleted streamflow by CNFD is higher than the non-depleted streamflow simulated by SVIHM. As a result, ADFs using CNFD as an input overestimate streamflow. This suggests that developing an approach to locally calibrate and refine ADFs using CNFD may have potential for streamflow depletion assessments in ungauged and unmodeled watersheds. For integration into decision-support applications, future work should also include explicit quantification of uncertainty associated with different structural and parametric components of ADF estimates to ensure reliability.

Incorporating stream drying, and associated temporal redistribution of streamflow depletion, is critical to accurately estimate streamflow and streamflow depletion in this domain at sub-annual scales. We demonstrate that reductions in hydrologic connectivity caused by stream drying can lead to substantial lags in the manifestation of streamflow depletion. These lags occur because, when the streams dry, continued pumping leads to increased groundwater depletion as the stream and aquifer are disconnected. When the hydrologic system rewets in the fall/winter rainy season, there are greater stream losses due to increased infiltration through the streambed until the depleted groundwater system is replenished and the stream-aquifer system is reconnected. We incorporate this process into ADF models using a simple water budget approach at the stream reach resolution and route the resulting changes in the timing of streamflow downstream through the river network. This representation of stream drying shows strong agreement with both SVIHM and observed streamflow and advance ADFs towards potential application as a water management decision-support tool.

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Data and Code Availability

ADFs are available in the streamDepletr package for R: https://cran.r-project.org/package=streamDepletr

SVIHM is available at: https://github.com/UCDavisHydro/SVIHM

The data and code used in this study are available on HydroShare: http://www.hydroshare.org/resource/f36f9b62549c46498bba89db66a8cbc5

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Declaration of interests

The authors have nothing to declare.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the lead author used ChatGPT in order to explore alternate programming approaches to create directed stream network graphs and incorporate stream drying, which were then tested by the author for suitability and efficiency. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Supplemental Information for "Lagged impacts of groundwater pumping on streamflow due to stream drying: Incorporation into analytical streamflow depletion estimation methods" by Zipper et al.

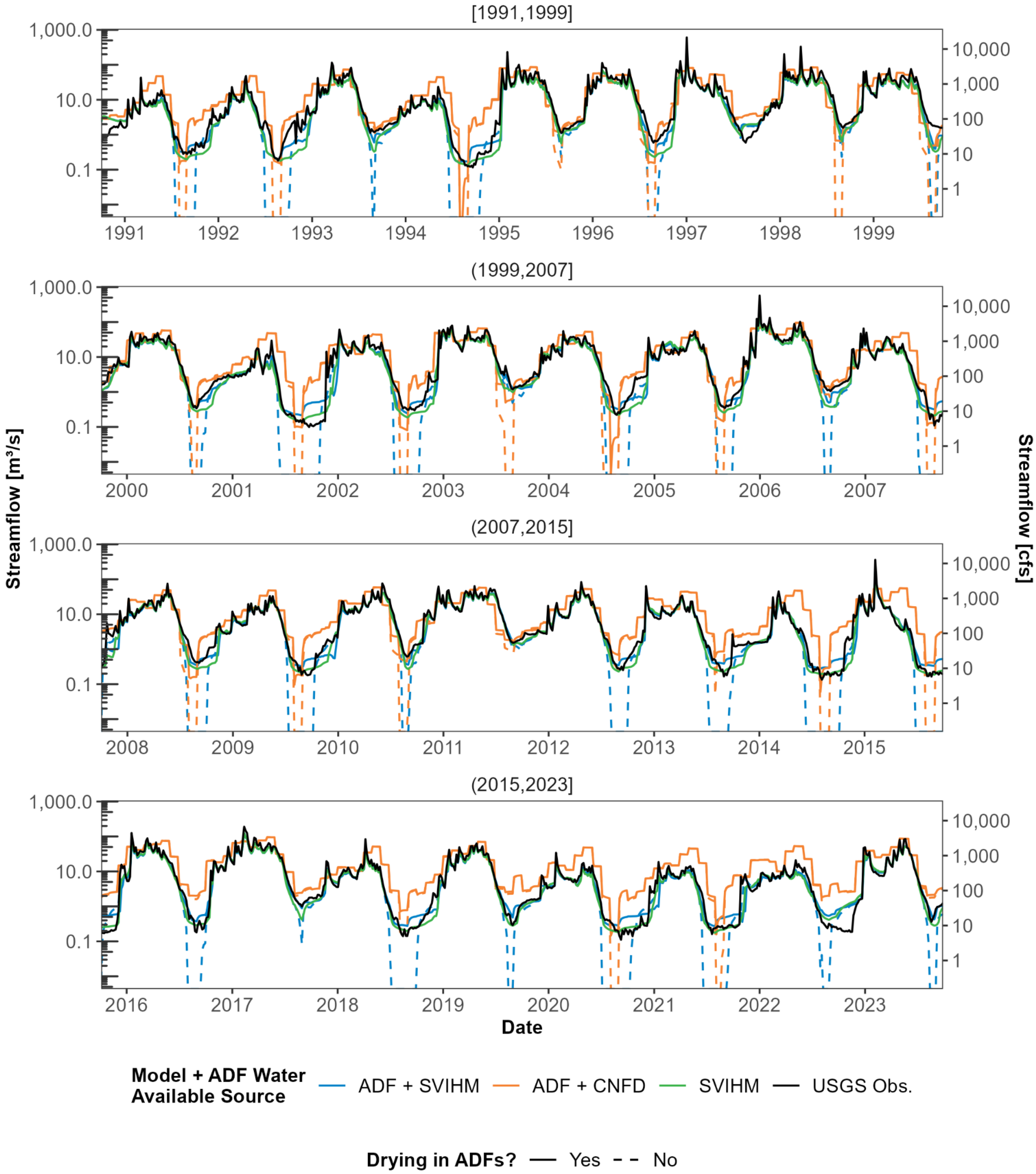
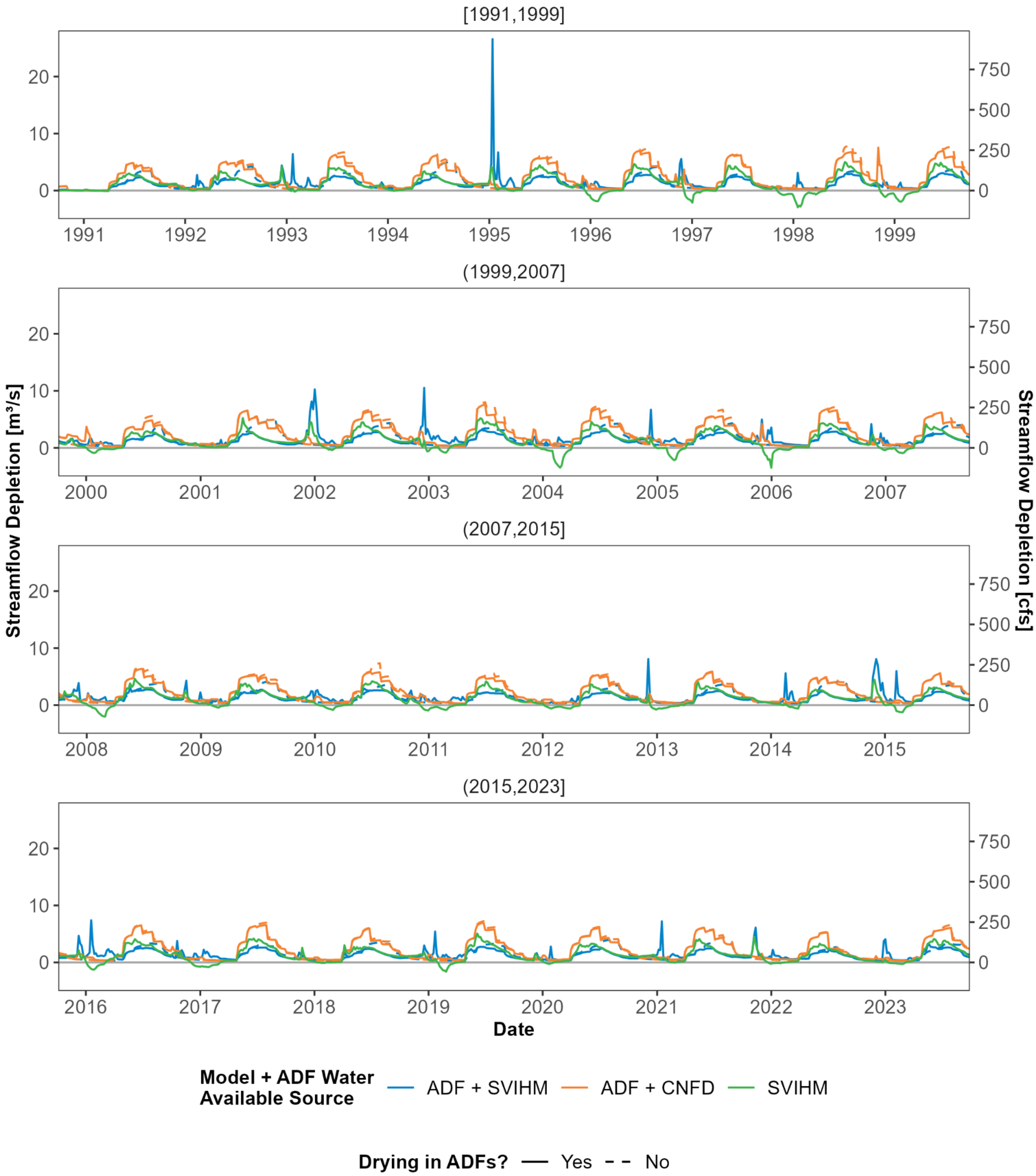


Figure S1. Streamflow comparison among ADFs, SVIHM, and observations at the watershed outlet for the 33 year study period.



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1204 Figure S2. Streamflow depletion comparison between ADFs and SVIHM at the watershed outlet for the 33 year
1205 study period.

1206

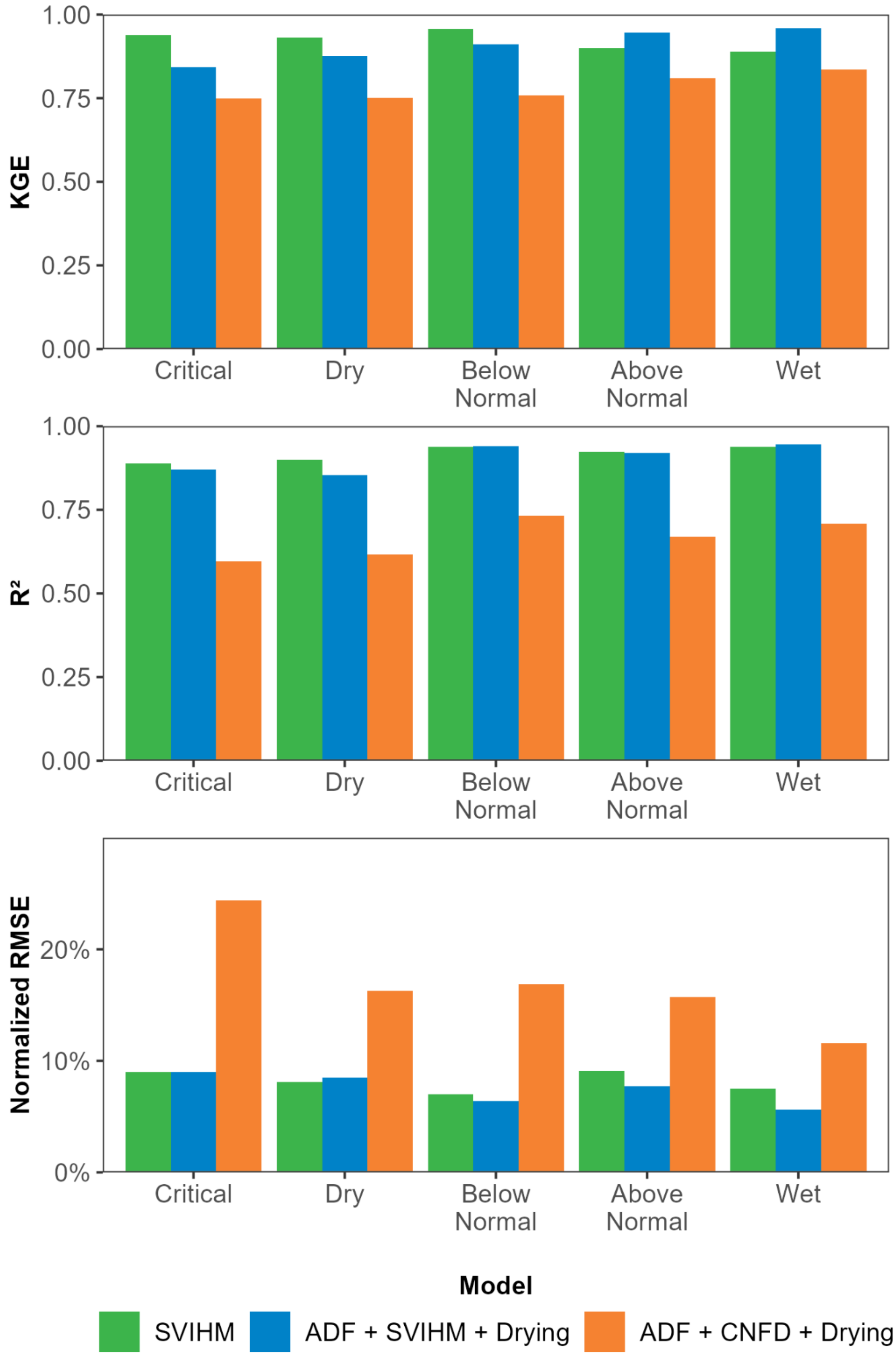

Figure S3. Model fit metrics by water year classification. Metrics are calculated via comparison to USGS gauge for log(Streamflow). ADF models include drying. Normalized RMSE is the RMSE divided by the range of observed values.

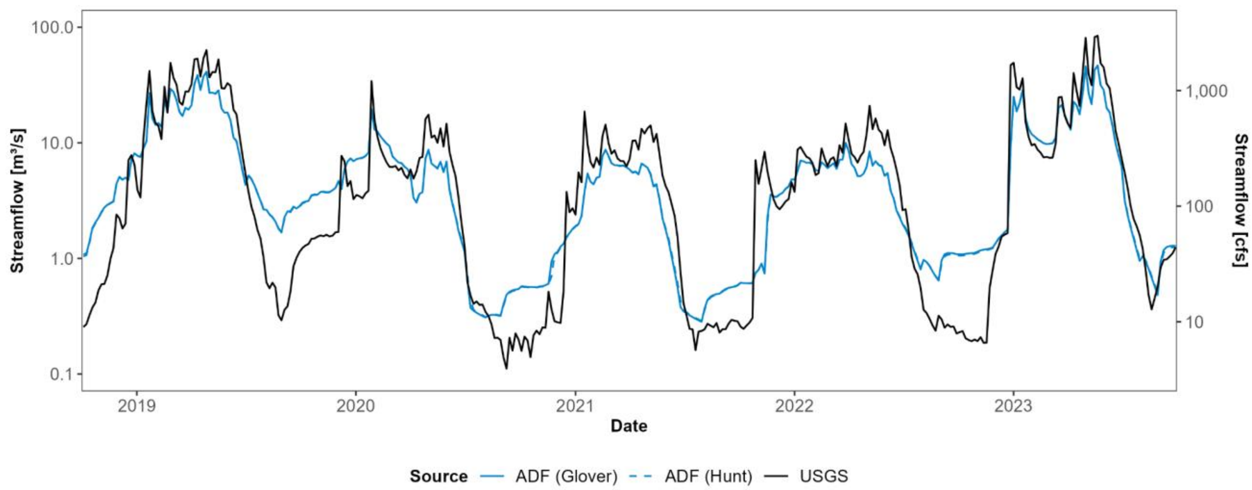

Figure S4. Evaluation of sensitivity of model to choice of analytical solution used in ADFs. The Glover and Hunt models produce near-identical results, so the solid and dashed blue lines overlie each other. This indicates that streambed conductance is not a limiting factor on streamflow depletion in this domain. All other figures in the manuscript use the Hunt model results.

Table S1. Summary of SVIHM model scenarios used in analysis. Scenarios 1 (Basecase) and 3b (No GW Irr Fields) are used in the main text.

<table>
<tr><th>ID</th><th>Scenario</th><th>Land cover or water source changes</th><th>SWBM natVeg root depth</th><th>natVeg kc for SWBM</th><th>natVeg MODFLOW extinction depth</th><th>Interpretation of difference from basecase</th></tr>
<tr><td>1</td><td>Basecase</td><td>Basecase land cover.</td><td rowspan="2">Basecase (2.4 m)</td><td rowspan="2">Basecase (0.6)</td><td rowspan="2">Basecase (0 m; 0.5 m in the Discharge Zone)</td><td>N/A</td></tr>
<tr><td>2</td><td>No Pumping</td><td>Basecase land cover.

Water source changes: GW-only → Dry Farming; mixed-GW-SW → SW only</td><td>Direct pumping effects, neglecting other land cover-driven changes in water balance. This is not a realistic possibility for real-world, but isolates pumping signal.</td></tr>
<tr><td>3A</td><td rowspan="4">No GW-Irrigated Fields</td><td rowspan="4">Assign NatVeg land cover to all GW and Mixed-GW-SW fields</td><td>1.2m</td><td>0.6</td><td rowspan="8">3.05 m</td><td rowspan="4">Direct pumping effects + difference in water balance due to natural veg replacing ag in GW irrigated fields</td></tr>
<tr><td>3B</td><td>2.4m</td><td>0.6</td></tr>
<tr><td>3C</td><td>1.2m</td><td>1.0</td></tr>
<tr><td>3D</td><td>2.4m</td><td>1.0</td></tr>
<tr><td>4A</td><td rowspan="4">Native Vegetation (unimpaired flow)</td><td rowspan="4">Assign NatVeg land cover to all cultivated fields</td><td>1.2m</td><td>0.6</td><td rowspan="4">Combined effect of all human modifications</td></tr>
<tr><td>4B</td><td>2.4m</td><td>0.6</td></tr>
<tr><td>4C</td><td>1.2m</td><td>1.0</td></tr>
<tr><td>4D</td><td>2.4m</td><td>1.0</td></tr>
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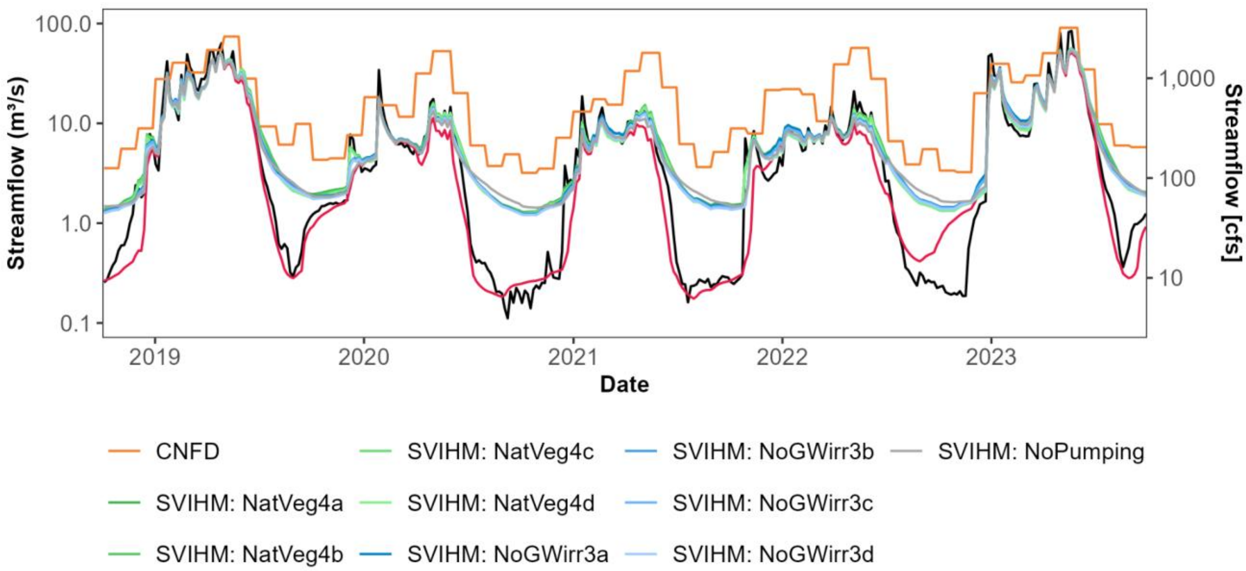

Figure S5. Comparison of streamflow at watershed outlet. The black line shows observed streamflow (source: USGS) and the red line shows the SVIHM basecase (pumped) scenario. The colored lines included in the legend include CNFD unimpaired flows and nine different SVIHM model configurations. The "basecase" (red) and "NoGWirr3b" (blue) scenarios are the basis for results shown in the main text. The other scenarios are meant to show sensitivity to vegetation parameterization, which is described in Table S1.

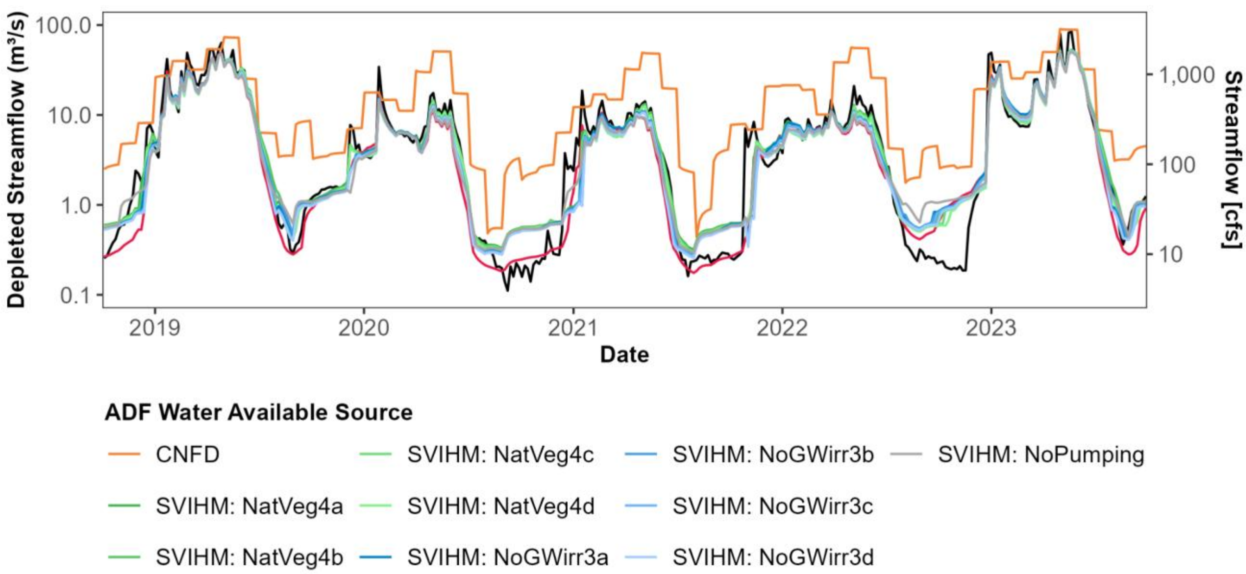

Figure S6. Comparison of depleted streamflow at watershed outlet based on ADF simulations using different water available data sources. The black line shows observed streamflow (source: USGS) and the red line shows the SVIHM simulated basecase (pumped) scenario. The colored lines show ADF predicted depleted streamflow using CNFD unimpaired flows and nine different SVIHM model configurations as the water available. ADF models on this plot include drying. The “basecase” (red) and “NoGWirr3b” (blue) scenarios are the basis for results shown in the main text. The other scenarios are meant to show sensitivity to vegetation parameterization, which is described in Table S1.

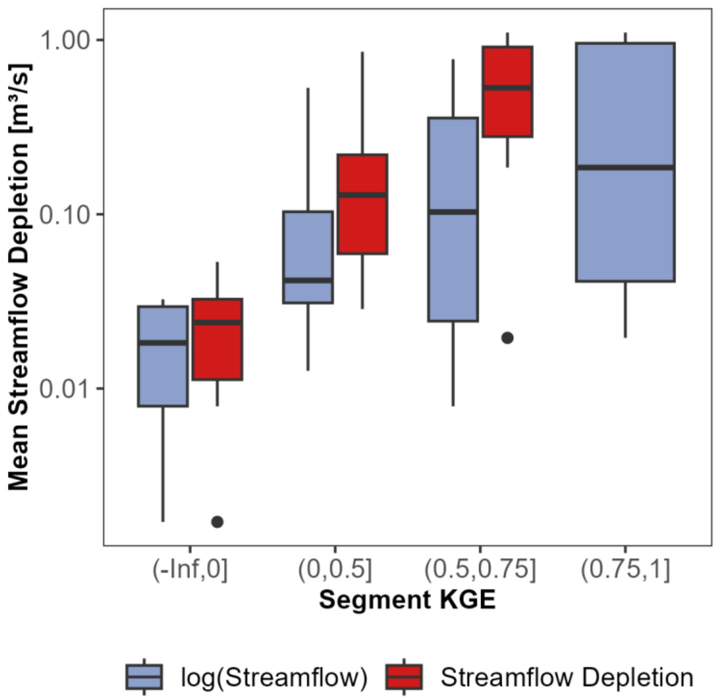

Figure S7. Segment-resolution agreement between ADFs and SVIHM as a function of segment mean streamflow depletion (from SVIHM) in each segment. These results show the ADF + SVIHM + Drying model configuration with water available and SVIHM streamflow depletion calculated using the the SVIHM no-pumping scenario (#2 in Table S1).

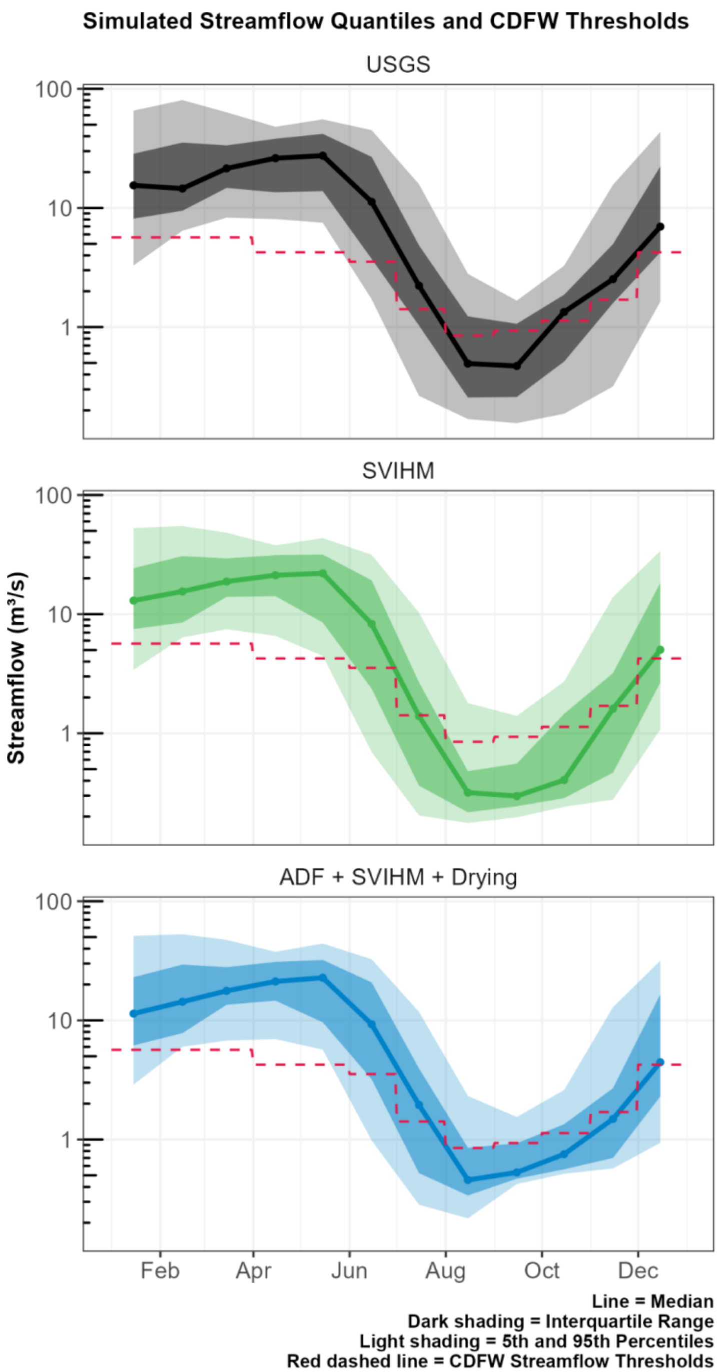

Figure S8. Streamflow drought thresholds (red dashed lined) and long-term median, interquartile range, and 5th-95th percentile range for streamflow from the USGS observations, SVIHM, and ADF + SVIHM + Drying models.