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The Role of Vadose Zone Storage Deficits in Modulating Groundwater Recharge and Streamflow in Seasonally Dry Watersheds

N. K. Benitez-Nelson[1], D. N. Dralle[2], W. J. Hahm[3], and D. M. Rempe[1]

[1]Jackson School of Geosciences, University of Texas at Austin, Austin, TX, USA, [2]Pacific Southwest Research Station, United States Forest Service, Davis, CA, USA, [3]Department of Geography, Simon Fraser University, Burnaby, BC, Canada

Key Points:

- Vadose zone moisture storage deficits control the seasonal timing and magnitude of groundwater recharge in seasonally dry catchments
- Deficit tracking may aid in estimation of rainfall needed to generate sustained summer streamflow in basins with limited field observations

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

N. K. Benitez-Nelson,
noahbeniteznelson@utexas.edu

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Abstract

In forested, seasonally dry watersheds, winter rains commonly replenish water storage deficits in the vadose zone before recharging underlying hillslope groundwater systems that sustain streamflow. However, the relative inaccessibility of the subsurface limits our understanding of how groundwater recharge is moderated by vadose zone storage deficits generated by plant-water uptake. Here, we compare groundwater recharge inferred from the storage-discharge relationship with independent, distributed estimates of deficits across 12 undisturbed California watersheds. We find accrued dry season deficits primarily driven by evapotranspiration insufficiently explain inter-annual variability in the amount of precipitation required to generate groundwater recharge due to continued deficit accumulation between wet season storms. Tracking the deficit at the storm event-scale, however, reveals a characteristic response in groundwater to increasing rainfall not captured in the seasonal analysis that may improve estimates of the rainfall required to generate recharge and streamflow on a per-storm basis. Our findings demonstrate the potential for existing public data sets to better capture water partitioning within the subsurface and thus improve the prediction of rainfall-runoff behavior and summer water availability in rainfall-dominated, seasonally dry basins using a combined deficit-recharge approach.

Plain Language Summary

Groundwater sustains plants and streamflow in seasonally dry forests when precipitation is infrequent. However, tracking basin-scale groundwater recharge dynamics is difficult due to limited subsurface accessibility and the need to extrapolate watershed storage dynamics from sparse field measurements. We present a method addressing these limitations using public data sets of streamflow, precipitation, and evapotranspiration. It demonstrates the importance of root zone storage (including both soil and rock moisture) in regulating rainfall volumes contributing to groundwater. This work provides a framework for better estimating per-storm water availability for streamflow in seasonal climates.

1. Introduction

Groundwater supplies a significant fraction of the global freshwater used for irrigation and human consumption (Bin Abdullah, 2005; Schmoll, 2006; Siebert et al., 2010) and sustains streamflows (Banks et al., 2009; Salve et al., 2012) that support ecosystems (Falke et al., 2011; Meyers et al., 2021; Miller et al., 2010). However, groundwater systems are simultaneously threatened by climate-induced changes to the hydrologic cycle (Cuthbert et al., 2019; Panagoulia & Dimou, 1996; Taylor et al., 2013) and anthropogenic overuse (Barlow & Leake, 2012; Famiglietti, 2014; Wada et al., 2012). Rising temperatures are increasing the frequency of extreme weather events (Trenberth, 2011) as the atmosphere retains and releases progressively greater water volumes (Skliris et al., 2016). The enlarged atmospheric reservoir demands greater land-surface moisture contributions, resulting in prolonged droughts (Qing et al., 2023), during which groundwater storage is expected to sustain humans (Famiglietti, 2014) and some deep-rooting plants (Allen et al., 2015; Meyers et al., 2021). Understanding groundwater recharge mechanisms is therefore essential for effective, sustainable water resources management and predicting the resilience of ecosystems reliant on aquifer systems (Earman & Dettinger, 2011).

Studying the dynamics of groundwater recharge at the catchment-scale across multiple basins at timescales relevant to subseasonal water resources management is complicated by the relative inaccessibility of the subsurface. Continuous ground-based observations of the unsaturated zone (comprising soil and rock moisture) and underlying groundwater are currently limited to intensive field-studies in select regions (e.g., Rempe & Dietrich, 2018). Though efforts have been made to create observation networks (e.g., Brantley et al., 2017; Dorigo et al., 2021), in situ and noninvasive direct ground measurements (especially those at depths deeper than 2 m) do not have the same coverage as products derived from satellite remote sensing methods (Oswald et al., 2024).

Satellite-derived estimates of terrestrial water storage, as an alternative to in situ measurements, are limited by their spatial and temporal resolution. Gravity Recovery and Climate Experiment (GRACE) and Follow-On (GRACE FO)-derived total water storage variations, for example, are only available as 100 × 100 km monthly pixels prior to the application of modeling (Vishwakarma et al., 2021) or machine-learning (Jyolsna et al., 2021) downscaling techniques—which typically only improve the spatial resolution of the GRACE/GRACE-FO output. Additional methods must be employed to distinguish between groundwater and water held in the unsaturated zone, including water partitioning using ground-based measurements (Frappart & Ramillien, 2018) and signal decomposition (Andrew et al., 2017). Satellite-derived soil moisture products (e.g., from microwave observations) are available at higher resolutions but only capture changes in the top centimeters of the soil surface and require ancillary soil data to determine absolute soil moisture values (Oswald et al., 2024).

Hydrologic modeling provides an effective alternative to tracking subsurface water storage in lieu of direct (ground) and indirect (satellite) observations. Streamflow derived from groundwater, or "baseflow," quantified by separating the event rainfall-runoff response as represented by the storm hydrograph (Hewlett & Hibbert, 1967), has traditionally been used as the basis for tracking changes in the otherwise hidden groundwater reservoir (Blume et al., 2007). In the application of this technique, antecedent soil moisture is often considered a primary control on the runoff ratio–the fraction of streamflow generated per unit precipitation. Incorporating dynamic, physically based estimates or direct measurements of soil water content into hydrologic models of streamflow generation has generally improved simulations of observed processes (e.g., Hawkins & Ellis, 2010; Karnieli & Ben-Asher, 1993; Oubeidillah et al., 2019; Wyatt et al., 2020), but not always (e.g., Zhang et al., 2011). The cause of this discrepancy has variably been attributed to storm intensity and generation of overland flow (Castillo et al., 2003), lack of a dynamic soil profile (Zhang et al., 2011), hydrogeologic differences across basins (Hawkins & Ellis, 2010), or the measure of soil moisture itself (Lekshmi et al., 2014).

Modeling water flow beyond the soil layer and through the unsaturated zone is often based on parameterizing subsurface conditions and ascribing initial conditions based on limited in situ data that may or may not represent the actual conditions of the entire watershed. Here, we demonstrate the role of unsaturated soil and rock moisture deficits in regulating the volume of water available for streamflow using publicly available in situ and remotely sensed data sets that broadly cover the contemporaneous United States, with the overarching goal of highlighting the potential to improve existing rainfall-runoff models by better incorporating subsurface water routing processes. We build upon a recently developed method of numerically estimating recharge from streamflow to track wet season groundwater contributions (Dralle et al., 2023). Where Dralle et al. (2023) used groundwater wells across a heavily-researched hillslope to monitor evolving unsaturated zone storage, we employ a mass-balance approach based on plant-accessible water volumes (Wang-Erlandsson et al., 2016) to scale our analysis of vadose zone hydrologic regulation across watersheds. This allows us to track the partitioning of rainfall across an additional 23 undisturbed basins differing in lithology, degree of vegetation, and size (Table S1 in Supporting Information S1) to test the hypothesis, across as many basins as possible, that refilling vadose zone storage delays streamflow activation by changing the timing and volume of groundwater recharge. We limit our analysis to undisturbed California basins where asynchronous seasonal water and energy limitation generates large soil and rock moisture deficits that inhibit recharge, tracking basin water partitioning at both seasonal and storm-event scales to identify the greatest recharge-deficit signal. We hypothesize mixed findings in existing literature regarding the role of antecedent moisture in streamflow generation in similar basins can be explained by methods which either do not account for the entirety of vadose zone storage or are insufficiently fine to capture subseasonal dynamics.

2. Methods

2.1. Study Sites

We focus on watersheds gaged by the United States Geological Survey (USGS) with Mediterranean-type climates, where large seasonal and intra-seasonal swings in subsurface storage allow us to best test our recharge-deficit approach. Asynchronous seasonal water and energy input results in the accrual of large vadose zone storage deficits over a long summer dry period, followed by winter wet season rainfall that replenishes soil and rock moisture. We further filter USGS sites following Hahm et al. (2019) to identify rainfall-dominated (<20%

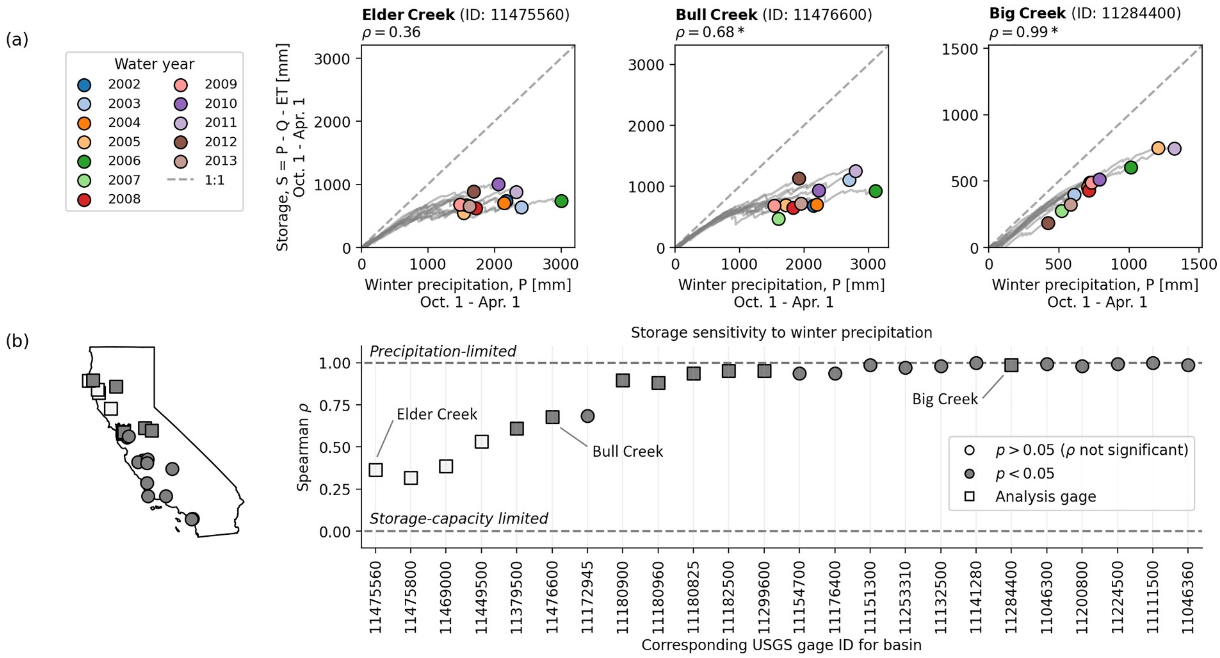

Figure 1. Method of determining the dependence of subsurface winter storage (S) on winter precipitation (P) across select undisturbed Californian basins. (a) For each water year, S is calculated as the remainder of the catchment mass-balance and plotted as a function of cumulative winter precipitation (October 1st to April 1st). The gray lines show the seasonal progression of S (calculated daily). Early wet season rainfall primarily increases S, generating minimal streamflow. In basins where subsurface storage is more likely to be annually refilled (where S plateaus), further P does contribute to streamflow, resulting in a curved line. If all precipitation went into storage without drainage to groundwater or evapotranspiration, catchments would plot along the dashed 1:1 line. The Spearman rank correlation coefficient (ρ) is calculated for each watershed; asterisks denote significance at $p < 0.05$. (b) Spearman rank correlations across basins and location of basins in the greater state of California. Filled symbols denote significance at $p < 0.05$. Those watersheds where wet season precipitation exceeds dry season accrued vadose zone storage deficits for at least 5 years over a 20 years analysis period (2000–2020) highlighted with square markers. Calculation of ρ restricted to 2002–2013 water years to match the original Hahm et al. (2019) data set and minimize non-stationary conditions introduced by mass tree mortality at the end of the period (USDA, 2016). We diverge from Hahm et al. (2019) in using actual, instead of potential, evapotranspiration in our calculation of S. Plotting space based on Figures 2 and 3 of Hahm et al. (2019).

precipitation as snow) watersheds with at least a decade of complete hydrologic fluxes, limited urbanization (cumulative developed area <10%), and an unimpaired stream network (no dams upstream of gage). Of the over 13,500 stations in the USGS gage network (U.S. Geological Survey, 2016), 24 catchments met the stated criteria (Table S1 in Supporting Information S1).

The selected basins span the state of California and have previously been classified into two groups based on the sensitivity of seasonally dynamic water storage to winter precipitation (using the Spearman correlation coefficient, ρ, between storage and annual precipitation) (Hahm et al., 2019). Catchments where seasonal rainfall annually exceeds storage deficits generated in the dry season (and thus the inferred subsurface storage capacity) are defined as storage-capacity limited ($\rho \rightarrow 0$). Because storage is replenished every year, and limited by storage capacity rather than precipitation, the seasonal winter storage is not correlated with winter precipitation. In contrast, precipitation-limited basins are identified where large storage-capacities relative to annual wet season rainfall result in winter storage that is highly dependent on winter rains ($\rho \rightarrow 1$). We recalculate the correlation coefficient for all watersheds following Hahm et al. (2019) using actual, instead of potential, evapotranspiration (Figure 1), defining annual storage as the remainder of the catchment mass balance (the difference between precipitation and the sum of discharge and evapotranspiration). Of our 24 filtered watersheds, 4 are defined as intermediate to storage-capacity limited and 20 as precipitation-limited.

2.2. Conceptual Model of Groundwater Recharge Across the Hillslope

We present our conceptual model of hillslope recharge in Figure 2. Wet season precipitation fills unsaturated (vadose zone) storage that drains to the underlying groundwater system supporting streamflow (Dralle et al., 2023). Bare-surface evaporation, transpiration from soil and rock moisture, and drainage to underlying

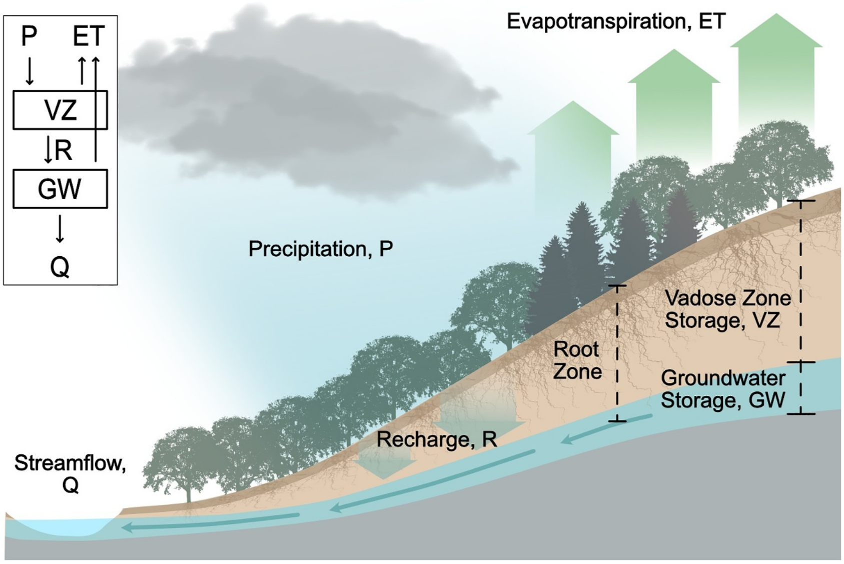

Figure 2. Conceptual diagram of hillslope recharge for an undisturbed mountainous catchment with negligible contributions from snowmelt and fog. Plants access moisture for transpiration from the thin soils (dark brown) and thick weathered bedrock (light brown) comprising the unsaturated (vadose) zone. Deeper rooting plants (dark brown lines) may also access seasonal groundwater storage (light blue). Additional evaporation from the upper layers of soil comprise the total flux from the land surface to the atmosphere (ET). As root zone storage deficits are replenished by wet season rainfall (P), water is increasingly routed through the vadose zone (VZ) to recharge (R) the groundwater system (GW) that supports streamflow (Q). Although precipitation, evapotranspiration, and recharge are presented as local processes, we conceive these fluxes as distributed across the hillslope from the stream to the ridge. The inset mass-balance shows the relationship between the modeled reservoirs (vadose zone storage containing the root zone, groundwater storage supplying baseflow) and fluxes (rainfall, recharge, evapotranspiration, and streamflow).

groundwater deplete vadose zone storage during the dry season and create a deficit. We make the following assumptions to track hillslope processes at the basin-scale:

- Inter-basin groundwater flow (the exchange of water between catchments) is negligible,
- Water is primarily routed through the vadose zone to local groundwater (negligible overland flow or throughflow via bypassing pipe and macro-pore flow),
- Water leaves the catchment primarily as measurable surface streamflow or evapotranspiration (minimal subsurface flow beneath the stream).

2.3. Groundwater Recharge From the Catchment Mass-Balance

The conservation of mass equation for the groundwater storage reservoir, S_{gw}, adapted from Sayama et al. (2011), provides the basis for our approach:

$$dS_{gw} = (R - Q - E_{gw})\,dt, \tag{1}$$

where R represents groundwater recharge, Q discharge, and E_{gw} evapotranspiration from groundwater storage. At our study sites, discharge from groundwater includes both stormflow and baseflow (Rempe & Dietrich, 2018; Salve et al., 2012). Combining Equation 1 with the catchment sensitivity function $g(Q)$ developed by Kirchner (2009) (building upon the recession analysis of Brutsaert and Nieber (1977)) allows us to capture the sensitivity of observable flow to otherwise hidden changes in groundwater storage (S_{gw}):

$$g(Q) = \frac{dQ}{dS_{gw}} = \frac{dQ/dt}{dS_{gw}/dt} = \frac{dQ/dt}{R - Q - E_{gw}}. \tag{2}$$

To be practically useful, we simplify the sensitivity function by identifying times when R and E_{gw} are small relative to Q and therefore negligible in the catchment mass balance (see Section 2.3.1). At the Elder Creek watershed (USGS ID: 11475560), groundwater is over 20 m deep along the ridge during the dry season (Rempe & Dietrich, 2018). We assume plant extraction of groundwater in the summer is similarly limited across the other study sites:

$$g(Q) \approx \frac{-dQ/dt}{Q} \text{when } R, E_{gw} \ll Q. \tag{3}$$

After the sensitivity function is derived, recharge can be calculated from the entirety of the streamflow timeseries regardless of non-negligible rainfall and plant groundwater extraction by rearranging Equation 2:

$$R = \frac{dQ/dt}{g(Q)} + Q. \tag{4}$$

We further define the recharge ratio as the fraction of precipitation refilling the hillslope groundwater reservoir over a given time period (Dralle et al., 2023; Jasechko et al., 2014). On a seasonal basis, the recharge ratio is mathematically defined as the ratio of cumulative recharge to cumulative precipitation:

$$\text{Seasonal recharge ratio} = \frac{\sum(R_{wet})}{\sum(P_{wet})}. \tag{5}$$

An expanded derivation of Equation 5 is provided in Dralle et al. (2023). We plot the cumulative recharge ratio continuously over the wet season throughout our analysis, starting on the first rainfall event occurring after October 1st to avoid an undefined ($P = 0$) recharge ratio and ending on April 1st with the onset of the dry season.

2.3.1. Estimating the Sensitivity Function

Estimating groundwater recharge with the sensitivity function requires fitting $g(Q)$ when recharge and transpiration from groundwater are sufficiently low compared to discharge (Kirchner, 2009). To avoid $E_{gw} \gg Q$, we follow Dralle et al. (2018) in restricting streamflow recessions used to fit $g(Q)$ from November-March. Winter energy-limitation in California's seasonal Mediterranean climate causes discharge, on average, to greatly exceed the rate of evapotranspiration across study sites. The first and last days of individual recessions (continuous periods of declining streamflow) are removed to negate the greatest contributions from recharge at the limits of the recession duration. This represents a divergence from the common practice of excluding streamflow recessions during days with significant rainfall that has traditionally ensured $P, R \ll Q$ (Ajami et al., 2011; Dralle et al., 2018, 2023; Kirchner, 2009; Wlostowski et al., 2021). We show the difference in our method of extracting and fitting streamflow recessions to that described in Dralle et al. (2023) at the site of the original method development (Figure S2 in Supporting Information S1). The method used herein provides a more expansive timeseries for fitting the sensitivity function and results in a better fit of the dynamic power-law function across basins despite the inclusion of recessions occurring during non-negligible rainfall. Our approach yields a timeseries of R that follows the same basic behavior as Dralle et al. (2023) without overestimating R for sudden changes in discharge accompanying large storms.

We exclude zero-flow discharge from our calculation of recharge, as the sensitivity function can only be applied to measurable streamflow. Changes in the remaining daily streamflow timeseries (dQ/dt) are estimated using the variable time step method (Rupp & Selker, 2006) applied by Dralle et al. (2018) following Palmroth et al. (2010). We bin dQ/dt following Kirchner (2009) to fit $g(Q)$ with the dynamic power law of Wlostowski et al. (2021):

$$g(Q) = \frac{a\left(Q/\overline{Q}\right)^{b(Q)}}{Q}, \tag{6}$$

where

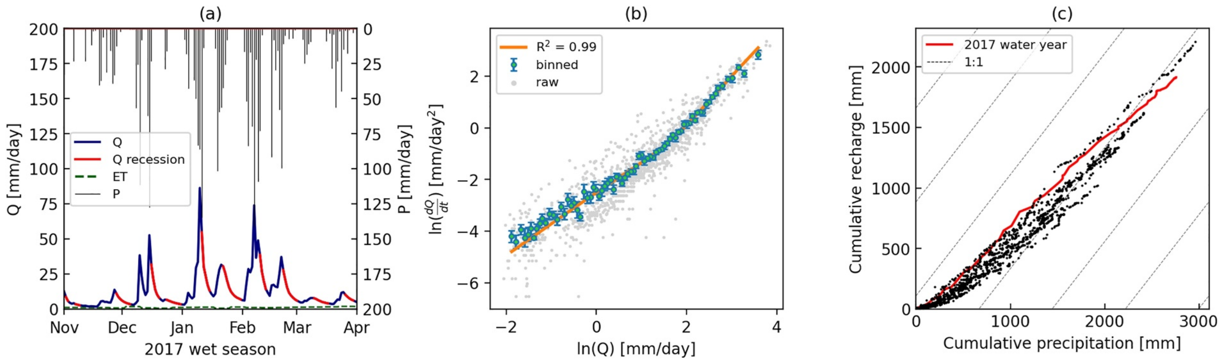

Figure 3. (a) Recessions of USGS gaged streamflow are extracted from the winter hydrograph. (b) The sensitivity function is derived from fitting the natural log of extracted Q and the natural log of changes in Q with a dynamic power law function that approaches a linear asymptote at hydrograph extremes. (c) R is calculated using the sensitivity function and plotted in a cumulative space against P, yielding a logistic form. The data in this figure are derived from the 2017 wet season (a) and the entire range of available data (b,c; 2000–2020) for the Elder Creek watershed (USGS gage ID: 11475560).

$$b(Q) = b_L + (b_U + b_L)\,\frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{\ln(Q) - \ln(\overline{Q})}{\ln(\sigma)\sqrt{2}}\right)\right]. \tag{7}$$

The power law exponent, $b(Q)$, in Equation 6 controls the behavior of the quadratic outside of the range of observed streamflow recessions to a lower, b_L, and upper, b_U, linear asymptote through a lognormal cumulative distribution function of Q with mean and standard deviation $\ln(\sigma)$. Our method of identifying streamflow recessions, binning and fitting $g(Q)$, and calculating R is shown in Figure 3. The results of fitting Equation 6 to the respective streamflow recessions of each basin are shown in Figure S3 of Supporting Information S1.

2.3.2. Storm-Event Analysis

The runoff ratio, or runoff coefficient, has historically served as the primary method of tracking the watershed response to rainfall on an event basis (Sherman, 1932). These runoff coefficients may be determined using either (a) the total streamflow resulting from the rainfall event or (b) the event flow as determined by hydrograph separation. For case (a), the arbitrary determination of where to stop calculating the total generated streamflow can lead to incomparable results. In case (b), different method selections can lead to further ambiguity of the runoff coefficient term (Blume et al., 2007).

While the event runoff coefficient is reliant on inconsistent definitions and methodologies to quantify the response of surface streamflow to rainfall, the event recharge ratio is defined as the directly observable (Bhaskar et al., 2018) or modeled (Grande et al., 2022) gross increase in groundwater from distinct rain events. As positive changes in streamflow are typically limited to periods of measurable rainfall in our daily timeseries (Figure 3a) and our numerical estimation of recharge is dependent on the derivative of streamflow, the majority of recharge occurs during periods with measurable rainfall (Figure 4). However, we add a 1-day lag between the end of each rainfall event and the start of calculating storm event recharge to avoid capturing additional contributions to the groundwater reservoir from delayed hillslope drainage (relative to instantaneous precipitation). Continuous measurements of the hillslope water table in the Elder Creek basin (USGS gage 11475560) identified a lag-to-peak time between the rainfall event centroid and peak groundwater response of approximately 30 hr across all wells (Rempe, 2016), supporting our conservative requirement for a dry day to follow each rainfall event. The lack of corresponding groundwater elevation measurements across other study sites hinders our ability to dynamically adjust the lag for each site.

The storm event recharge ratio for events occurring from a time t_1 to time t_2 is thus defined by the equation:

$$\text{Storm event recharge ratio} = \frac{\int_{t_1}^{t_2+1} R(t)d\tau}{\int_{t_1}^{t_2} P(t)d\tau}. \tag{8}$$

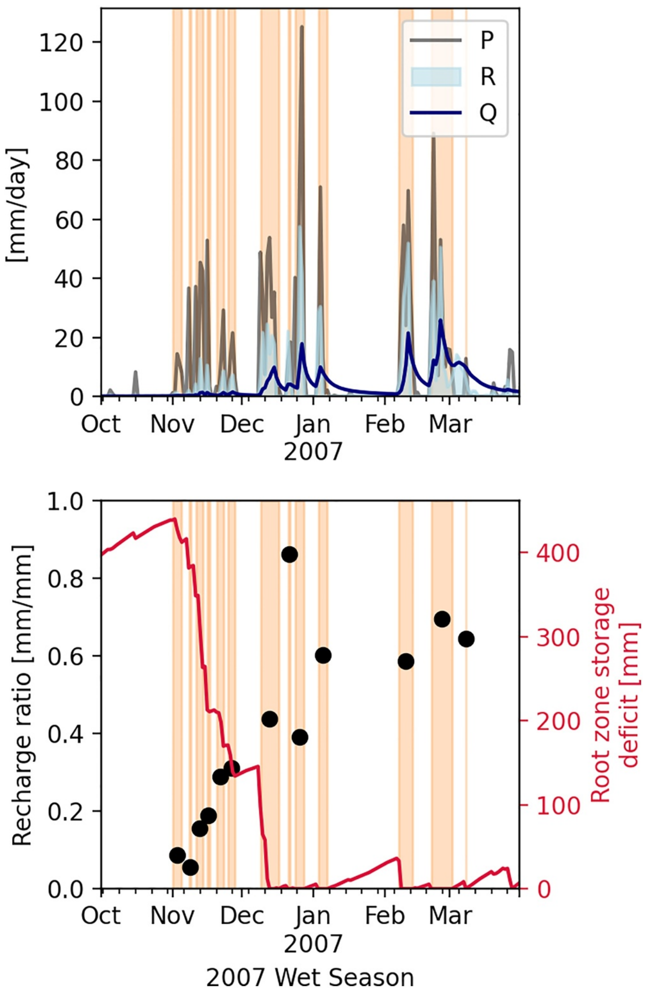

Figure 4. Identification of storm events to track the evolution of the storm-event recharge ratio. Storms are identified as distinct precipitation events with a total catchment averaged volume exceeding 10 mm occurring at least 2 days after another large storm event (top panel, orange shading). Total recharge over the storm duration is divided by total precipitation to derive the recharge ratio (bottom panel, black marker). The data in this figure is derived from the 2007 wet season at the Elder Creek watershed (USGS gage ID: 11475560).

We identify storms with greater than 10 mm of total rainfall in applying Equation 8. Those storms occurring within 2 days of a previously identified event are excluded to avoid conflating recharge signals. We show our method of identifying storms and calculating the storm event recharge-ratio in Figure 4.

2.4. Calculating the Root Zone Storage Deficit

The root zone storage deficit, D, defines plant-accessible subsurface storage as the cumulative difference between evapotranspiration and incoming precipitation; when cumulative precipitation exceeds cumulative evapotranspiration, the deficit is constrained to disallow negative values (Wang-Erlandsson et al., 2016). The D includes all subsurface water volumes that plants may access, including both unsaturated (soil and rock moisture) and saturated (bedrock groundwater) water reservoirs. In the case of net lateral inflow of water to the root zone, the D may continue to grow without stopping. (This may also arise due to biases in the precipitation and evapotranspiration flux data sets.) In our analysis, we identify and exclude those basins where the annual exceedance of ET over P leads to a "runaway" D (see Section 3.3, discussion in Section 4.3). We assume that in those basins remaining after the application of this filter plants either (a) do not have unlimited access to groundwater volumes for transpiration, or (b) the portion of evapotranspiration derived from groundwater is minimal compared to plant extraction of unsaturated soil and rock moisture.

Methods of calculating the deficit with P and ET have existed since the 1960s (Grindley, 1960, 1968) and seen extensive historical use in the agricultural industry (e.g., Hough & Jones, 1997; Thompson et al., 1981). However, previous efforts to apply the deficit as a proxy for recharge (e.g., Finch, 2001; Rushton & Ward, 1979) have struggled to overcome the limitations imposed by historical data sets. Modern measurement techniques, yielding highly resolved spatial and temporal P and ET fluxes, now allow us to track subsurface storage across distinct basins on a daily recurrence. We follow the McCormick et al. (2021) adaptation of Dralle et al. (2021) in estimating root zone storage, starting our analysis after the first complete water year (exceeding 360 days) to obtain an initial non-zero deficit:

$$D(t_{n+1}) = \max\left(0, D(t_n) + \int_{t_n}^{t_{n+1}} (F_{out} - F_{in})\, dt\right) \tag{9}$$

where F_{out} defines the out-flux of water equal to ET and F_{in} the in-flux of water equal to P.

2.5. Data Sources and Processing

Daily discharge is measured at USGS gage stations and reported through the National Water Information System (NWIS; U.S. Geological Survey, 2016). We query the NWIS for daily volumetric discharge at each study site and convert Q to a length scale (mm/day) using the drainage area upstream of the respective USGS gage. We use the Google Earth Engine geo-spatial computational platform (Gorelick et al., 2017) to access a statistically interpolated daily precipitation product (Oregon State's PRISM daily precipitation; Daly et al., 2008, 2015) and remotely sensed 8-day average evapotranspiration product (Penman-Monteith-Leuning Evapotranspiration, PML_V2; Gan et al., 2018; Zhang et al., 2016, 2019), which we linearly interpolate to a daily timeseries. We calculate watershed P and ET by averaging pixels falling within the drainage area to yield daily timeseries of rainfall and evapotranspiration for each basin between 2000 and 2020.

In identifying a physical mechanism to explain the strength of remotely sensed root zone storage deficits in capturing variable groundwater recharge, we calculate the percentage of the basin area covered in woody plants using the USGS National Land Cover Database (Dewitz & U.S. Geological Survey, 2021) following McCormick et al. (2021). We similarly determine the mean soil thickness to lithic bedrock using the US Department of Agriculture (USDA) gNATSGO41 product (Soil Survey Staff, 2020) and report the root zone storage capacity (S_r) as the maximum deficit over the analysis period (Wang-Erlandsson et al., 2016). The hydrogeology of each basin is reported in Table S1 of Supporting Information S1.

3. Results

3.1. Partitioning of Outflows Across Basins

We compare mean annual hydrologic fluxes (2000–2020) across the original 24 basins of Hahm et al. (2019) in Figure 5 to assess how progressively wetter catchments partition P between ET and streamflow (Q). In Figure 5a, ET scales with P when P is below 1,000 mm/year. At higher P, ET remains between 600 and 700 mm/year. The points in Figure 5a are colored by the relationship between catchment storage and precipitation (Figure 1) based on the Hahm et al. (2019) framework. As expected, catchments colored in brown (high correlation coefficient, ρ) show a strong relationship between P and ET (Figure 5a), while catchments with a low correlation are offset from the 1:1 gray dashed line. In contrast, Figure 5b shows that annual Q scales with P in an approximately linear relationship in catchments where P is greater than 1,000 mm/year and storage sensitivity to winter precipitation is low. A weaker relationship between Q and P is evidenced in drier catchments with a high ρ. These patterns can be explained at an annual scale by the relationship between annual P and the vadose zone storage capacity: ET is limited by the plant-accessible volume of vadose zone storage capacity, and rainfall in excess of the vadose zone storage capacity drains to groundwater and is converted to streamflow. Given the rapid response of storm-event recharge to storm rainfall once root zone storage deficits are refilled (Figure 8), plants access a significant fraction of available rock and soil moisture at the study sites included in the analysis (denoted with square markers in Figure 5) such that plant-accessible subsurface storage is a suitable proxy for the recharge-limiting vadose zone storage capacity. Figure 5c shows good agreement between fluxes into (P) and out of (ET and Q) respective catchments (i.e., water budget closure at an annual timescale), which supports the use of the selected data products for our analyses.

3.2. Evolution of Recharge Throughout the Wet Season

Figure 6 shows the relative response of measured streamflow and calculated groundwater recharge to the first 1,000 mm of wet season rainfall (for all water years, 2000–2020) in two catchments with contrasting winter storage-rainfall dependence: Elder Creek (USGS gage #11475560, $\rho = 0.36$) and Big Creek (#11284400, $\rho = 0.99$). Early wet season storms generally do not produce streamflow (blue marker) and generate minimal groundwater recharge (red marker) across both basins regardless of storage-rainfall dependence. However, the groundwater system responds more rapidly to precipitation in storage-capacity limited Elder Creek than precipitation limited Big Creek. We continue exploring this initial observation across the 24 study sites using recharge alone.

3.3. Accounting for Accrued Dry Season Vadose Zone Storage Deficits

We test if accounting for accrued dry season vadose zone storage deficits at the first rainfall of the wet season $\left(D_{first\_rain}\right)$ corrects the observed difference between wet season cumulative precipitation and cumulative recharge (Figure 5) in Figure 7. Only those basins where storage is replenished by wet season precipitation for at least 5 water years are shown ($n = 12$). We apply this filter to mask basins where bias in the hydrologic balance and/or unquantified processes (e.g., lateral flow, induced groundwater recharge) result in emitted evapotranspiration exceeding incoming rainfall across the 2000–2020 analysis period (following McCormick et al., 2021; Stocker et al., 2023). The plots in Figure 7 are colored by the basin ρ. We show the plotting space for all basins in Figure S4 of Supporting Information S1.

If, in our conceptual model (Figure 2), vadose zone storage plays an insignificant role in the volume of groundwater recharge generated over the wet season, then we would expect to see total wet season recharge (R_w) perfectly scale with excess total wet season precipitation, defined as the difference between total wet season precipitation and evapotranspiration ($P_w - ET_w$), in a 1:1 relationship across all catchments regardless of the relative volume of catchment storage and precipitation. To capture the degree of 1:1 scaling, we define the relationship between $P_w - ET_w$ and R_w using the Nash-Sutcliffe model efficiency coefficient (NSE; Nash &

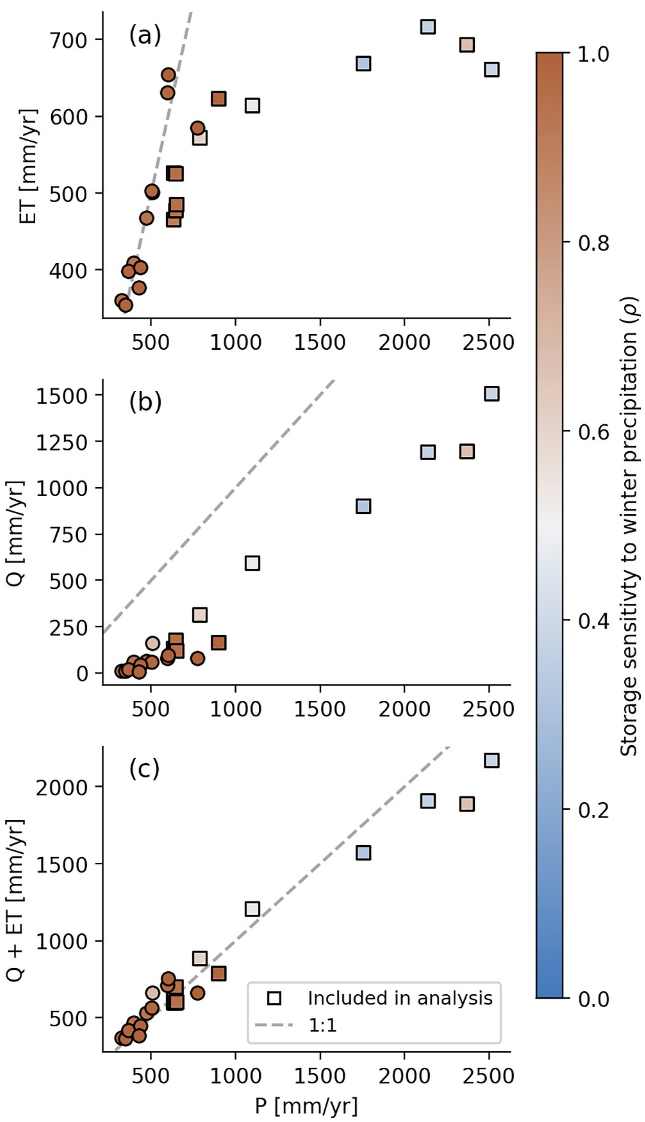

Figure 5. (a) Remotely sensed mean annual evapotranspiration (PML_V2, mm/year) against statistically interpolated mean annual precipitation (PRISM, mm/year) spatially averaged across respective basins between 2000 and 2020. (b) Mean annual streamflow (mm/year) as measured by USGS gage stations over the same period against mean annual P. (c) Mean annual mass-balance closure across basins, the 1:1 line (dashed, gray) indicates perfect closure in contributing (P, mm/year) and draining ($Q + ET$, mm/year) water fluxes between 2000 and 2020. Those watersheds remaining after additional filtering (Figure 7) highlighted with square marker. 1:1 (dashed gray) line shown for all panels.

Sutcliffe, 1970), where a 1:1 agreement would result in a NSE = 1 in Figure 7. The relationship between $P_w - ET_w$ and R_w is fit using a linear regression. We do not fix the y-intercept at 0 as wet season rainfall may not initially result in wet season recharge. R_w linearly scales with $P_w - ET_w$ (circular markers) in wetter basins with low ρ but is generally offset by a combination of slope and origin from the 1:1 gray dashed line. Drier catchments with high ρ also fall beneath the 1:1 line, but the slope between R_w and $P_w - ET_w$ is increasingly less than 1 (black dotted line). Subtracting the accrued dry season deficit at the onset of winter rains $\left(D_{first\_rain}\right)$ from $P_w - ET_w$ (square markers) partially corrects for divergence from the 1:1 gray dashed line in basins with a low ρ by shifting the line of linear regression toward the origin, but has minimal impact on the diminished slope observed in basins with a high ρ (dashed-dotted line). Thus, variations in the root zone storage deficit at the start of the wet season cannot fully explain differences in the volume of recharge generated per unit excess precipitation over the wet season. We therefore repeat our analysis on a per-storm basis to explore the role of intra-seasonal deficit dynamics in mediating groundwater recharge in response to precipitation.

3.4. Event-Scale Analysis Reveals Dependence of Groundwater Recharge on Refilling Vadose Zone Deficit

Implicit in the seasonal (or early seasonal, Figure S5 in Supporting Information S1) comparison of recharge and precipitation in Figure 7 is the assumption that vadose zone storage deficits monotonically decrease over the wet season from continued, regular rainfall. The effect of inter-storm variability on recharge ratios (the amount of recharge generated per unit precipitation) and the potential continued accumulation of deficit is thus obscured. Dralle et al. (2023) noted considerable soil and rock moisture drawdown in the dry periods between successive wet season storm events in their analysis of rainfall-groundwater dynamics across a heavily monitored Californian hillslope. Inter-storm periods resulted in considerable variation in recharge ratios, as evapotranspiration from the upper unsaturated zone and drainage to groundwater from the lower unsaturated zone depleted soil and rock moisture. Consequently, successive storms served to replenish both the accrued dry season deficit and the deficit generated during the inter-storm periods.

To capture intra-seasonal, inter-storm variability in unsaturated zone storage, and overcome the assumption of a monotonically decreasing deficit identified by Dralle et al. (2023), we plot the storm-event response of recharge, moderated by the deficit at the start of the event, to rainfall in Figure 8 (see Figure S6 in Supporting Information S1 for the recharge-rainfall relationship alone). The x-axis shows precipitation in excess of the deficit at the start of the storm event, where values less than 0 may be considered storms for which root zone storage is still being replenished. The small, but non-negligible, recharge prior to the deficit being reset may be attributed to the inability of the pixel-scale deficit to completely capture fine variations in subsurface moisture replenishment across the landscape. The recharge ratio approaches 1 as the basin reaches field capacity, reflecting additional rainfall contributing almost entirely to the underlying groundwater table. Inferred recharge after the deficit is reset (>0 on the x-axis) generally does not exceed precipitation in excess of the deficit except during very intense storm events (e.g., USGS gage 11379500).

Differences in the volume of hydrologic fluxes across basins make it difficult to compare variability in the recharge-precipitation excess relationship. Within Supporting Information S1, we conduct a limited case-study using hourly discharge and rainfall at Elder Creek (USGS gage ID: 11475560) to assess whether the variability in recharge prior to the deficit being reset can be eliminated by increasing the temporal resolution of our

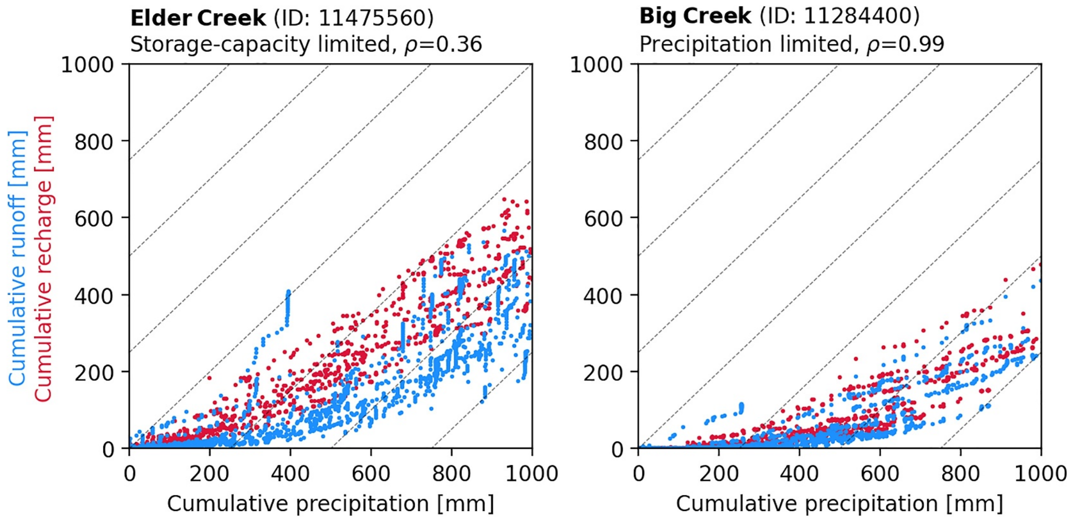

Figure 6. Response of streamflow (USGS-gaged discharge per basin area) and recharge (estimated) at Elder Creek (left) and Big Creek (right) to winter wet season rainfall. At the start of the wet season, streamflow exhibits a further delayed response to precipitation relative to recharge before the two approach a slope of one (gray dashed lines). This response is more distinct in storage-limited Elder Creek, where storage is weakly sensitive to winter precipitation ($\rho = 0.36$, Figure 1), than precipitation limited Big Creek ($\rho = 0.99$). We use recharge in our continued analysis to best capture refilling groundwater storage and directly observe processes in the reservoir.

analysis. Hourly timeseries of rainfall and discharge allow us to more accurately identify storms and accompanying recharge, decreasing the observed variation before the deficit resets and around the 1:1 line after storms refill root zone storage (Figure S1 in Supporting Information S1). However, the lack of hourly precipitation data across the remainder of the 12 filtered basins prevents us from conducting this analysis elsewhere.

Regardless, the daily storm-event analysis sufficiently demonstrates key relationships between vadose zone storage, rainfall, and recharge at the catchment scale. Across the filtered Hahm et al. (2019) undisturbed basins, minimal recharge occurs before rainfall refills root zone storage. The recharge that does occur may be attributed to the rapid replenishment of near-channel root-zone storage deficits, as found in comparable hillslope analyses (Dralle et al., 2023; Rempe & Dietrich, 2018; Salve et al., 2012). Once the subsurface reaches field capacity, additional precipitation contributes to increasing volumes of groundwater recharge in an approximately 1:1 relationship. The assumption of a monotonically decreasing deficit in the cumulative seasonal analysis obscures the role of accrued dry season deficits in moderating the recharge ratio. Inter-storm dry periods, during which the root zone storage deficit increases, are a critical component of the deficit-recharge relationship. While this is observable with moderate success in the daily analysis, hourly timeseries exemplify the relationship even better but lack the broad spatial availability.

4. Discussion

4.1. Vadose Zone Storage Drives Partitioning of Rainfall

Event recharge exhibited a strong relationship with event precipitation in excess of the deficit across filtered study catchments (Figure 8). We used the Hahm et al. (2019) framework to describe the basin dependence of subsurface storage on winter precipitation and observed that the root zone storage deficit of Wang-Erlandsson et al. (2016) and numerical recharge estimation of Dralle et al. (2023) capture variable vadose zone storage that limits contributions to underlying groundwater regardless of the relative volume of winter rainfall to subsurface storage. The root-zone storage deficit, in short, functionally represents the "threshold" in the transition from the "fill" to "spill" precipitation-groundwater response (Detty & McGuire, 2010; Meerveld & McDonnell, 2006; Saffarpour et al., 2016), although the transition between fill and spill behavior is initiated by the replenishment of moisture deficits instead of the overflow of bedrock depressions. In their continental, multi-decadal analysis, MacDonald et al. (2021) found that high storage capacity corresponds to low long-term aquifer recharge across Africa. However, in our basin-scale, subseasonal analysis, we find zone storage limits recharge regardless of the volume

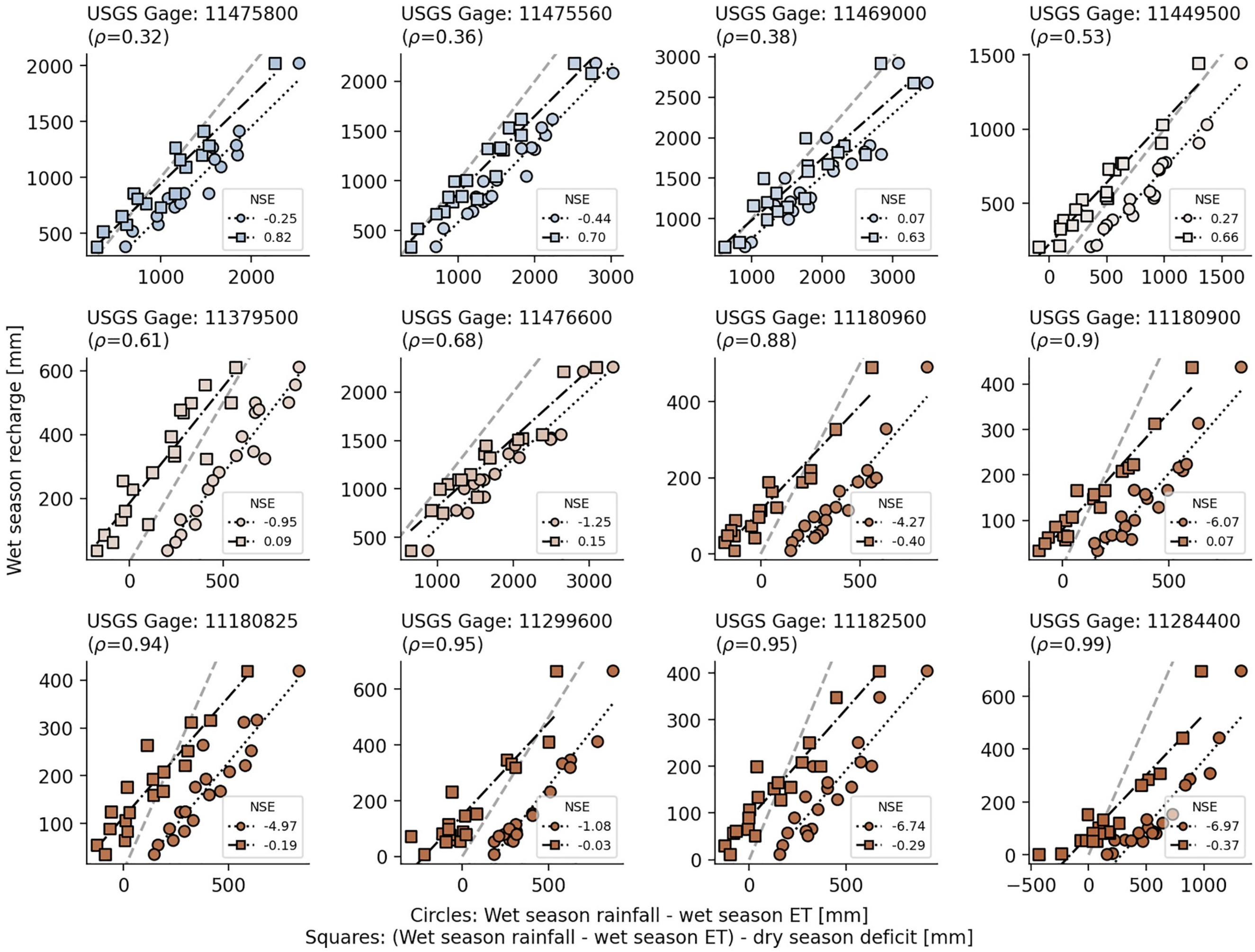

Figure 7. Total wet season recharge (R_w, mm) against excess wet season precipitation ($P_w - E_w$, mm) and wet season precipitation exceeding the accrued dry season deficit ($P_w - E_w - D_{first\_rain}$, mm) for each watershed. A linear regression is fit to $P_w - E_w$ (dotted black line, circular markers) and $P_w - E_w - D_{first\_rain}$ (dashed-dotted black line, square markers), respectively, and the NSE calculated for both. Accounting for the deficit at the start of the water year brings the relationship between wet season recharge and precipitation closer to the hypothesized 1:1 relationship (dashed gray line, NSE = 1). However, this correction works better at storage-capacity limited ($\rho \to 0$) than precipitation-limited ($\rho \to 1$) basins. Only those watersheds where total wet season precipitation exceeds the accrued dry season deficit $\left(P_w - D_{first\_rain} > 0\right)$ for at least 5 water years are included in the continuing analysis. Marker color represents storage sensitivity to winter precipitation (see Figure 5). The plotting space for all basins shown in Figure S4 of Supporting Information S1.

of subsurface storage. "Wetter" wet seasons will not result in more groundwater recharge if vadose zone rock and soil moisture are severely depleted (as noted in Lapides et al., 2022).

This study also reinforces our understanding that accrued dry season deficits can greatly impact streamflow generation deep into the wet season regardless of basin composition (Table S1 in Supporting Information S1). We observed the control of root zone storage deficits on groundwater recharge rates across watersheds regardless of size (16.3–642.1 km^2), coverage by woody vegetation (63.16%–100%), and depth to bedrock (0.65 ± 0.45 to 1.99 ± 0.15 m). However, we could not identify a deficit-recharge relationship in those basins where the deficit is not annually replenished, half of our 24 undisturbed, seasonal, and rainfall dominated study sites experienced multi-year deficit accruals that obscured the deficit-recharge signal. In these watersheds, generally located in California's hotter, drier south, we observed streamflow generation despite high storage deficits (Figure S7 in Supporting Information S1). We hypothesize overland or macropore flow are dominant water routing pathways allowing the minimal rainfall that does fall across such basins to bypass unsaturated soil and rock storage. Our observations could also be a simple byproduct of variability in the fast recharge response of the near-channel hillslope (as identified in Dralle et al., 2023) that does not resolve until further rainfall occurs (Figure 8).

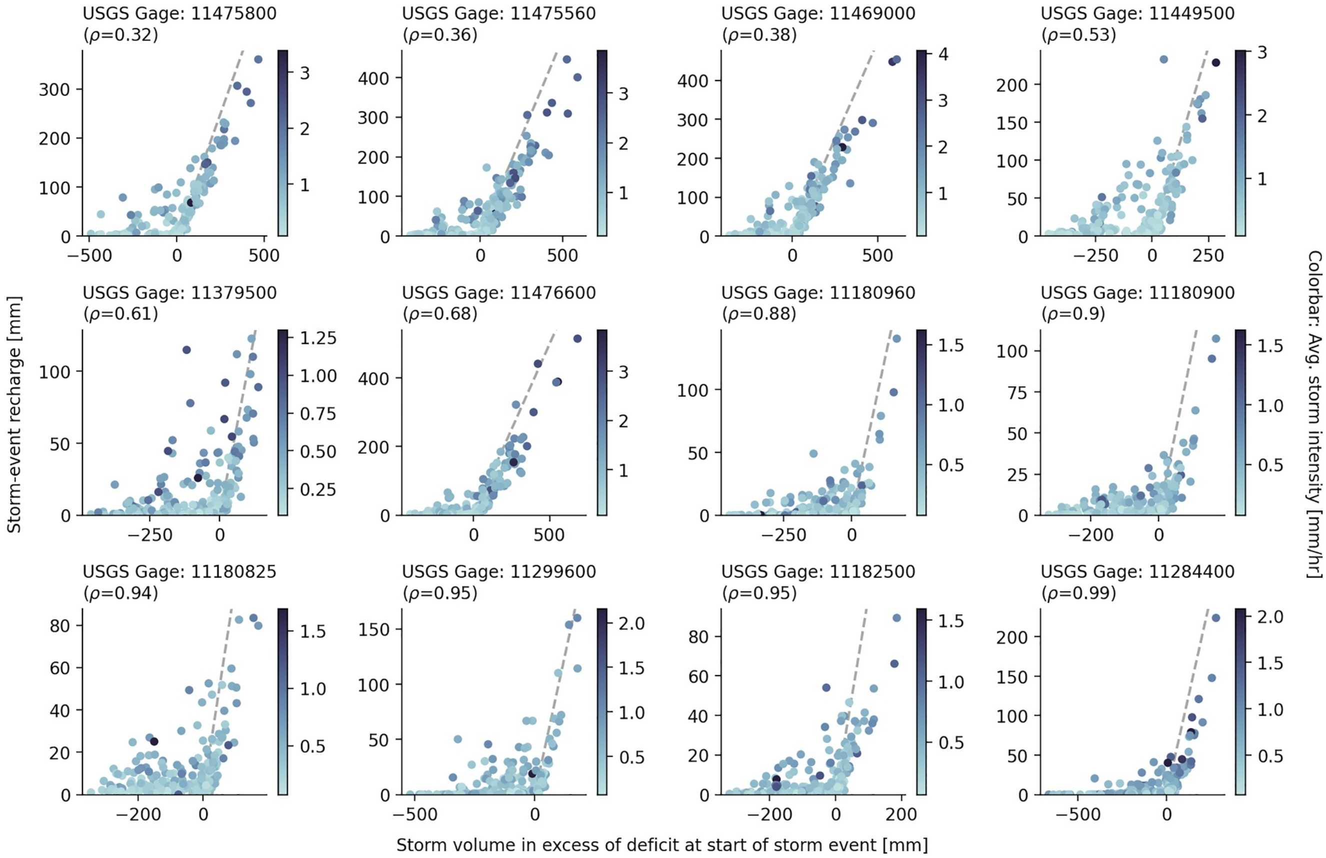

Figure 8. Storm-event recharge plotted against total rainfall in excess of vadose zone storage deficits across filtered basins. When event rainfall is greater than the outstanding deficit, and the vadose zone (spatially averaged across the watershed) has reached field capacity, event recharge and precipitation approach a 1:1 relationship (gray dashed line).

Further research is needed to distinguish between near-channel storage activation and water routing that bypasses the vadose zone.

4.2. Tracking the Deficit May Improve Hydrologic Models Ability to Estimate Streamflow

The mechanistic water-balance analysis outlined herein does not rely on approximated soil water storage parameters to estimate the control of unsaturated zone deficits on groundwater recharge dynamics as is often found in hydrologic models (e.g., Bieger et al., 2017; Hamman et al., 2018; Markstrom et al., 2015). For example, the Precipitation-Runoff Modeling System (PRMS), a process-based distributed-parameter watershed model (Markstrom et al., 2015), simulates the daily storage and movement of water across and within the "soil-zone" based on antecedent conditions and soil properties. These properties are more often than not derived from public data sets such as the Natural Resource Conservation Services Web Soil Survey (e.g., Gannett et al., 2017), encapsulating water transmission in the uppermost soil layers (Soil Survey Staff, 2020). Accounting for "antecedent," "activation," or "threshold" soil moisture has previously been demonstrated to significantly improve watershed water quantity models (e.g., Karnieli & Ben-Asher, 1993), predictions (e.g., Oubeidillah et al., 2019; Wyatt et al., 2020), and direct estimates of groundwater recharge (e.g., Peterson & Western, 2014). We propose integrating the role of root zone water storage deficits, including both soil and rock moisture reservoirs, in regulating groundwater recharge could result in similar improvements.

Hydrological models vary in their complexity, functionality, and applicability across watersheds and scales (Keller et al., 2023). As noted by Orth et al. (2015), increasing model complexity does not necessarily correspond with improved performance, and selecting the "best" model for a given task is often highly dependent on the availability and quality of input climate and land (sub)surface data. Our presented analysis is computationally simple and, despite its geographically limited application, employs climate and land-surface data sets with broad spatial and temporal coverage across the contemporaneous United States. Integrating the root zone storage deficit and numerical recharge methods in existing water quantity models may support modeling efforts in remote, data-limited headland basins when near-surface soil survey data sets are insufficient and intensive field measurements of subsurface structure would otherwise be needed to accurately simulate hydrologic fluxes and processes (e.g., Camporese et al., 2019; Chen et al., 2023). However, we recognize the limitations of our presented analysis and the need to address these caveats before implementation. We discuss these challenges in detail and suggest avenues of continued research in the following section.

4.3. Limitations of the Recharge-Runoff Method

Targeting rainfall-dominated, seasonally dry watersheds with unimpaired stream networks and highly vegetated, undisturbed hillslopes inherently limits our analysis to select basins within distinct climate zones (Table S2 in Supporting Information S1). The need for continuous timeseries of water balance fluxes, with sufficient spatial coverage and resolution to estimate daily groundwater recharge and variations in the root zone storage deficit, not only further hinders broad application but may also introduce substantial uncertainty. For instance, discrepant ET (PML_V2) and P (PRISM) flux estimations caused the total volume of water evapotranspired to slightly exceed the total volume of water entering some basins (Figure 5a). While this may be indicative of plants reducing water held in deep bedrock for transpiration that was accumulated prior to the onset of our study, the imbalance nonetheless lead to a runaway cumulative root zone deficit that halved the number of basins available for the event-scale analysis ($n = 24$ to $n = 12$).

Cumulative systematic error in the data products used in our analysis could result in erroneous estimations of independently calculated R and D. However, good agreement in the water balance across the 24 basins, with varying geologic and vegetative composition (Figure 5c), supports our selection of hydrologic data sources (e.g., PML_V2 evapotranspiration, Figure S8 in Supporting Information S1), as does the characteristic response of R to event P in excess of D (Figure 8). Further, the observed relationship between R and D is not diminished when other data sources are employed (see Text S1 and Figure S1 in Supporting Information S1) and is indicative of the strength of the Wang-Erlandsson et al. (2016) and Dralle et al. (2023) methods in capturing the moderation of recharge by soil and rock moisture deficits driven by plant water-extraction. Although we defend the selection of data products used in the analysis, we recognize hydrologic timeseries should be validated wherever possible with independent field observations.

While inter-basin groundwater exchange can be substantial in headwater basins (Schaller & Fan, 2009), the analysis presented here relies on the assumption that no inter-basin groundwater flow occurs such that the watershed boundaries define the control volume for a hydrologic mass balance. This assumption may introduce uncertainty into the water balance. In watersheds where such exchanges are substantial, the magnitude and even the sign of inferred storage changes could be biased, particularly during low-flow periods when groundwater contributions represent a larger fraction of total discharge. Nonetheless, we expect the deficit refilling to impact the timing of streamflow response.

The unknown effects of evolving watershed hydrology on the ability of the root zone storage deficit to capture changes in basin streamflow generation due to changing land-use and climate forcing also remains untested. The assumption of unchanging basin characteristics, and thus "stationary" hydrologic processes, is increasingly violated by global climate-induced changes in the terrestrial atmosphere, surface, and subsurface (Koutsoyiannis, 2006). The increasing range of arid, seasonal climates across the mid-latitudes (Cui et al., 2021; Feng et al., 2019) reflects shifting climates, instead of temporary changes in weather, that may permanently modify basin hydroclimates. As an extreme example, Australia's millennium drought (beginning in the late 1990s and ending in 2011) significantly altered storage-discharge dynamics across many southeastern watersheds (Fowler et al., 2022) and led to the hypothesis that some basins may remain in a state of hydrological drought long after meteorological droughts end (Peterson et al., 2021). We advocate for continued research to test if the combination of the Wang-Erlandsson et al. (2016) root zone storage and Dralle et al. (2023) recharge estimation sufficiently captures groundwater recharge as a function of vadose zone storage in basins undergoing substantial hydrogeologic transformation.

5. Conclusion

This work explored the role of root zone storage moisture deficits in moderating the response of groundwater recharge to precipitation across seasonally dry, undisturbed watersheds spanning California. We estimated the deficit using distributed, publicly available hydrologic fluxes and compared it to groundwater recharge calculated from streamflow alone using a recent adaptation of the storage-discharge relationship by Dralle et al. (2023). Our analysis across 12 watersheds revealed that the control of deficit on recharge is best captured at the daily scale, as seasonal analyses obscure deficit accumulation between wet season storms when evapotranspiration and groundwater drainage deplete the vadose zone. Plotting the groundwater recharge derived from event precipitation in excess of outstanding root zone storage deficits reveals a characteristic increase in the available water for streamflow as moisture deficits are replenished. This finding supports extensive literature regarding the role of antecedent soil moisture in controlling streamflow generation at the basin-scale in basins where streamflow is primarily fed by shallow subsurface flow or groundwater. Critically, however, our analysis does not rely on intensive field instrumentation. In capturing both upper soil and deep rock moisture, the mechanistic water-balance approach outlined in this study has the potential to surpass models of streamflow generation based on estimated soil water storage parameters. However, additional work is needed to extend the model domain beyond the California basins included in the analysis. Our work contributes to a growing body of literature seeking to better understand, and more easily quantify, mechanisms of groundwater recharge to promote the sustainable management of this critical freshwater reservoir.

Data Availability Statement

All data products are derived from publicly available data sets hosted by the National Water Information System (U.S. Geological Survey, 2016) and in Google Earth Engine (Gorelick et al., 2017), with analyses conducted in the Google Colaboratory programming environment (Bisong & Bisong, 2019). The datasets generated in this study are available in Hydroshare at https://www.hydroshare.org/resource/b0f021bdc474474bbae9037f89e2c1d2/ (Benitez-Nelson et al., 2024). A repository of the code developed for the analysis is available in GitHub at https://github.com/noah-beniteznelson/recharge-deficit (Benitez-Nelson, 2024).

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