Missing snowmelt runoff following drought explained by root-zone storage deficits

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Missing snowmelt runoff following drought explained by root-zone storage deficits

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Water resources management in mountainous regions hinges on forecasting runoff during annual snowmelt periods. However, extreme droughts are altering snowpack-runoff relationships. The current megadrought in the Western United States provides a case in point: in 2021 in California, the historically reliable relationship between April 1 snowpack and runoff failed—much less streamflow arrived than was predicted. Several factors have been proposed to account for this 'missing' streamflow, including changes in: evapotranspiration, rainfall, snowmelt rate, and subsurface moisture conditions. Here, we use hydrologic data from 13 minimally disturbed basins and 6 water supply basins in the Sierra Nevada to demonstrate that the root-zone storage deficit (i.e., the net depletion of plant-accessible water from soil and weathered bedrock via evapotranspiration) is the dominant driver of snowmelt runoff reductions in years following drought. Transpiration in excess of precipitation in drought years generates large deficits that must be met prior to significant streamflow generation. We introduce a mass balance model that captures this effect to motivate model structures for forecasting models. By accounting for deficits in models for snowmelt runoff, overprediction of 2021 streamflow decreased from a total of ≈100% to <12% at study sites in the Sierra Nevada. Our findings indicate that the relationship between snowpack and runoff will evolve as plant ecosystems respond to climate change and alter subsurface water storage dynamics. Through this climatic transition, root-zone storage deficits will play an essential role in snowmelt runoff prediction, and this study provides a framework for adapting forecasting models with readily-available data.

Sierra Nevada | Forecasting | Water resources | Evapotranspiration | Snowpack

Introduction

Mountain snowpack is an essential water reservoir for 1.9 billion people globally (2). However, the accessibility of this water depends on how snowmelt runoff is generated. Historically, managers have relied on statistical relationships between snowpack and subsequent runoff for forecasting (3), but changes in climate can alter these relationships. Recently, following a severe drought in California, streamflow forecasts from historically reliable snowpack-runoff relationships (4) far exceeded actual streamflow (see for example, Figure 1a-b). This led scientists and the public alike (e.g., 5, 6) to wonder—where did the missing snowmelt go?

Previous work has proposed that shifts in streamflow generation from a given water input (snowpack) arise from differences in evapotranspiration (ET) due to changes in evaporative demand (7–9), snowmelt rate (10), and/or vegetation community (11–13). Antecedent moisture conditions have also been proposed to alter the relationship between water inputs and resulting streamflow (e.g., 8, 14–16), including the role of rainfall inputs during the winter season and subsurface moisture conditions at the start of the winter season. Both of these factors can be tied to a form of runoff generation in which significant runoff is generated only after infiltrating water replenishes subsurface storage (17, 18). After the subsurface dries (typically through withdrawal of root-zone moisture by ET as shown in Figure 1d, 18–30), infiltrating water goes first to replenishing this moisture deficit and then towards generating streamflow. Less water input prior to snowmelt (i.e., winter rainfall) or more evapotranspiration during or prior to snowmelt (i.e., winter and spring ET) can limit how quickly the storage deficit is replenished—the precondition for significant streamflow generation. In this way, subsurface moisture conditions interact with above-ground factors to mediate runoff generation from snowpack.

Subsurface moisture deficits occur in soils as well as the underlying weathered bedrock, which can account for a large portion of root-zone water storage (20, 27, 31, 32). Although there have been advances in large-scale observation of shallow soil moisture conditions (33), deeper storage is less easy to monitor (26). Storage changes recorded by GRACE (34) are not finely resolved and include water storage effects (e.g., deep groundwater) that may not be relevant to the root-zone, and modeled subsurface water storage is contingent on the reliability of model parameterization and available soil textural databases, which cannot account for storage dynamics

Significance Statement

Essential water supply from snowpack may become more difficult to predict as the climate changes. Following a recent drought in California, the traditionally used model for snowmelt runoff failed. Here, we present a model that accounts for this model failure by incorporating the role of root-zone storage dynamics in the production of snowmelt runoff. Through transpiration, montane forests generate water storage deficits in the soils and weathered bedrock that comprise the root-zone. These deficits must be replenished by rain and snowmelt before significant runoff generation can occur. Overprediction of 2021 post-drought runoff in California can be primarily attributed to unprecedently large root-zone storage deficits. Adding a measure of deficit reduced 2021 streamflow prediction error from ≈100% to <12%.

DND conceived of the study. DAL and DND formulated the hydrological model. DAL compiled data, conducted analyses, generated graphics, and wrote the initial manuscript. WJH and DND reviewed analysis code. All authors were involved in idea generation, significant manuscript revision, and review of the final manuscript.

The authors have no conflicts of interest to declare.

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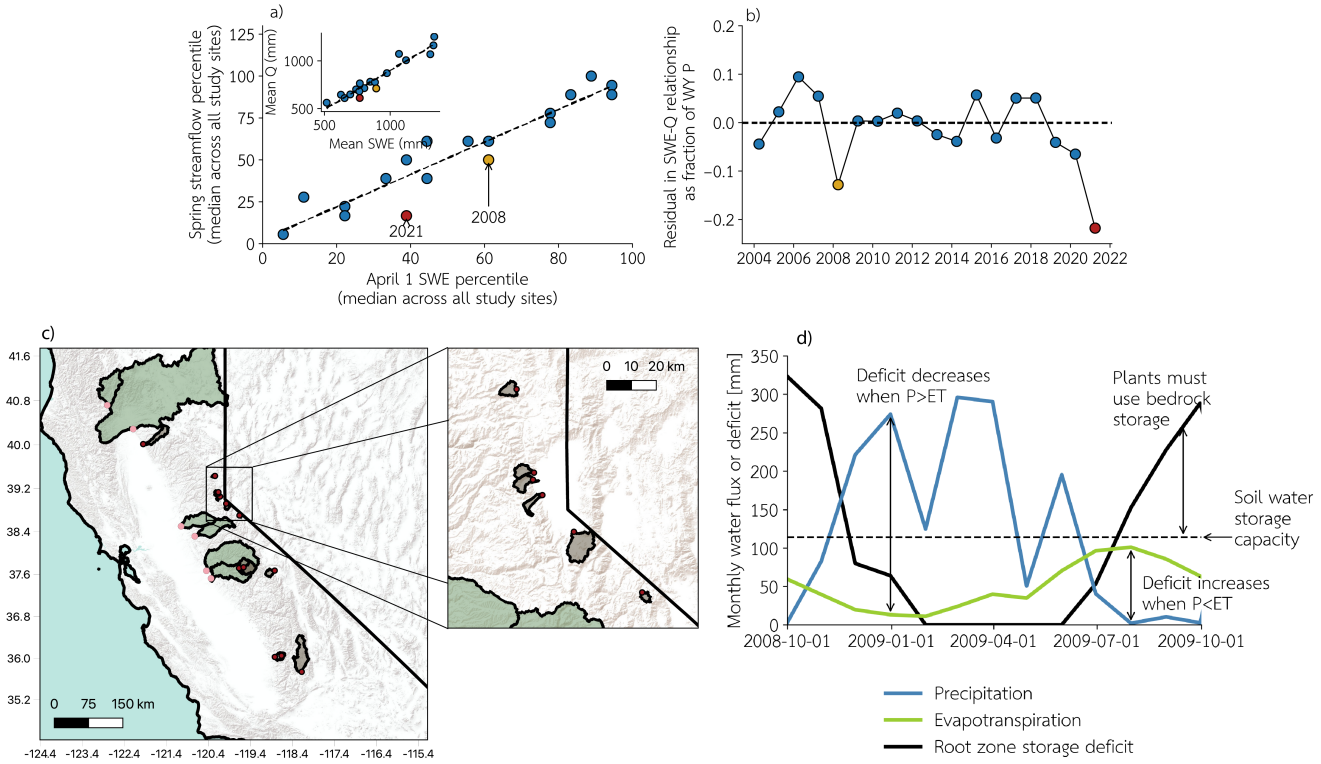

Fig. 1. (a) Linear relationship between April 1 snow water equivalent (SWE) and spring (April-July) streamflow summarized at 13 minimally disturbed sites as the relationship between median April 1 SWE percentile and median spring streamflow percentile for each year within the study period (2003-2021). This regression model is of a similar form to the one used by the California Department of Water Resources to produce streamflow forecasts. Inset shows the same plot for the mean value of April 1 SWE and spring streamflow among the 13 minimally disturbed sites. Points that fall above the dashed line are years where the linear model under-predicts streamflow, and points that lie below the line are years where the linear model over-predicts streamflow. 2021 and 2008 are highlighted as particularly large negative residuals. SWE data is from SNODAS (1). (b) Median residual in the SWE-spring streamflow relationship among the 13 minimally disturbed sites as a fraction of April 1 SWE. (c) Map of study watersheds in the Sierra Nevada. Red dots mark gage locations at watershed outlets for minimally disturbed sites shaded in grey, and pink dots for basins important for water supply shaded in green. (d) Explanatory plot for root-zone storage deficit for one water year. At the beginning of the wet season, the deficit decreases (storage fills up) to 0 and remains there until ET exceeds P again in the dry season, and the deficit grows until the beginning of the next wet season. Deficits in excess of the soil water storage capacity indicate plant use of water stored below soil in weathered bedrock.

in underlying bedrock (35).

An alternative approach for estimating runoff-mediating subsurface moisture conditions is to track the balance between fluxes entering and exiting the root-zone. Spatially distributed, running, near real-time plant-driven water storage dynamics throughout both soil and bedrock can thus be quantified from precipitation and ET timeseries (36–38). Considering storage deficits in runoff prediction (39) or as a harbinger of drought (40, 41) is not new, but the widespread availability of distributed and increasingly reliable ET, precipitation (36), snow cover (37), and snow water equivalent (SWE) datasets now make it possible to monitor deficits in mountainous regions at large scales.

In this study, we introduce a mass-balance model for snowmelt driven runoff in a Mediterranean environment (wet winter, dry growing season) that explicitly incorporates the root-zone water storage deficit to explore the following hypothesized explanations for snowmelt runoff reduction (see Figure 2 for a schematic):

1. Less rainfall fell than usual during the winter or spring
2. Snowmelt rate was slower than usual
3. Evaporative demand was higher than usual during the winter

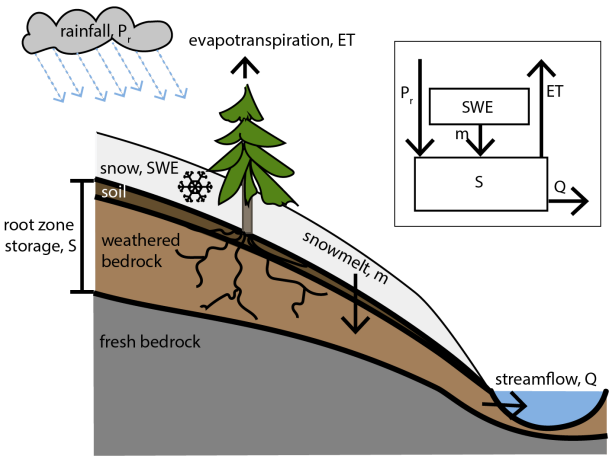

Fig. 2. Conceptual hillslope diagram of mountain hydrology. Thin soils cover a deep, weathered bedrock zone that plants may access throughout the dry season. Snow accumulates during the winter and melts into the subsurface, while rain directly replenishes the subsurface. Evapotranspiration reduces water in storage, and streamflow is generated once a subsurface storage deficit is replenished. The inset diagram shows the two modeled water reservoirs (snow and root-zone storage) and fluxes (rainfall, snowmelt, evapotranspiration, and streamflow).

4. Evaporative demand was higher than usual during the spring

5. The root-zone water storage deficit at the start of the wet season was larger than usual.

We validate our mass balance model against observed spring streamflow at 13 minimally disturbed sites in the Sierra Nevada (see the 'Materials and methods' section for more details), and then develop a multiple linear regression model to quantify which drivers have the largest impact on snowmelt runoff. Based on results from the multiple linear regression analysis, we quantify improvement in snowmelt runoff forecasts in 2021 at 13 minimally disturbed watersheds as well as 6 watersheds important for California's water supply. While we specifically explore the fate of the 'missing' 2021 snowmelt runoff in California, our goal is to understand how subsurface water storage dynamics—in combination with other previously studied mechanisms—inform forecasting of snowmelt runoff in general.

Results

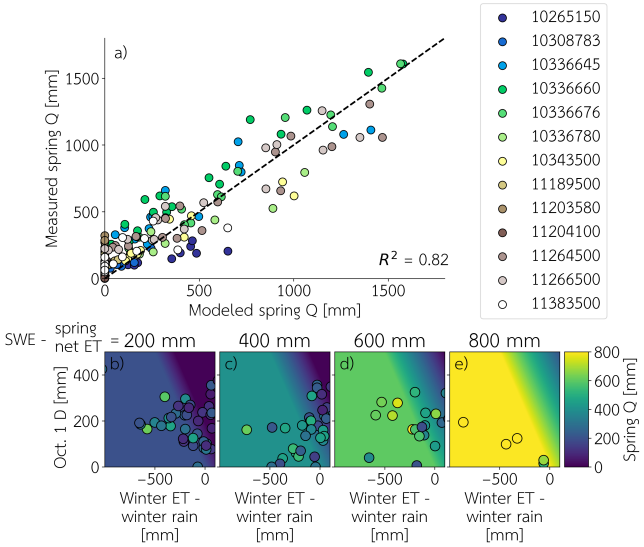

Fig. 3. (a) Comparison between measured spring streamflow at minimally disturbed study sites and predicted streamflow based on Equation 1. Legend refers to USGS streamgauge ID. (b-e) Heatmaps showing how modeled streamflow varies based on each model parameter. Within each panel: winter ET - winter rain increases moving right, and October 1 deficit increases vertically. Moving to the right between panels, April 1 SWE - (spring ET - spring rain) increases. Points plotted on heatmaps represent a single water year for a study site and are colored by measured spring streamflow. Points are plotted on the heatmaps if $SWE - ET_{net}N_{melt}$ is within 100 mm of the value labeled for each panel.

The mass balance model of root-zone storage (Equation 1; see Materials and Methods for model description) accurately predicts measured spring streamflow ($R^2 = 0.84$ for one-to-one line, see Figure 3a) at 13 minimally disturbed sites in the Sierra Nevada (grey sites in Figure 1c). Panels b-e plot these same predictions, showing scatter points colored by actual spring streamflow against heatmaps generated from the mass balance model. Good model performance despite a lack of tunable parameters suggests that the model captures the primary mechanisms for spring streamflow generation at the study sites.

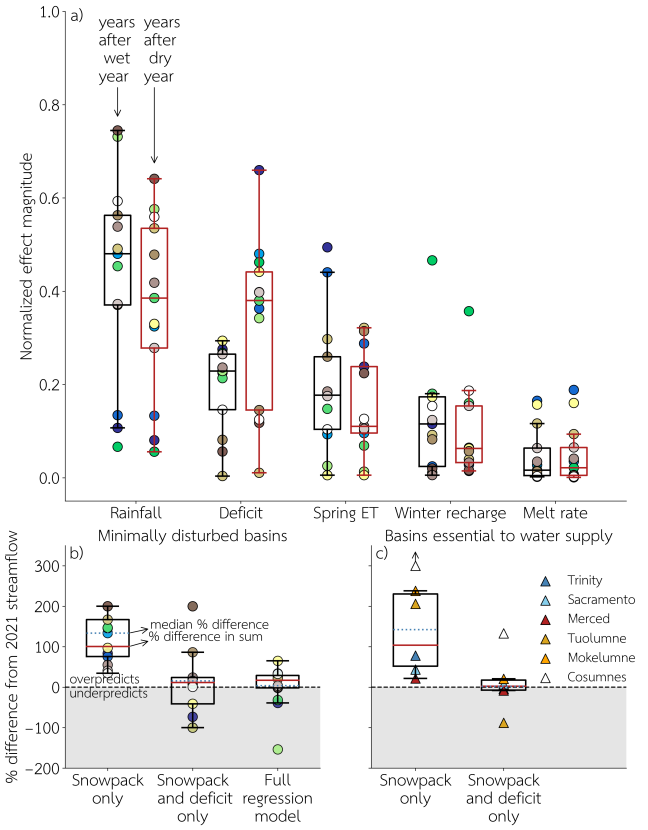

Fig. 4. a) Normalized effect magnitude of each variable included in the multiple linear regression for snowmelt runoff at all sites, comparing the set of years following wet years to years following dry years during the study period. Snowpack is consistently the most important variable and is excluded from this plot. Variable names are described for the water balance feature they represent, but rainfall, deficit, spring net ET, and winter recharge are relative to water year precipitation in the model to reduce correlation among variables, and melt rate is relative to spring net ET. Box and whisker plot shows median value across all sites. Effect size is the coefficient for a given variable multiplied by the median absolute value of the variable for years following wet (black) or dry (red) years. Normalization is achieved by scaling the effect sizes for each site so that their absolute values sum to 1, and the magnitude of these normalized values is reported. Panels b) and c) show performance of regression models at 13 minimally disturbed sites (b) and 6 basins important for California's water supply (c) for the year 2021. A linear regression model using only April 1 SWE overpredicts the total 2021 spring streamflow at all minimally disturbed sites by 100% (median 134%), while the full linear regression model or a model using April 1 SWE and October deficit as a fraction of winter precipitation overpredicts the total by 17 or 12% (median of 15 or 4%), respectively. At the 6 basins important for California's water supply, a linear regression using only April 1 SWE overpredicts median streamflow by 143%, versus 2% with a model using April 1 SWE and October deficit. Legend for panels a) and b) is the same as for Figure 3a.

root-zone storage deficit is important for determining runoff from snowpack. We regressed spring runoff (April-July, proxy for snowmelt runoff) on the variables identified in the storage-based modeling framework (Equation 2) at the 13 minimally disturbed sites to quantitatively rank the importance of different physical drivers of snowmelt runoff generation during years following both wet (above 75th percentile of annual precipitation) and dry (below 25th percentile of annual precipitation) years (Figure 4a). Model outcomes in both wet and dry years are most sensitive to snowpack, followed by rainfall since the amount of precipitation is the first-order control on snowmelt runoff. Rainfall, however, does not explain significantly lower model performance in years following wet versus dry years (median difference of 0.18 in R^2, see Supplemental Information

Table 4 for site-specific details) since the effect size is similar. In contrast, the effect size of the deficit is substantially larger following dry years than wet years so that the deficit is as important as rainfall following dry years. In fact, the deficit is the only parameter that shows a substantial difference in effect size following dry years, suggesting that large deficits generated during dry years play an essential role in reducing snowmelt runoff in the following year. See Supplemental Tables 3 and 4 for effect sizes for all variables at all sites on wet and dry years.

With rare exceptions, the sign for each effect size matches the expected sign based on hypothesized model mechanisms at all sites (see Supplemental Table 3), providing further evidence for the proposed conceptual framework. No more than one site shows an unexpected sign for any parameter except for the melt rate, which has an unexpected sign at 4 sites. Given the melt rate's small effect sizes and unexpected effect signs, we conclude melt rate is relatively insignificant in comparison to other explanatory variables. The median R^2 value for multiple linear regression models across the study sites is 0.93.

We also trained a single random forest model to predict spring streamflow at all sites based on the same set of input parameters (model performance $R^2 = 0.98$) since a linear model may not account for complex interactions between the hydrologic processes used in the regression. Results from the random forest analysis also support the hypothesized mechanisms, and contribution of parameters to model outputs as measured by feature importance confirms that October 1 deficit and spring net ET are important drivers of snowmelt runoff, whereas the melt rate is less important. See Supplemental Information S6 for more details.

Using deficits increases predictive power of forecasting models. A linear regression model using only snowpack (Figure 1a) replicates the 2021 "missing" streamflow phenomenon with a similar magnitude of error in 2021 (4). By adding a term representing the deficit (linear regression using only snowpack and deficit), model performance improves to a median of $R^2 = 0.85$, a median improvement of 0.05 over a model using only snowpack. For site-specific details, see Supplemental Table 3.

When focusing on anomalous years such as the 2021 water year, gains in model performance are substantially larger than the modest improvement in R^2 would suggest (See Supplemental Information Figure S4 for details on improved model performance on a year with underprediction). Figure 4b shows predictions for 2021 streamflow at the minimally disturbed sites using the full multiple linear regression model, snowpack and deficit only, and snowpack only. Each regression model is trained on data from the full study period. Using only snowpack, the model over-predicts the 2021 total streamflow from all sites by 100%. Using the full regression model, total streamflow is only over-predicted by 17%, and with snowpack and deficit it is over-predicted by only 12%. For each site, the median overprediction using a regression model with only snowpack is 134%, with the full regression model 4%, and with snowpack and deficit 15%.

We tested our model on minimally disturbed basins. However, given that the deficit is calculated using remotely-sensed evapotranspiration, it should be sensitive to spatial variation in land-cover or forms of disturbance, such as fire, that are known to impact patterns of plant water use (42–45). This suggests our model may be applicable to larger and more complex basins. We therefore also applied the model to six watersheds central to California's water supply (green basins in Figure 1c and Supplemental Information S1 for additional site information). As shown in Figure 4c, adding a term to a linear regression model to represent the deficit improves error in prediction of 2021 streamflow from a total of 104% to 2% overprediction or a median of 143% to 2%. Therefore, incorporating the root-zone storage deficit into models for spring streamflow from snowpack substantially improves model performance for water resources-relevant forecasting, especially following dry years.

Discussion and conclusions

Large drought-induced root-zone storage deficits at the start of the 2021 wet season led to the "missing" streamflow phenomenon. Adding a term to describe root-zone storage deficit decreased total overprediction of 2021 snowmelt runoff in a linear regression model from a 100% to 12%, an essential improvement for water resources management. Among the terms indicated to be most important, only the October 1 deficit can be quantified prior to the snowmelt season for the purpose of improved snowmelt runoff forecasting.

Managers and researchers have long recognized the importance of subsurface moisture conditions for subsequent runoff (e.g., personal communication with Sean de Guzman, chief of the California Department of Water Resources Snow Surveys and Water Supply Forecasting Section, and 18–30, 39); however, incorporating root-zone water storage dynamics into forecasting presents a challenge. This is due to both the limited available data on water storage in weathered bedrock, as well as the challenge of understanding interactions between different drivers of root-zone dynamics. The presented model quantitatively captures the expected importance of subsurface moisture conditions for runoff forecasting, providing a low-complexity solution to the problem of runoff prediction (36, 37). The model captures snowmelt runoff well following dry years, which is essential given the projected increase in "whiplash" (alternation between extreme wet and dry years, 46). A further implication of our findings is that runoff generation in the Sierra is probably not dependent on infiltration-excess overland flow processes, which should be relatively insensitive to root-zone storage deficits (47). Instead, the agreement between the presented model and data supports the hypothesis that replenishment of root-zone storage deficits is required for significant runoff generation to occur, which is more consistent with saturation overland (48) or subsurface (49) flow generation mechanisms.

Climate change is impacting the reliability and predictability of water supply in many different ways, just one of which is post-drought reductions in expected snowmelt runoff. Root-zone storage deficits provide a means of monitoring changing conditions, but operationalizing deficits in real-time requires the development of frequently-updated, reliable, large-scale ET and P datasets. Multiple data products are being developed and tested in the community to support urgent needs for research and management applications, and the present study provides yet more motivation to continue honing these essential datasets.

Materials and methods

Table 1. Table of notation.

Variable	Dimensions	Description
Q	L	Total runoff during snowmelt period
SWE	L	Snowpack at start of snowmelt period
P	L	Water year total precipitation
m	L/T	Snowmelt rate
ET_s	L/T	Mean spring ET rate
ET_w	L	Total winter ET
P_s	L/T	Mean spring rainfall rate
P_w	L	Total winter rainfall
ET_{net}	L/T	Spring ET rate - spring rainfall rate
N_{melt}	T	Duration of snowmelt period
D_{oct1}	L	Deficit at start of wet season

Mass-balance snowmelt runoff model. Here we expand upon a stochastic hydrological model (50) that incorporates storage as a simple 1-d bucket to describe annual runoff dynamics and plant water availability in Mediterranean catchments. In the original model, precipitation P [L] contributes water to storage during the wet season, and evapotranspiration ET [L] removes water from storage primarily during the dry season. Streamflow is generated only if the subsurface storage reservoir is full. The root-zone is treated as a single storage reservoir representing a thin soil layer underlain by deep weathered bedrock (Figure 2), as is common in forested mountainous environments (27, 51–53). The model does not specify where water is stored within the root-zone or its energy state (e.g., saturated versus unsaturated). Nor does it mechanistically specify how groundwater produces streamflow at the hillslope-channel boundary, only that water input volumes in excess of the deficit generate flow in the stream.

In our model formulation, storage dynamics evolve annually over three hydrological seasons: a winter wet season when rain enters storage and snow accumulates, a snowmelt season when rain and snowmelt enter storage, and a dry summer season. ET draws from storage at different rates in each season. Starting at the beginning of the wet season, there is a deficit generated by the previous dry season that shrinks with water input during the winter wet season and snowmelt periods (Figure 1d). Once the deficit is reduced to 0, streamflow is generated. When ET exceeds snowmelt and rain in the spring, streamflow stops, and the deficit grows again until the start of the next wet season. Snowmelt runoff emerges as the net water input during the melt season (snowmelt and precipitation less ET) once the deficit has been met. This mass balance results in an expression for snowmelt runoff (Q [L]), in which each of the proposed factors that could impact the relationship between snowpack and streamflow appear as variables:

$$Q = \begin{cases} \text{if } P_w - ET_w > D_{Oct1}: \\ \quad \max(0, SWE - (ET_s - P_s)N_{melt}) \\ \text{otherwise:} \\ \quad \max(0, SWE - (ET_s - P_s)N_{melt} - \\ \qquad\qquad D_{Oct1} + (P_w - ET_w)) \end{cases} \quad [1]$$

Notation is defined in Table 1. Both conditions are bounded by zero since streamflow cannot be negative. A negative value for either condition indicates that water demand from ET exceeds water availability from rain and snowmelt, so streamflow must be zero. In Equation 1, all of the hypotheses listed at the end of the introduction for missing snowmelt appear: (1) rain appears in ET_{net}, P_w, and P_s, (2) snowmelt rate appears in $N_{melt} = SWE/m$, (3) ET appears in ET_s and ET_w, and (4) the deficit appears as D_{Oct1}. For a full description of the model, see Supplemental Information S2 and S3.

We validated our mass balance model against observed spring streamflow at 13 minimally disturbed sites in the Sierra Nevada and then developed a multiple linear regression model to quantify which drivers have the largest impact on snowmelt runoff. Results of the multiple linear regression analysis were used to develop a model structure for an improved forecast model, which was tested at the 13 minimally disturbed watersheds as well as 6 watersheds important to California's water supply.

A regression model for snowmelt-driven runoff. We performed exploratory data analysis to determine which hypotheses listed at the end of the introduction best explain snowmelt runoff at the study sites (Figure 1c). See Supplemental Information S1 for details on study sites and site selection criteria, and Supplemental Information S5 for additional details on exploratory analysis. To determine which mechanisms have the most explanatory power for deviations from the snowpack-runoff relationship, we developed a multiple linear regression equation at each study site:

$$Q = C_1\ SWE + C_2\frac{D_{Oct1}}{P} + C_3\frac{ET_{net}N_{melt}}{P} + C_4\frac{ET_w - P_w}{P} + C_5\frac{P_w + P_s}{P} + C_6\frac{m}{ET_{net}} + C_7, \quad [2]$$

where $C_1, ..., C_7$ are fitted parameters.

Each variable other than SWE is expressed as a fraction of water year precipitation (except for m/ET_{net}). Expressing variables relative to water year P strengthens the relationship between variables and residuals in the SWE-Q relationship, similar to the finding of Hahm et al. (50) that the ratio between water year P and storage, not storage alone, is important for determining hydrological outcomes. This normalization also has the effect of minimizing correlation between variables since many model variables are correlated with water year P. In Equation 2, $ET_{net}N_{melt}/P$ and $(ET_w - P_w)/P$ capture effects of variable ET (Hypotheses 3 and 4 in the conceptual runoff model section), $(P_w + P_s)/P$ captures effects of variable rainfall (Hypothesis 1), m/ET_{net} captures effects of variable snowmelt rate (Hypothesis 2), and D_{Oct1}/P captures effects of variable root-zone storage deficit (Hypothesis 4). We also used a random forest model to corroborate the findings of this regression approach; see Supplemental Information S6 for additional details.

Data sources and data processing. Details on site selection criteria for the 13 minimally disturbed basins and site characteristics for all study basins are found in Supplemental Information S1.

Streamflow data were obtained from the National Water Information System (NWIS, 54) using the package hydrofunctions (https://hydrofunctions.readthedocs.io/en/master/). Daily snow water equivalent was obtained using SNODAS (1). Precipitation data were obtained from PRISM (55). Evapotranspiration and temperature data were obtained from PML V2 (56–58) and MODIS (59). PRISM, MODIS, and PML V2

were accessed via the Google Earth Engine Python API (60). Evaporative stress index (ESI) data were obtained from ClimateServ (61–64). ESI provides a measure of ET anomalies over time using thermal satellite imagery. A higher ESI indicates a larger positive ET anomaly, whereas lower or negative values indicate depressed ET. For comparison with root-zone storage deficit, we included soil water storage capacity (65) as processed by McCormick et al. (27).

For the majority of the study period, we use the PML V2 data set for ET. This data set, when combined with PRISM, captures subsurface storage deficits consistent with field measurements (27). Since PML V2 is not yet available through the 2021 water year, we extended the PML V2 data set using MODIS ET. We bias-corrected MODIS ET to PML V2 using a basin-specific linear relationship for each study watershed. For most watersheds, the correlation between PML V2 and MODIS ET is strong (median R^2 >0.4, see Supplementary Code (66)).

Snowmelt rate was calculated from daily SNODAS data as in Barnhart et al. (10):

$$m = \frac{\Sigma|min(\Delta SWE_t, 0)|}{\Sigma\Delta_t}, \quad [3]$$

where the numerator is the sum of all daily differences in SWE on days when SWE decreases, and Δ_t is 1 on days when SWE decreases and otherwise 0.

The root-zone storage deficit was calculated following Wang-Erlandsson et al. (36) and Dralle et al. (37). The only difference here is that instead of using only precipitation and evapotranspiration (36) or approximating information about snow using snow cover (37), we used SNODAS data directly to represent accumulation and melt of snowpack. For a full description of deficit calculations, see Supplemental Information S3.

ACKNOWLEDGMENTS. We would like to thank Sean de Guzman, chief of the California Department of Water Resources Snow Surveys and Water Supply Forecasting Section, for providing insight into how runoff is forecast in California. Funding was provided by Simon Fraser University, a Natural Sciences and Engineering Research Council of Canada Discovery Grant, and the USDA Forest Service Pacific Southwest Research Station with funds administered by Oak Ridge Institute for Science and Education (ORISE).

Open research

Data and code generated for this publication are available in an online data repository (66, https://github.com/lapidesd/CA_missing_freshet,). Raster maps of percentiles of April 1 SWE are available at https://www.hydroshare.org/resource/4b940b8593a4416e954a47bbbc58c568/ (67). Primary analyses are available as Google Colab notebooks: (i) exploration of relationship between April 1 SWE and spring runoff at each study site (https://colab.research.google.com/drive/1tv8kbIe9EY3vFdAQzbJTfE7RmDpM9uQG?usp=sharing), (ii) calculation of all quantities used in analysis and exploring the four hypotheses stated at the end of the introduction (https://colab.research.google.com/drive/1hq-qqlIR_LuEyZ5s5RPddnqDLBo4M309?usp=sharing), (iii) development of a random forest model and a multiple linear regression model for spring streamflow and examines the results (https://colab.research.google.com/drive/1jPtdcESsGPfB2H6MC-W7metpiFSqe799?usp=sharing), (iv) implementation of the model described in Section (https://colab.research.google.com/drive/197Hglpe3kkThdblSFz-9U9h63lvdQzE9?usp=sharing, and (v) exploring predictive improvement by adding the deficit at 6 economically import watersheds in California (https://colab.research.google.com/drive/1_igz4g_mbTntAkPZv3SJGwnYIRUEEBFE?usp=sharing).

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Supplementary Information for

Missing snowmelt runoff following drought explained by root-zone storage deficits

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This PDF file includes:

Supporting Information Text

Site description and site selection

California experiences a Mediterranean climate with cool, wet winters and hot, dry summers. In much of California, wet season precipitation arrives as rain, but mountainous regions such as the Sierra Nevada predominantly receive snow. Mediterranean regions generally have highly variable annual precipitation (1) and are subject to rapid switches between drought and flood conditions (2, 3). California has a particularly variable climate due to the added influence of complex topography (4). In the past decade, California has experienced extreme drought (5–7) that resulted in extensive wildfires (8, 9) and tree mortality (10–12), and periods of extraordinarily high precipitation (13, e.g., winter 2016-2017;) that resulted in widespread flooding (13) and landslides (14).

Site	Stream name	Gage location	Area [km^2]	MAP [mm]	Snow percent	Mean Annual Q [mm]
Pristine basins:						
10336780	Trout Creek	-119.972, 38.9199	95	893	67	315
10336645	General Creek	-120.118, 39.0518	19	1202	58	740
10336660	Blackwood Creek	-120.162, 39.1074	29	1486	59	1018
10336676	Ward Creek	-120.157, 39.1321	25	1549	61	885
10343500	Sagehen Creek	-120.237, 39.4315	27	976	65	319
10308783	Leviathan Creek	-119.656, 38.7012	11	635	60	50
11383500	Deer Creek	-121.948, 40.0140	539	1484	32	499
11189500	SF Kern River	-118.173, 35.7374	1373	477	36	72
11204100	SF Tule River near Reservation	-118.813, 36.0241	248	798	25	128
11203580	SF Tule River near Chololo Camp	-118.654, 36.0482	52	996	44	278
11266500	Merced River at Pohono Bridge	-119.666, 37.7168	831	1213	60	685
11264500	Merced River at Happy Isles Bridge	-119.558, 37.7315	469	1199	68	673
10265150	Hot Creek	-118.817, 37.6688	177	814	72	262
Basins essential for California water supply:						
11525500	Trinity River	-122.804, 40.7193	1862	1445	17	405
11377100	Sacramento River	-122.187, 40.2885	23051	972	27	426
11270900	Merced River	-120.332, 37.5216	2748	1032	29	399
11289650	Tuolumne River	-120.442, 37.6663	3983	1098	37	222
11319500	Mokelumne River below Merced Falls	-120.720, 38.3127	1408	1265	38	612
11335000	Cosumnes River	-121.045, 38.5002	1388	1073	13	292

Table S1. Catchment attributes for study sites. Streamflow and basic site information are from NWIS (15), and climate information are derived from GAGES-II (16).

To explore drivers of low streamflow in 2021 in California, we examined a set of minimally disturbed, gauged watersheds in the Sierra Nevada (Figure 1c in main text). Sites were selected in the Sierra Nevada that met the following criteria:

1. no upstream dams (16),
2. >20% precipitation falls as snow annually on average (16),
3. watershed boundaries were delineated in NHD+ (17),
4. <5% developed land cover (18),
5. <5% cultivated land cover (18),
6. <35% burned area between 1990 and 2020 (19),
7. <20% logged area (20),
8. at least 10 years with continuous streamflow from April 1 - September 1 (15),
9. streamflow record includes 2021 (15).

All gages that met these criteria were reviewed manually to ensure hydrographs appear unmodified and snowmelt-dominated. We identified 13 catchments that met the selection criteria (Table S1), spread throughout the Sierra Nevada. The sites encompass a range in size from 11 to 1,373 km^2, annual precipitation from 369 to 979 mm, and a mean streamflow from 0.3 to 190 m^3/s. About half of the sites drain to the west, while the remaining sites (primarily those in the Tahoe area) drain to the east. Additionally, six basins essential to California's water supply were also included to demonstrate applicability of the presented methods to larger and more complex basins (bottom of Table S1).

Model description

Hahm et al. (21) developed a stochastic hydrological model incorporating root zone storage as a simple 1-d bucket that describes annual runoff dynamics in Mediterranean catchments. Similar to Figure 2 in the main text, the model describes a landscape with thin soil but a substantial weathered bedrock zone that stores plant-accessible water. The entire soil and weathered bedrock zone is treated as a single plant-accessible storage reservoir S [L]. During the wet season, precipitation P [L] contributes water to storage, and evapotranspiration ET [L] removes water from storage primarily during the dry season. Streamflow is generated only if the subsurface storage reservoir is full.

Hahm et al. (21), however, did not consider the scenario in which deficits were not replenished and could carry over between years. Evidence from field observations of soil and rock moisture and tree mortality (22, 23) and from water balance approaches using satellite data products (24–26) shows that root zone storage deficits can grow over multiple years, meaning that the deficit can vary substantially between years in a way that is important for vegetation response. Fowler et al. (27) also recently found that many hydrological models that lack the ability to generate multi-year deficits are unable to simulate streamflow conditions through multi-year droughts in Australia. Changes in subsurface storage (and deficit) give watersheds "memory" of prior precipitation that can persist. Peterson et al. (28) found that more than 8 years after the Millennium Drought in southeastern Australia, many watersheds had not returned to pre-drought conditions. They inferred that enhanced evaporation due to warmer conditions slowed recharge to the subsurface so that deficits generated during the Millennium Drought still were not satisfied. Thus, changes in ET can impact streamflow generation and also provide a feedback that strengthens the importance of subsurface storage deficit on streamflow.

Here, we extend the model presented by Hahm et al. (21) to allow for both multi-year deficit accrual and snow. To allow for multi-year deficit accrual, we explicitly track a timeseries of annual October 1 deficit so that initial water year conditions may vary between years, and to account for snow, we add a snowmelt period following the wet season (during which rain enters storage and snow accumulates), with the April 1 snowpack SWE [L] delivered at a rate of m [L/T]. Hahm et al. (21) assumed that cumulative wet season ET is constant from year to year, an assumption that was meant to reflect the fact that ET is energy-limited during the cold wet season in California. When considering the snowmelt period, though, ET total may not be constant between years since the length of the snowmelt period can vary substantially depending on the snowmelt rate m [L/T] and the size of the snowpack SWE. This dynamic can be accounted for in the snowmelt period by considering ET during the melt period and post-snowmelt growing period as energy-determined rates ET_s [L/T] and ET_{summer} [L/T] that last for the duration of the melt period and summer respectively. Then, the total warm season $ET_{warm} = N_{melt}ET_s + N_{warm\_dry}ET_{summer}$ [L], where N_{melt} [T] and N_{warm_dry} [T] are the lengths of the melt period and post-snowmelt growing season, respectively.

Thus, the extended model includes three seasons with distinct fluxes: a winter wet season, a snowmelt period, and a snowmelt-free growing season:

$$S_{Apr1} = min(S_{max}, max(0, S_{Oct1} + P_w - ET_w)), \quad [1]$$

$$S_{Aug1} = min(S_{max}, max(0, S_{Apr1} + SWE - (ET_s - P_s)N_{melt})), \quad [2]$$

$$S_{Oct1} = max(0, S_{Aug1} - ET_{summer}N_{warm\_dry}), \quad [3]$$

where S_{Apr1} [L] is the root zone storage at the start of the snowmelt period, S_{Aug1} [L] is the root zone storage at the start of the post-snowmelt growing period, and S_{Oct1} [L] is the root zone storage at the start of the winter wet season. S_{max} [L] is the maximum possible value of root-zone storage, ET_w [L] is winter ET, and P_w [L] and P_s [L/T] are winter and spring rainfall. Because storage is constrained between 0 and S_{max}, ET cannot occur if storage is empty, and runoff is generated if storage is full, which can happen during the winter wet season or during the snowmelt period. Equation 1 describes the winter wet season when rain increases storage and ET draws from storage, Equation 2 the melt period when SWE melts into storage and a net ET flux draws from storage, and Equation 3 the post-melt growing season when ET draws from storage. For simplicity, we define a single term $ET_{net} = ET_s - P_s$ that describes the potential net ET during the melt period, and ET_{summer} can be considered in the same way in regions with significant precipitation during the growing season.

By using the mass balance from Equations 1-3, streamflow during the snowmelt period is given by:

$$Q = \begin{cases} max(0, SWE - ET_{net}N_{melt}), & \text{if } P_w - ET_w > D_{Oct1} \\ max(0, SWE - ET_{net}N_{melt} - D_{Oct1} + (P_w - ET_w)), & \text{otherwise} \end{cases} \quad [4]$$

where Q [L] is total streamflow due to snowmelt, and D_{Oct1} [L] is the root zone storage deficit ($S_{max} - S_{Oct1}$) at the end of the preceding dry season. Both conditions are bounded by 0 since streamflow cannot be negative. A negative value for either condition indicates that water demand from ET exceeds water availability from rain, snowmelt, and storage, so streamflow must be 0.

In Equation 4, there are three terms that can cause the relationship between SWE and Q to be non-unique: (i) the total net ET flux during the melt period ($(ET_s - P_s)N_{melt}$), which is impacted indirectly by the melt rate m since $m = SWE/N_{melt}$, (ii) the root zone storage deficit at the end of the dry season D_{Oct1} (referred to as Oct. 1 deficit), which is driven by ET, precipitation, and runoff dynamics during prior years, and (iii) winter recharge ($P_w - ET_w$). Increasing total ET during the snowmelt period ($ET_{net}N_{melt}$) reduces streamflow generation. This ET term can be increased by increasing vegetation demand (increased ET_{net}), reducing spring rainfall (increased ET_{net}), or by slowing down the snowmelt rate m (increased length of N_{melt} for the same SWE). While increasing the October 1 deficit reduces streamflow generation, increasing winter recharge ($P_w - ET_w$) can increase streamflow generation. This can be achieved either by increasing P_w (decreasing annual snow fraction

since SWE remains constant) or decreasing ET_w (reducing winter ET), so long as storage is not already being filled up. See Supplemental Information S2 for a visual demonstration of how each parameter impacts Q. Any of these mechanisms could confound a linear regression model for streamflow based only on April 1 SWE.

Subsurface deficit calculations

To estimate a storage deficit in the subsurface (D), we adapted the method presented by Wang-Erlandsson et al. (25) and updated to account for snow cover by Dralle et al. (29). In this method, root zone storage deficit is calculated as the running difference between fluxes leaving (F_{out} [L/T]) and entering (F_{in} [L/T]) the system during a time interval defined by the sampling frequency of remotely sensed products. Generally, F_{out} is set equal to ET, neglecting streamflow, and F_{in} is set equal to precipitation. Dralle et al. (29) used snow cover data from satellite products to adjust fluxes in snow-dominated regions. Here, since we have access to explicit information on snow through SNODAS (30), we incorporate snow directly into the mass balance approach by defining F_{in} as

$$F_{in} = P_r + Q_m, \quad [5]$$

where P_r is precipitation falling as rain determined as precipitation when SWE does not increase, and Q_m is given by decreases in SWE. More precisely,

$$P_{r,t_n} = P_{t_n} - \max(\mathrm{SWE}_{t_n} - \mathrm{SWE}_{t_{n-1}}, 0), \quad [6]$$

where P_i is the total precipitation falling in timestep i and SWE_i is the SWE at time step i and

$$Q_m = \max(\mathrm{SWE}_{t_{n-1}} - \mathrm{SWE}_{t_n}, 0). \quad [7]$$

Following the deficit tracking procedure presented by Wang-Erlandsson et al. (25), we proceed by calculating the difference between F_{out} and F_{in} over a time interval from t_n to t_{n+1}:

$$A_{t_n \to t_{n+1}} = \int_{t_n}^{t_{n+1}} (F_{out} - F_{in})\, dt. \quad [8]$$

This accumulated difference ($A_{t_n \to t_{n+1}}$) is a *deficit*, so the signs of fluxes are reversed compared to a traditional mass balance. If the accumulated difference is negative, then no deficit has been accrued in the time step. So, a lower bound on root zone storage deficit for each time step is given by the maximum value of zero and the running sum of accumulated differences:

$$D(t_{n+1}) = \max(0, D(t_n) + A_{t_n \to t_{n+1}}) \quad [9]$$

Runoff is not needed to calculate accurate deficits. For a couple of reasons, it is neither appropriate nor necessary to account for runoff in root-zone storage deficit calculations. First, water drainage from the root zone during precipitation or snowmelt can sustain streamflow production for weeks, even months, following the drainage event. This temporal mismatch between root-zone drainage and flow generation in the stream implies that any deficit generation related to flow production likely occurred well before the observation of flow; therefore, using streamflow in deficit calculations would increase deficits at the wrong time. One approach for accounting for runoff in deficit calculations might be to incorporate a root-zone drainage term, which is not straightforward to measure or estimate. However, this is not necessary as the drainage flux should have a minimal impact on deficit growth; significant drainage occurs primarily when the deficit is small or zero due to water inputs (snowmelt or precipitation), and this root-zone drainage flux is likely smaller than the water fluxes that generate drainage (as is accepted in modeling studies and suggested by findings of runoff ratios smaller than 1 in empirical studies; 31–33), meaning that the net change to the deficit would be negligible. Since the deficit is small or zero when drainage occurs, and inputs likely exceed the drainage flux, true deficit growth is unlikely to occur during drainage events. As a result, neglecting drainage in deficit calculations should not have a significant impact on calculated root-zone storage deficits.

Factors that impact spring streamflow generation

Panel	S_{max}	ET_{warm}	ET_w	μ	sd	snowfrac	m
a	1,000	10-300	0	400	100	1	10
b	300	800	0	700	150	0.7	10-50
c	1,000	350	0	400	100	1	10
d	300	300	0	400	100	0.25-1	10

Table S2. Parameter values used to generated each subfigure in Figure S1: S_{max} is maximum root zone storage; PET is total potential evapotranspiration in the warm season; ET_w in the winter; μ and sd are parameters for the gamma distribution for annual precipitation; snowfrac is the fraction of annual precipitation that falls as snow; and m is the snowmelt rate.

As described in the main text, the relationship between April 1 SWE and spring streamflow is not unique. Within a mass balance framework, there are four factors that can drive lower spring streamflow: (a) more net spring ET (ET-rain), (b) a slower snowmelt rate, (c) a larger root zone storage deficit, or (d) less rainfall. Figure S1 uses the mass balance model to show directly how each of these four factors affects the resulting spring streamflow. For this exercise, we use this total ET_{warm} to set an

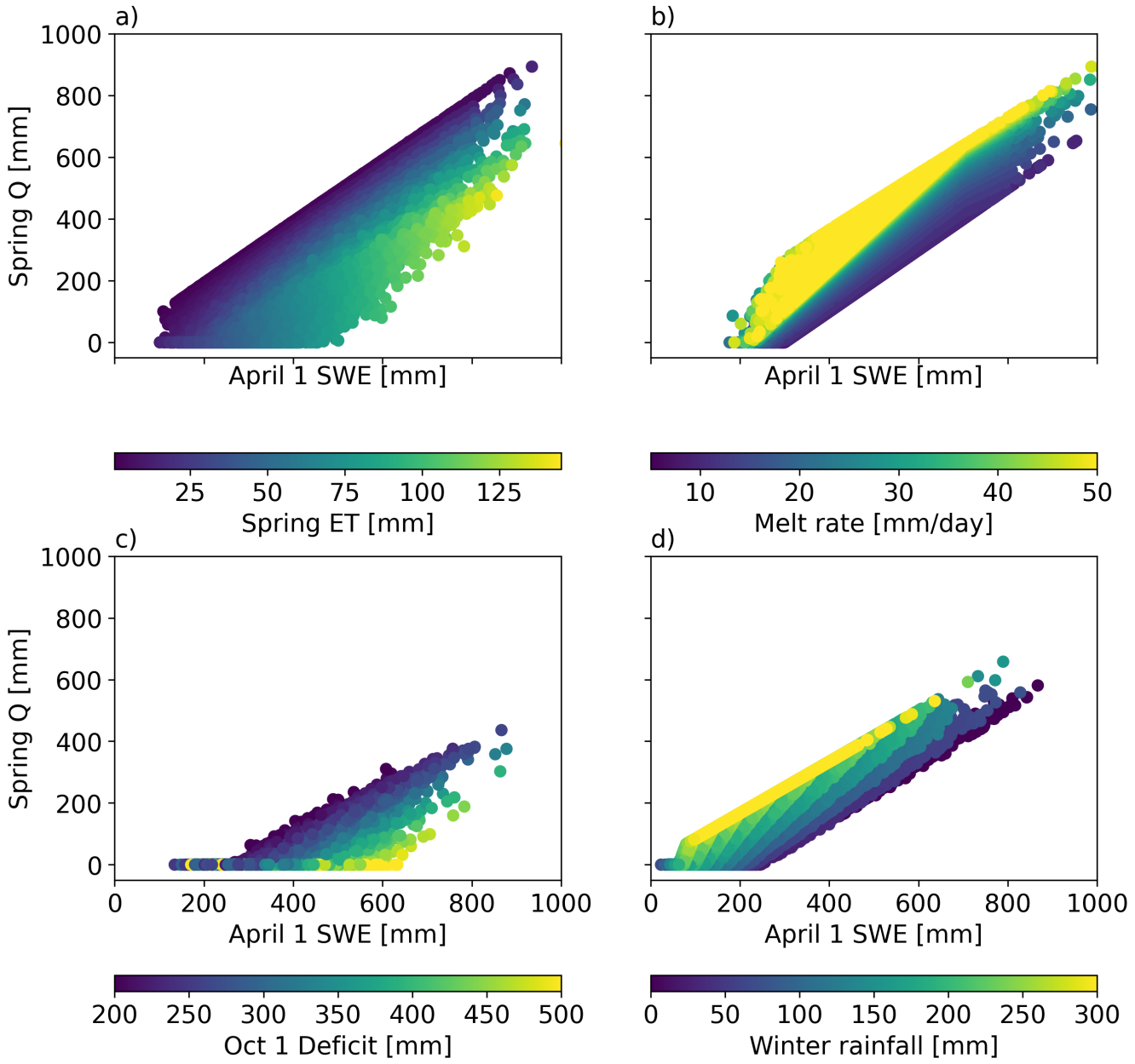

Fig. S1. Differences in (a) spring evapotranspiration (ET), (b) snow melt rate, (c) root zone storage deficit, and (d) winter rainfall can result in different spring streamflow from the same April 1 SWE, as shown by Monte Carlo simulations with annual precipitation P selected from a gamma distribution and April 1 SWE given as a fraction of P. Parameters used to generate this figure are shown in Table S2. Melt rate is calculated assuming a 180 day warm season.

average rate of ET during the warm season that is applied to both the snowmelt period and post-snowmelt growing season. We apply Equations 1-3 to track storage through time. Parameters S_{max}, ET_w, and $ET_{warm} = ET_s N_{melt} + ET_{summer} N_{warm\_dry}$ are the same each year, while P_w, P_s, SWE, and the partitioning of ET_{warm} between the snowmelt period and the snow-free growing season vary between years. A spinup period of 100 years is used to generate initial conditions. For each year, we select an annual precipitation from a gamma distribution. Since spring rainfall is included in the term ET_{net}, we do not explicitly include that rainfall in the annual precipitation. Instead, we allow SWE and P_w to add to the gamma-selected annual precipitation, with the partition described by a fraction ($snowfrac$). This setup still results in a gamma distribution for annual precipitation since the spring rainfall is constant. Throughout the simulation period, we track storage deficits generated at the end of each growing season, SWE, and snowmelt runoff claculated for each year using Equation 4. Parameters used to generate the figure are in Table S2.

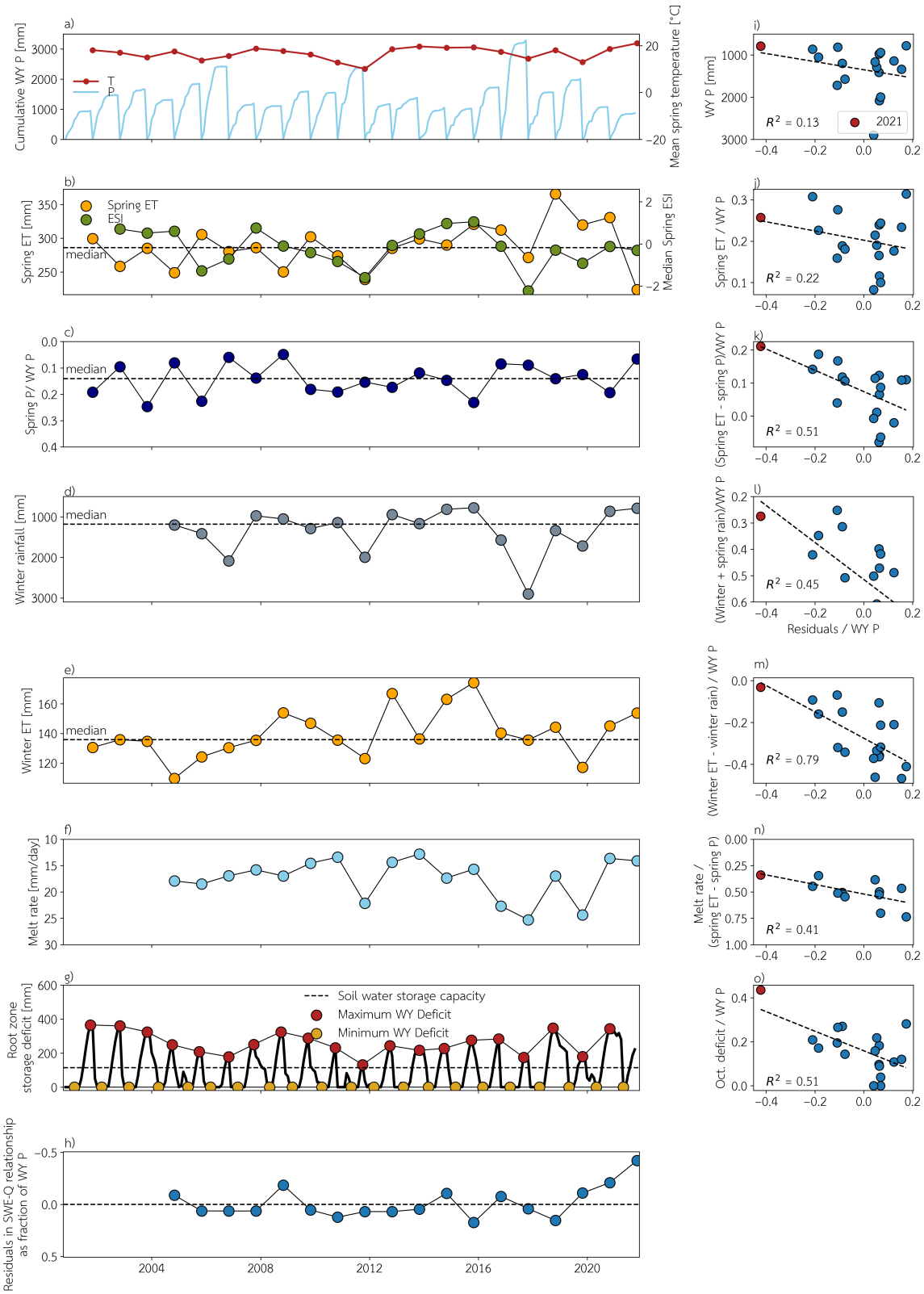

Fig. S2. Water year data for one representative study site (Ward Ck). Spring ET and spring P are for the months April-July. All panels are oriented so that moving vertically in the panel theoretically results in less spring streamflow. In particular, note that the y-axes for panels c, e, h, i, and m and the x-axis for panels g-k are reversed. As a result, all relationships in panels g-k should appear negative. Red scatter points in panels g-k mark the 2021 water year.

Exploratory analysis of variables that impact melt period streamflow

We performed exploratory data analysis to quantify the importance of each variable that appears in Equation 4 for explaining residuals in snowpack-runoff relationships. This analysis was used to select a minimal set of variables that both encompass

Table S3. Parameters for the multiple linear regression model to predict spring streamflow. For parameter descriptions, see Table 1 in the main text. Parameter values are shown multiplied by median absolute variable values among (top) top 25th percentile wettest years and (below) driest 25th percentile of water years and shown in units of mm for comparison. Values marked by an asterisk indicate that the sign is opposite to the expected sign based on hypothesized mechanisms. Parameter columns are listed in order of decreasing median effect size, so SWE has the largest effect size, and m/ET_{net} the smallest across the study sites.

Site	SWE	$\frac{P_w+P_s}{P}$	$\frac{D_{Oct1}}{P}$	$\frac{ET_{net}N_{melt}}{P}$	$\frac{ET_w-P_w}{P}$	$\frac{m}{ET_{net}}$
Wet years						
10336780	560	63	-15	2*	-0	-1*
10336645	929	61	-18	-2	-6	-10*
10336660	1195	21	-82	-2	-109	9
10336676	1268	144	-72	-5	-50	3
10343500	715	37	-28	0	-41	-78*
10308783	43	18	-19	-29	-5	53
11383500	118	236	-23	-6	-82	-2*
11189500	94	-26*	-0	-9	-9	8
11204100	31	212	-12	-25	12*	1
11203580	83	160	-17	-32	-42	6
11266500	1000	59	-15	-5	-36	22
11264500	927	77	-13	-10	-6	8
10265150	56	6	-3	-2	-12	1
Median	560	61	-17	-5	-12	3
Dry years						
10336780	156	126	-66	4*	-2	-1*
10336645	144	124	-99	-27	-38	-5*
10336660	472	21	-217	-96	-89	6
10336676	573	145	-199	-84	-38	2
10343500	240	73	-92	1	-32	-29*
10308783	2	20	-39	-64	-2	21
11383500	34	215	-63	-57	-57	-1*
11189500	9	-33*	-1	-23	-3	5
11204100	1	210	-49	-87	4*	0
11203580	6	162	-62	-134	-10	2
11266500	197	87	-112	-29	-25	17
11264500	225	118	-87	-18	-2	10
10265150	12	8	-61	-28	-2	1
Median	144	118	-66	-29	-10	2

Table S4. Performance of the multiple linear regression model to predict spring streamflow. For parameter descriptions, see Table 1 in the main text. R^2 values are shown for full model, a model using only April 1 SWE and D_{Oct1} / Winter P as variables, and a model only using April 1 SWE. The latter two models can both be run prior to snowmelt. The final two columns compare the R^2 value for a regression model using only April 1 SWE on the years following the top 25th percentile years versus the bottom 25th percentile of years in terms of annual precipitation.

Site	R^2 (all params)	R^2 (SWE, $\frac{D_{Oct1}}{P_w}$)	R^2 (SWE)	R^2 after wet years	R^2 after dry years
10336780	0.94	0.90	0.87	0.91	0.13
10336645	0.93	0.90	0.88	0.59	0.40
10336660	0.96	0.93	0.87	0.65	0.51
10336676	0.98	0.95	0.88	0.75	0.56
10343500	0.98	0.79	0.73	-1.64	0.30
10308783	0.87	0.64	0.63	0.88	-0.21
11383500	0.78	0.58	0.49	-1.93	-1.20
11189500	0.87	0.75	0.83	0.85	-0.75
11204100	0.91	0.72	0.49	-1.28	-25.06
11203580	0.92	0.73	0.64	-0.07	-8.11
11266500	0.96	0.92	0.91	0.60	0.75
11264500	0.93	0.90	0.89	0.38	0.84
10265150	0.81	0.71	0.65	-0.06	-0.23
Median	0.93	0.85	0.83	0.59	0.13

all of the proposed mechanisms for failure of the SWE-Q model but minimizes correlation between variables. To do this, we wanted to select only one variable to represent each proposed mechanism. Exploratory analysis was used to find one variable for each mechanism that most strongly correlates with residuals in the SWE-Q model.

Figure S2h shows the time series of residuals in the April 1 SWE-spring Q relationship (referred to hereafter as the SWE-Q

relationship). Across all sites, 2021 generally stands out as the largest negative residual as a fraction of WY P (note reversed y-axis). See the data supplement to review residual timeseries for all study sites (34). This finding indicates that less streamflow arrived than expected, and the missing streamflow was a substantial portion of the water budget. Based on the parsimonious model described in the main text, we explore four hypotheses to explain why 2021 spring streamflow was lower than expected at the 13 study sites. Results are shown in Figure S2 for Ward Creek (site 10336676), but results across the study sites are qualitatively similar (34, see data supplement;). We selected Ward Creek since it has the highest-performing multiple linear regression model but is otherwise representative of the trends and site characteristics across the study sites.

Hypothesis 1: ET was larger than usual.

Spring net ET was unusually high. In 2021, spring ET was lower than usual (Figure S2b) despite high spring temperatures (Figure S2a). The Evaporative Stress Index (ESI) data indicate that plants were water-stressed in 2021 (Figure S2b). While ET was not higher than usual, spring ET accounted for a larger fraction of the annual water budget than usual since annual precipitation was very low (Figure S2a). However, spring ET alone does not explain the magnitude of the residual from the SWE-Q relationship in 2021. Spring ET / WY P explains only 22% of variance in the residuals at Ward Creek (Figure S2j), compared to 13% explained just by WY P (Figure S2i). Over all sites, the median R^2 is 22% for Spring ET / WY P.

Spring rain accounted for a much smaller fraction of annual precipitation than usual in 2021, about half of the median (Figure S2c). As with spring ET in 2021, though, spring P fraction was not outside the range of previously observed values.

Since net spring ET (ET_{net}) is defined as the difference between spring ET and spring rain, the deviations in the individual terms are combined in ET_{net}. Neither spring ET nor spring rain were outside the range observed in prior years, but ET_{net} was unprecedented in 2021 (red scatter point in Figure S2k). ET_{net} both singles out 2021 as a unique year and explains 51% of variance in the residuals at Ward Creek (Figure S2i). Across all sites, the median R^2 value between residuals and ET_{net} is 0.38.

Winter recharge was unusually low. A primary control on winter recharge is winter rainfall P_w since snow does not recharge until it melts. Winter rainfall in 2021 was lower than usual, among the lowest winter rainfall years in the study period (Figure S2d) but not outside the range of previously observed values. The other factor controlling winter recharge is winter ET. While spring ET was low in the 2021 WY, this was not the case for winter ET, which was higher than normal (Figure S2e). This finding is exaggerated as a fraction of WY P since 2021 was a dry year (Figure S2m). As with ET_{net}, ($ET_w - P_w$) / WY P singles out 2021 as a particularly extreme year with the highest relative ET_w in the study period, an observation that holds for 9 of the 13 study sites, and accounts for 79% of variance in the residuals at Ward Creek. Across all study sites the median variance explained is 38%, indicating that winter recharge has a predictive power similar to spring net ET.

Hypothesis 2: Winter and spring total rainfall was lower than usual. Both winter rainfall and spring rainfall were lower than usual in the 2021 water year. When combining all winter-spring rain (similar to a snow fraction), rain / WY P explains 45% of the variance in the residuals in the SWE-Q relationship at Ward Creek (Figure S2l). Across all sites, the median is 25%.

Hypothesis 3: Melt rate was unusually slow. By examining Figure S2f, it is clear that the melt rate in 2021 was slower than usual at Ward Creek, among the slowest melt rates observed in the time period 2003-2021, although not outside the previously observed range. A slow melt rate can reduce streamflow by allowing plants to take greater advantage of snowmelt for ET, which means that it is not melt rate alone but its ratio to ET_{net} that drives the impact of melt rate on streamflow generation, since $m = SWE/N_{melt}$ (see Equation 4). In 2021, the ratio m/ET_{net} was the smallest observed during the study period, and it explains 41% of the variance in the residuals at Ward Creek (Figure S2n). At all other study sites, though, m/ET_{net} generally explains less than 20% of variance or even less than 5% for most sites, with a median of 6%.

Hypothesis 4: Root zone storage deficit was unusually large. Each year, the root zone storage deficit grows during the dry season and shrinks during the wet season (black line in Figure S2g). The maximum deficit each year (red dots, estimated by October 1 deficit for all analyses for simplicity), provides information about how much water was removed from storage during the preceding dry season(s) by ET. Note that the October 1 deficit is always larger than the soil water storage capacity, indicating that plants access water stored in weathered bedrock. The minimum deficit each year (yellow dots) provides information about wet season replenishment of root zone storage. For Ward Creek shown in Figure S2g, the minimum deficit is always 0, but it can be nonzero and even grow across multiple years at other sites—see the data supplement for study sites that demonstrate deficit carry-over between years (34). In 2021, a large deficit was generated—among the largest during the study period. As with the other hypothesis variables, though, the significance of the 2021 deficit is much clearer when compared to the annual water budget. Figure S2o shows that the deficit as a fraction of the annual precipitation was more than 50% larger than the largest observed value in previous years. Thus, the deficit strongly identifies 2021 as an outlier, consistent with observations of substantial missing streamflow, and the root zone storage deficit explains 51% of the variance in residuals in the SWE-Q relationship at Ward Creek. At nearly all study sites, the October 1 deficit in 2021 was the largest or second-largest deficit recorded in the study period (as a fraction of WY P). Some sites have R^2 values greater than 0.7, while others have values less than 0.1, with a median of 0.32.

These exploratory analyses motivated the choice of variables included in the multiple linear regression model. The outcomes of the multiple linear regression are summarized in Table S3 for (top) wet years and (bottom) dry years. Performance comparison between different linear regression models is in Table S4.

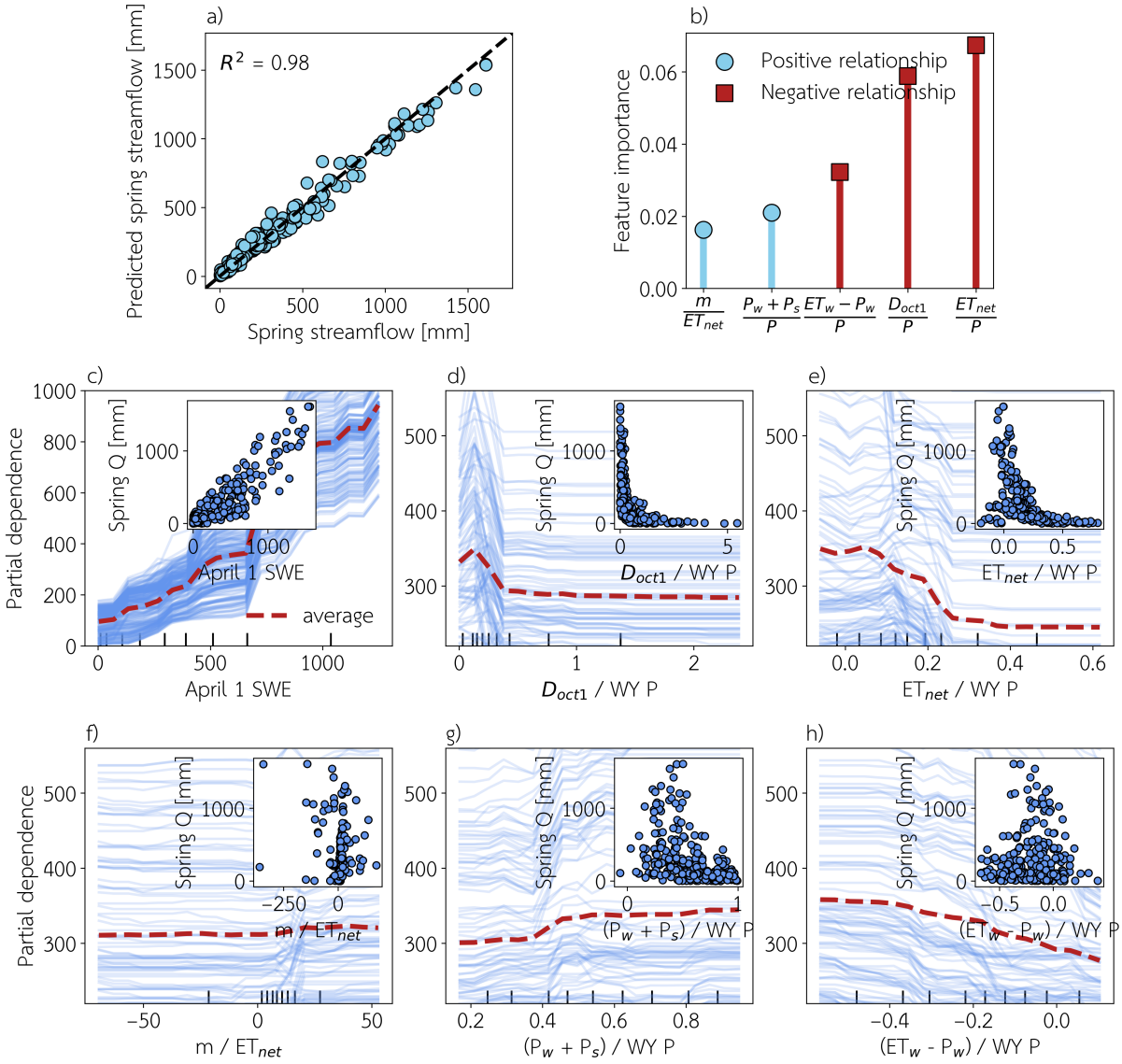

Fig. S3. (a) Performance of random forest model for spring streamflow trained for all study sites. (b) Feature importance for parameters included in random forest model, except for April 1 SWE, which is significantly more important than all other parameters. (c)-(h) are partial dependence plots with the average partial dependence shown as a red dashed line. Panels (d)-(e) are zoomed in, which excludes some of the blue lines but allows for the functional shape of the relationships to be more clearly seen. For comparison, scatter data for the relationship between each parameter and measured spring streamflow is shown as an inset to each subplot.

A random forest model for spring streamflow

In this study, we developed a multiple linear regression model for each study site to explain spring streamflow production from snowmelt. However, while the model presented in the main text shows linear relationships among all variables for idealized catchments, the relationships between each investigated variable may not be linear for real catchments. To capture more complex relationships among the variables, we also developed a random forest model, using the same set of variables described in Table 1 in the main text. Since random forest models are data-driven and flexible, we chose to train a single random forest model using data from all sites. Performance of the random forest model was exceptional (Figure S3a, $R^2 = 0.98$), and feature importance (Figure S3b) supports similar conclusions to the effect size results using the multiple linear regression model. The exact ordering of feature importance is not identical to the ordering implied by the multiple linear regression, but both models support the conclusion that the melt rate does not provide much predictive power, and the deficit provides a substantial amount of predictive power. Partial dependence plots (Figure S3c-h) shows the functional form of the learned relationship between each variable and the output (spring streamflow). These functional forms are nearly monotonic, with small deviations from monotonic behavior likely due to co-variability of variables with parameters not included in the model. In all cases, the general direction of the relationship matches our hypotheses in the main text: (c) higher SWE results in higher streamflow, (d) larger deficit results in smaller streamflow, (e) more spring ET results in less streamflow, (f) a faster melt rate results in more streamflow, (g) more rainfall results in more streamflow, and (h) less winter ET results in more streamflow. Insets show the

raw data used to train the model. For the most predictive variables, the learned relationship is clearly visible in scatter plots of raw data as well, providing additional confidence in the results.

Including the deficit in a model for snowmelt runoff improves performance on under-predicted years

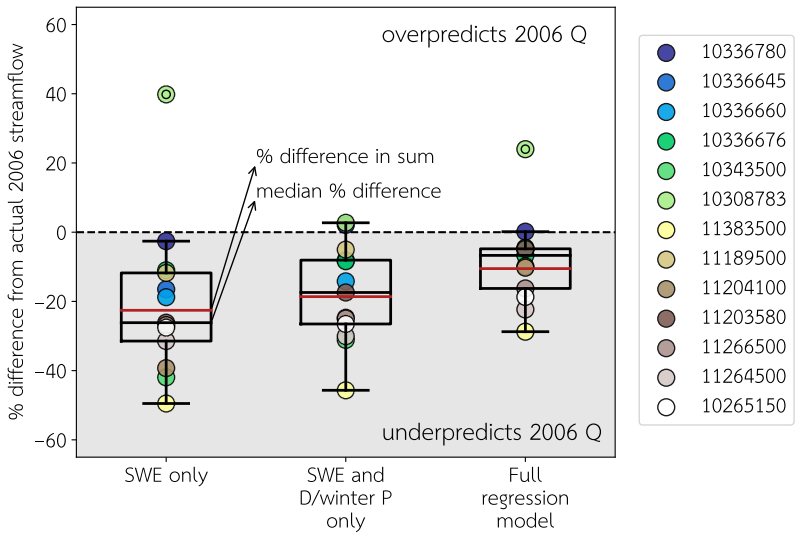

Fig. S4. Performance of regression models at 13 study sites for the year 2021. A linear regression model using only April 1 SWE underpredicts the total 2006 spring streamflow at all sites by 23% for total streamflow across all sites (median 26%), while the full linear regression model or a model using April 1 SWE and October deficit as a fraction of winter precipitation underpredicts the total by 19 or 11% (median of 17 or 7%), respectively.

In the main text, we explored the importance of the deficit for capturing snowmelt runoff on years with anomalously low runoff. Here, we explore the importance of the deficit for capturing snowmelt runoff on years with anomalously high runoff, such as 2006. Figure S4 demonstrates that including the deficit drastically reduces the extent to which streamflow is underpredicted from a median of 26% to 17%. While not as striking as the result for 2021, this difference is still important for management applications and demonstrates that the deficit can improve predictions for all anomalous years, not just overpredicted years.

Including the deficit in a model for snowmelt runoff improves performance on larger, disturbed basins of economic importance

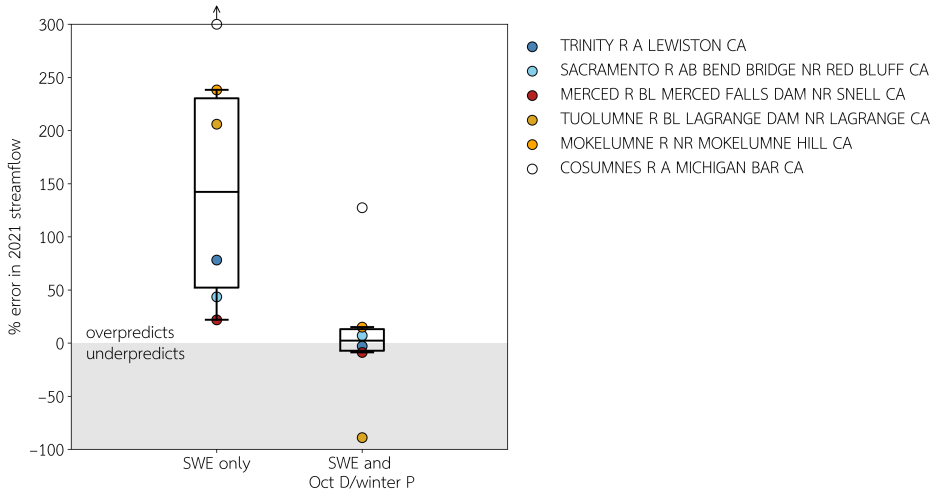

Fig. S5. Comparison of performance of a linear regression model based only on April 1 SWE and one using both April 1 SWE and October 1 Deficit / winter precipitation. Error is reduced from a median of 143% to 2%.

For this study, we selected a set of minimally disturbed watersheds to test our model. However, the basins where snowmelt runoff predictions matter for water supply are much larger, more complex, and more disturbed than the study sites. To

demonstrate that our model is still relevant to these basins, we tested whether adding October 1 Deficit to a linear model for snowmelt runoff for these basins. The improvement in model performance applies also to these larger, more complex and disturbed basins (Figure S5), reducing median model error from 143% to 2%. Outliers for Cosumnes and Tuolomne only appear to have large percent error since the actual streamflow is very small.

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