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Relationships between snowpack, low flows and stream temperature in mountain watersheds of the US west coast

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Abstract

Water temperatures in mountain streams are likely to rise under future climate change, with negative impacts on ecosystems and water quality. However, it is difficult to predict which streams are most vulnerable due to sparse historical records of mountain stream temperatures as well as complex interactions between snowpack, groundwater, streamflow and water temperature. Minimum flow volumes are a potentially useful proxy for stream temperature, since daily streamflow records are much more common. We confirmed that there is a strong inverse relationship between annual low flows and peak water temperature using observed data from unimpaired streams throughout the montane regions of the United States' west coast. We then used linear models to explore the relationships between snowpack, potential evapotranspiration and other climate-related variables with annual low flow volumes and peak water temperatures. We also incorporated previous years' flow volumes into these models to account for groundwater carryover from year to year. We found that annual peak snowpack water storage is a strong predictor of summer low flows in the more arid watersheds studied. This relationship is mediated by atmospheric water demand and carryover subsurface water storage from previous years, such that multi-year droughts with high evapotranspiration lead to especially low flow volumes. We conclude that watershed management to help retain snow and increase baseflows may help counteract some of the streamflow temperature rises expected from a warming climate, especially in arid watersheds.

KEYWORDS

low flow, snowpack, storage, streamflow, water temperature, watersheds

1 | INTRODUCTION

In mountain watersheds of the Western United States, summer streamflow can be highly variable from year to year. While summer flows represent a small proportion of a basin's overall water resources, they can represent an important limiting factor for ecological processes (Poff et al., 1997). Summer stream temperatures are also important for many biotic processes, including the life cycles of salmonid fish (Isaak et al., 2012; Webb et al., 2008). In California's Sierra Nevada, stream temperatures are predicted to increase by approximately 1.6°C for each 2°C rise in air temperature, leading to a reduction in habitat for cold-water fish species (Null et al., 2013). Summer water temperatures in unregulated streams of the Northwestern USA have been found to be warming in recent decades, a trend attributed both to changing air temperature and discharge volumes (Isaak et al., 2012, 2018). While rising water temperatures and lower streamflows may be inevitable in a future climate, mitigation and preparation for these changes will rely on a strong understanding of climate change's impacts on summer streamflows.

While this work is motivated by rising water temperatures, there are very few long-term datasets of water temperature in unregulated streams of the western USA (Arismendi et al., 2012). However, streamflow measurements are much more abundant, and streamflow volume is an important driver of summer water temperatures (Isaak et al., 2012; Webb et al., 2008). This has important management implications, since streamflows can be modified by human efforts (e.g., river and wetland restoration; Ohara et al., 2013; Tague et al., 2008) and this could complement other management efforts to reduce stream temperature (e.g., by shading through restoring or maintaining riparian vegetation; Fuller et al., 2022; LeBlanc & Brown, 2000). Therefore, much of this study's focus is on summer low flows (which we refer to as Qmin).

Our study focuses on the Sierra Nevada and Cascade mountain regions, where most precipitation falls in the winter. Summer water availability is therefore limited both by a lack of rainfall and seasonal increases in potential evaporation. Snowpack water storage has declined throughout the western United States in recent decades due largely to warmer temperatures (Knowles et al., 2006; Mote et al., 2005, 2018). Climate change is expected to cause even greater evaporative demand, lower peak snowpacks and less streamflow and aquifer recharge originating as snowmelt (Hatchett et al., 2022b; Li et al., 2017; McEvoy et al., 2020; Meixner et al., 2016). Under a lower snow future, even if total precipitation remains unchanged the amount of water contributing to summer flows may be reduced due to changes in the timing and rate of water inputs to the system and/or increased water vapour losses (Gordon et al., 2022; Huntington & Niswonger, 2012). Previous work has shown that the fraction of a watershed's precipitation falling as snow and the amount of time that snow persists on the ground are both positively correlated with the relative magnitude of its summer baseflow (Gordon et al., 2022; Jenicek et al., 2016). This suggests that reductions in snow fraction or earlier snowmelt would reduce the magnitude of summer low flows.

Cooper et al. (2018) explored the variation of annual Qmin in relation to annual variations to peak snow water equivalent (SWE), winter precipitation (Winter P) and summer potential evapotranspiration (PET) in the maritime Western US mountains. They found that in snow-dominated catchments, Qmin increased 0.43% for every 1% increase in Peak SWE, increased 0.50% for every 1% increase in winter P and decreased 2.1% for every 1% increase in PET. Qmin was more sensitive to these climatic variables in the more arid Sierra Nevadas compared with the Cascades. Cooper et al. (2018) pointed out that although low flows were least sensitive to SWE, SWE might have a disproportionate impact on stream temperatures. While informative, these analyses only evaluated each driving variable independently, and did not account for their combined effects. They also did not address 'memory' in the hydrologic system (e.g., storage carryover from previous years) which can have a strong influence on baseflows (Wolf et al., 2023). For example, Godsey et al. (2014) found that Qmin values in California's Sierra Nevada were sensitive to the previous year's snowpack, and decreased 9%–22% for every 10% decrease in peak SWE. Summer precipitation may also be the main driver of low flows in more humid catchments, making it another important variable to consider (Kinnard et al., 2022).

In this study, we aim to better understand the sensitivity of water temperature to climatic variability. We start with an exploration of water temperature's sensitivity to climate variables directly (e.g., precipitation and air temperature) and sensitivity to mediating variables that also respond to climate (e.g., streamflow). We then further investigate streamflow volume, an important predictor of water temperature, by expanding on the climate sensitivity analysis of Cooper et al. (2018) using catchments with long records of both streamflow and snowpack. Our objectives are to better understand the sensitivity of Qmin volume and timing to both climate and antecedent water storage. Our analyses examine the importance of each variable both independently and as an ensemble of co-occurring drivers using multiple linear regression. This information will help to better understand how climate change may impact the aquatic ecosystems of mountain watersheds in future summers, and how these impacts may vary geographically.

2 | DATA AND METHODS

2.1 | Study area

We selected mountain watersheds in California, Western Nevada, Oregon and Washington with over 30 years of both streamflow and SWE data and at least 30% of annual precipitation falling as snow on average (Figure 1, Tables 1 and A1). We only considered streams with minimal human disturbance (as described by Newman et al., [2015]) in order to study the climate sensitivity of streamflow without complicating factors such as reservoir management. All watersheds selected have their dry season in June–August (Addor et al., 2017), with most precipitation falling in winter (Table 1). Most of the watersheds are at least 50% forest-covered, with the exception of Donner und Blitzen which is dominated by grasslands (Table 1).

2.2 | Streamflow and water temperature data

Daily streamflow and water temperature data (where available) were obtained from USGS gaging stations (USGS, 2022). Specific stations are listed in Table 1. Streamflow analyses were limited to May 15 through October 31 of each year, a period which encompasses the snowmelt recession and summer baseflow of all watersheds studied (Figure 2) as well as the highest water temperatures. We defined annual minimum summer flow (Qmin) as the smallest 15-day median streamflow during this period, following Godsey et al. (2014) and Cooper et al. (2018). All flows are reported in millimetres per day, the flow volume divided by basin area, in order to provide a more direct comparison between watersheds of varying sizes (Table 1). All chosen

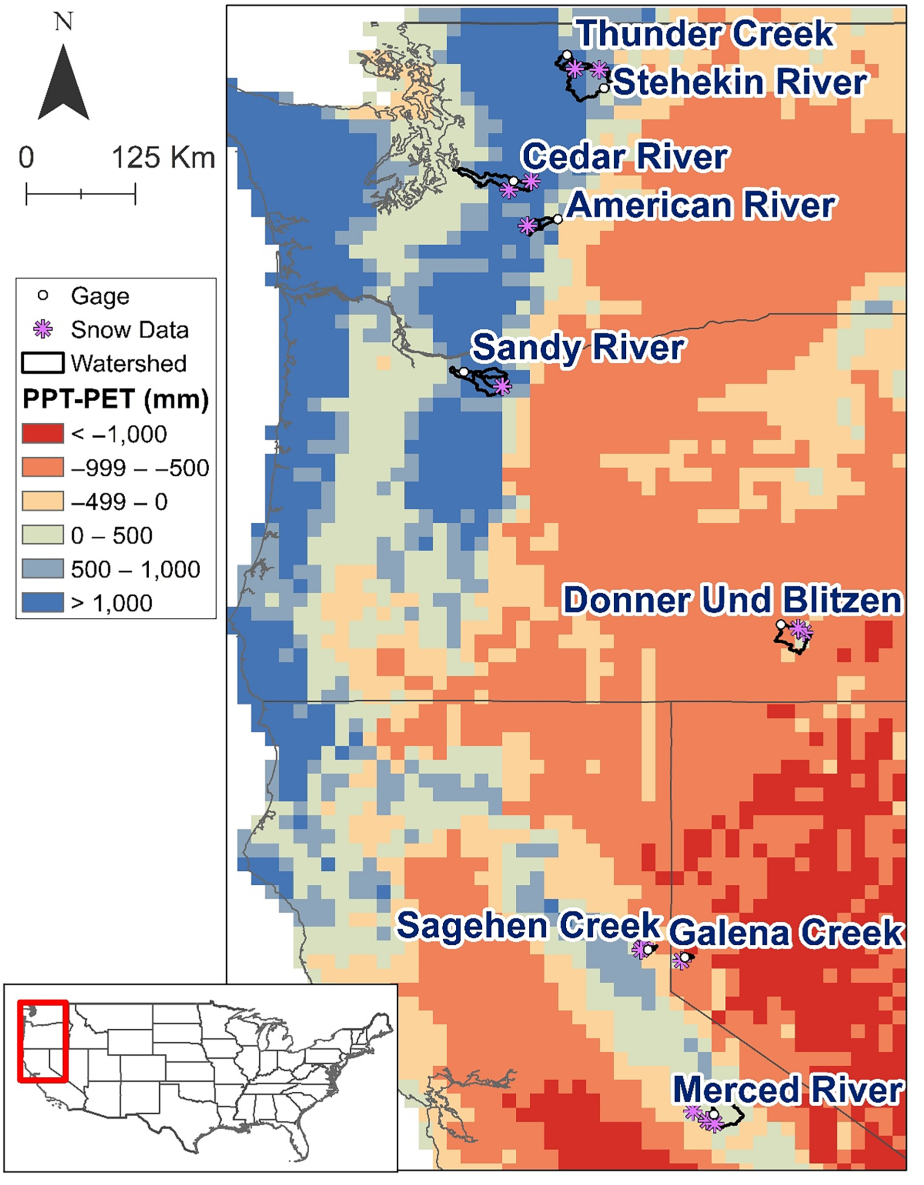

FIGURE 1 Map of USGS gages used for flow data (white dots) and locations of snowpack measurements (purple asterisks). Black outlines show the HUC10 or HUC12 watersheds draining into each gage. Colours denote mean annual potential water deficit given by precipitation (PPT) minus potential evapotranspiration (PET). PPT-PET is calculated from PRISM data for water years 1992–2021 using climateengine.com.

watersheds have minimum flows that remain above zero every summer.

2.3 | Snowpack and climate data

SWE data were obtained from the SNOTEL network (daily values) and snow course measurements (monthly values) available from the United States Department of Agriculture (USDA, 2022) using their report generator tool (https://wcc.sc.egov.usda.gov/reportGenerator/). Specific snow measurement sites are given in Table A1.

For sites where monthly snow course data were available for a longer period than daily snow records, we combined both monthly and daily data in order to have the longest period of record possible as well as most complete time series. In years when daily SWE data were available, peak SWE was calculated directly as the maximum of all daily SWE data. In years when only monthly snow course data were available, we calculated peak SWE as $a + bS_{monthly}$. $S_{monthly}$ is annual peak SWE from monthly snow course data, and a and b are model coefficients fit via linear regression using peak daily SWE (the target variable) and $S_{monthly}$ (the predictor variable) from years when both monthly and daily snow data were available.

Gridded monthly climate data (precipitation, PET, etc.) at 4 km resolution from TerraClimate were downloaded from climateengine.org (Huntington et al., 2017). The TerraClimate dataset provides estimates of climatic variables from 1958 through the present (Abatzoglou et al., 2018). We chose to use this gridded dataset since continuous measurements of all climate variables were not always available at weather stations near our study watersheds for the desired time period. For those streams where we analysed stream temperature, we also obtained daily air temperature from nearby weather stations (details in Table A1).

TABLE 1 List of watersheds used in this study.

Gage name	Merced R at Happy Isles bridge, Yosemite CA	Galena Creek at Galena Creek State Park NV	Sagehen C near Truckee CA	Donner und Blitzen River near Frenchglen OR	Sandy River near marmot OR	American R near Nile WA	Cedar R near Cedar Falls WA	Stehekin R at Stehekin WA	Thunder ck near Newhalem WA
USGS Gage #	11264500	10348850	10343500	10396000	14137000	12488500	12115000	12451000	12175500
Years Flow and Snow Data	91	31	68	42	43	61	40	90	73
Years Water Temp. Data	36	None	25	11	None	5	24	None	None
Gage Lon. (W)	119.56	119.86	120.24	118.87	122.14	121.17	121.62	120.69	121.07
Gage Lat. (N)	37.73	39.35	39.43	42.79	45.4	46.98	47.37	48.33	48.67
Mean Elev. (m)	2633	2042	2157	1613	1055	1453	900	1510	1539
Mean Slope (m/km)	131	136	81	58	111	144	130	227	246
Area (km^2)	472	22	27	518	676	206	111	830	274
Forest Fraction	0.58	0.51	0.9	0.01	0.99	0.99	0.99	0.82	0.79
Mean Snow Fraction	0.91	0.83	0.71	0.47	0.32	0.64	0.34	0.72	0.69
Aridity (PET/P)	1.15	1.18	1.1	2.18	0.32	0.46	0.27	0.48	0.4
Median Q50 Date	22-May	9-May	23-Apr	4-May	2-Mar	9-May	9-Mar	30-May	13-Jun
Median Summer P/Winter P	0.09	0.1	0.07	0.26	0.06	0.14	0.14	0.21	0.28

Note: Rows give the USGS gage number, number of years when both streamflow and snowpack data are available, years when water temperature data are available, stream gage longitude and latitude, watershed area, fraction of the watershed that is forested, mean fraction of annual precipitation falling as snow, mean aridity (total potential evapotranspiration divided by total precipitation for each water year), median day when 50% of the water year's streamflow has passed the gauge (Q50) and median summer precipitation (P) divided by median winter P. Catchment attributes (mean elevation through aridity) are from Addor et al. (2017).

2.4 | Statistical analyses

We tested two different linear models for predicting daily mean water temperature during the hottest months of July and August. These models were designed to test the relative sensitivity of water temperature to streamflow and snowmelt versus air temperatures:

1. Median 15-day streamflow and daily mean air temperature are the only predictors.
2. Streamflow, daily mean air temperature and preceding winter's peak snowpack are all predictors (the snowpack value is the same for each day within a given year, while the other two predictors vary daily).

We also explored the annual patterns of water temperature by calculating the correlation of peak water temperature (defined as the maximum 7-day average water temperature for a given year) with the following annual-scale predictors:

- Qmin—Lowest 15-day median flow for May 15–October 31 for a given year
- Air T—Mean air temperature for either the day of peak water temperature, previous week or previous 2 weeks.
- Peak SWE—Greatest SWE measured in the prior winter. A primary goal of this study is to expand on previous studies showing baseflow sensitivity to SWE.
- Qmin Prior—Magnitude of Qmin from the previous summer. This variable is selected as a proxy for subsurface water storage. This assumes that summer low flows are dominated by baseflow conditions, baseflow rates decrease as groundwater storage is depleted (Brutsaert, 2005), and total subsurface water storage is highly correlated with groundwater (saturated zone) storage. We

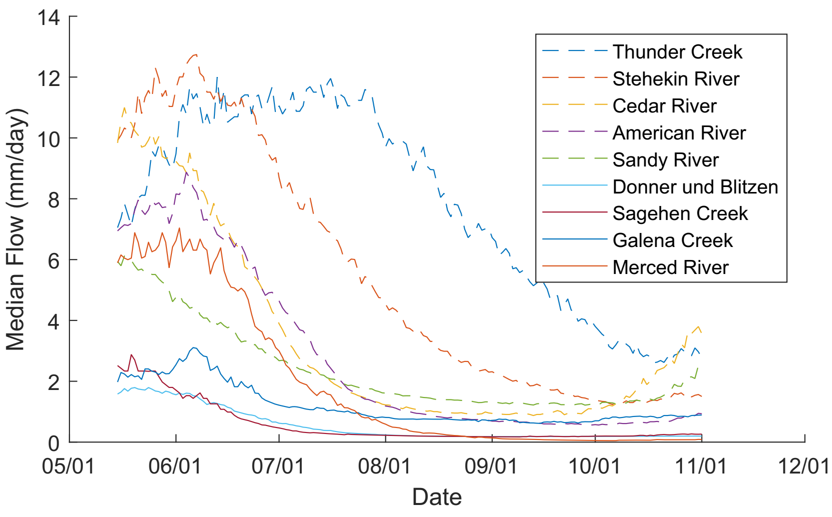

FIGURE 2 Median streamflow for May 15–November 1 at each gage (normalized by watershed area). The four most southern watersheds, all with aridity index >1, are shown in solid lines while less arid watersheds are shown in dashed lines.

also tested alternative indices related to carryover storage, such as P-PET-Q, which had weaker relationships to Qmin and stream temperature on average (See SI section on Alternative Storage Metrics).

- Water Year P–Total precipitation falling during the current water year. If the volume of water added to the system is more important than volume of water stored as snowpack, then P is expected to be a stronger predictor than Peak SWE.
- Summer P–Total precipitation from May 15 through the date of Qmin in each water year. This captures water added to the system after snowfall has generally ended.
- Winter P—Total precipitation from October 1 to May 14 of each water year. This variable allows us to test whether snowpack storage (i.e., Peak SWE) or the volume of winter P is more important.
- SWE Fraction—The ratio of peak SWE to water year P. This metric gives a relative measure of the proportion of precipitation falling as rain without relying on uncertain estimates of snowfall.
- Prior X weeks P—Total precipitation in the $X = 2$, 4 or 8 weeks leading up to the first day Qmin is reached each year. The purpose of this variable is to capture short term impacts of precipitation on Qmin.
- Aridity—Ratio of water year's total PET to precipitation (PET/P). This variable captures the amount of atmospheric demand relative to water availability.
- Summer PET—Total PET from June 1 through August 31. This tests the sensitivity of Qmin to water demand separate from supply, focusing on the period of peak demand.
- Runoff Ratio—Ratio of water year total streamflow to precipitation (Q/P). This variable is included to test whether Qmin volumes are strongly related to the watershed's streamflow generation efficiency at the annual scale.
- Peak Flow—Maximum 15-day median streamflow for the water year.
- Q50—Date when 50% of total water year flows have passed through the gage. Earlier flow timing may lead to lower peak flows as snowmelt recession would start earlier. This is a commonly-used metric of streamflow timing shifts (Gordon et al., 2022).
- P80—Date when 80% of total water year precipitation have fallen. For our study area, this percentage should encompass the majority of winter P. If this variable is strongly related to Qmin volumes, it indicates that the timing of precipitation is important to low flows.
- DOY Q Rise—Date when 15-day median streamflow first rises at least 0.1 mm above Qmin again (following the last day when flow is at Qmin level). This metric is meant to capture the onset of significant late summer or early fall rainfall that puts an end to the summer streamflow recession, and is capped at November 1.

We used stepwise linear regression to further explore these hydroclimatic factors' effects on water temperatures. Using the stepwiselm function in MATLAB R2018b, different candidate predictor variables from the list above were added to or removed from linear models predicting peak water temperature depending on whether they improved or diminished model performance according to the sum of squared error, Akaike Information Criterion (AIC), Bayesian Information Criterion and R^2 (https://www.mathworks.com/help/stats/stepwiselm.html).

Once the linear modelling and correlation analyses confirmed that summer streamflow volume (and Qmin in particular) were strongly related to water temperatures, we explored the relationships between climate variability and Qmin. This approach allowed us to better understand the mechanisms by which climate change could affect water temperatures, as well as increase our sample size since flow data are more readily available than water temperature data. We calculated the correlation between each of the predictor variables in the bullet list above with Qmin and Qmin timing (the day of year when Qmin is first reached). These correlation analyses provide a first order insight into the relationships between different variables, and help to identify which variables may be more important in some watersheds compared with others.

We then explored combined impacts of multiple variables using two separate linear models for predicting Qmin volume and timing:

1. Storage model: Peak SWE (representing snowpack storage) and previous year's Qmin (a proxy for groundwater storage carryover from the previous year) are the only predictors.

2. Storage + Demand model: Includes the above storage terms as well as measures of atmospheric demand (Aridity and Summer PET) and summer water inputs.

For the Storage + Demand model, many of the predictor variables had high correlations with other predictors, which could impede our ability to draw useful interpretations from the model coefficients (Heinze et al., 2018). We therefore selected a Storage + Demand model for each watershed by first testing every possible combination of the following variables: Peak SWE, Qmin Prior, Aridity, Summer PET and Summer P. For each watershed, we then selected the variable combination that resulted in the lowest AIC value while still having all correlations between predictor variables <0.6. When two AIC values were similar, we selected the model with the highest R^2 value. We also used stepwise linear regression to explore the full range of potential predictors listed above.

All multiple linear regression models described above take the form:

$$y(t) = c_0 + c_1\hat{x}_1(t) + \ldots + c_n\hat{x}_n(t), \tag{1}$$

where y is the dependent variable (e.g., Qmin), c represents model coefficients, t represents a given year (or day for the daily temperature model) and $\hat{x}_1 \ldots \hat{x}_n$ represent n separate normalized predictor variables (e.g., Peak SWE). All predictor variables were mean-subtracted and normalized by their standard deviation to create predictors that have a mean of zero and standard deviation of one ($\hat{x} = \frac{x-\bar{x}}{\sigma_x}$, where $\bar{x}$ is the mean and σ_x is the standard deviation of x). This normalization allows for more meaningful comparison of the model coefficients between watersheds and between different predictor variables (i.e., a coefficient of 1 means that increasing the predictor variable by 1 standard deviation will increase Qmin by 1 mm).

We also calculate the relative sensitivity of Qmin or temperature to certain predictors. We define relative sensitivity as the ratio of changes relative to the mean:

$$\text{Relative Sensitivity} = \left(\frac{\Delta y/\bar{y}}{\Delta x_i/\overline{x_i}}\right) = \frac{c_i\overline{x_i}}{\sigma_{x_i}\bar{y}}, \tag{2}$$

where y and $\bar{y}$ represent the independent variable (Qmin or temperature) and its mean over all years; x_i, $\overline{x_i}$ and σ_{x_i} represent a single predictor variable and its mean and standard deviation, respectively; and c_i represents the linear model coefficient of the normalized version of x from Equation (1). If relative sensitivity is greater than 1, then a given percent change in x will lead to a higher percent change in y.

3 | RESULTS

3.1 | Daily water temperature

In linear models predicting daily mean summer (July and August) water temperature, smoothed daily streamflow always had a negative coefficient. Therefore, higher flows generally indicate colder water temperatures. Mean daily air temperature was a more important predictor (larger magnitude model coefficient) than streamflow volume for Merced and Sagehen, but streamflow was more important in the more northern Cedar River (Figure 3a, Table S5). A 1°C increase in air temperature was associated with a smaller increase in stream temperature in Cedar River compared with the more southern watersheds (Figure B3). Streamflow and air temperature only explained approximately 40%–70% of the variance in water temperature (as shown by the R^2 values in Figure 3d and Table S5). For all streams except Merced, adding the previous winter's peak SWE as a predictor led to slight improvements in model fit (increases in R^2 and decrease in AIC_c), with negative coefficients indicating that a higher peak SWE was associated with lower summer stream temperatures (Figure 3b,d, Table S5). Accounting for peak SWE in this manner decreased the sensitivity of water temperature to flow volume in all watersheds except Merced (Figures 3 and B3). Qmin Prior was also tested as a potential predictor, but including this variable did not substantially change any coefficients shown in Figure 3 and Table S5 and did not improve model fit.

3.2 | Annual peak water temperature

Peak water temperature nearly always occurred earlier than the annual Qmin, since the date of Qmin often came after air temperatures had begun dropping in late summer/fall. Even so, annual maximum water temperature was more closely linked with that year's Qmin (correlation ranging from −0.48 to −0.87) than with mean streamflow in the week leading up to the peak temperature (correlation ranging from −0.20 to −0.77). Air temperature in the week leading up to peak water temperature had a significant positive correlation with peak water temperature for all streams except Merced River (Table 2).

Mean streamflow and air temperature were tested as predictors across periods of 1 day to 4 weeks prior to and including the day of peak water temperature, and 1 week was found to give the highest correlation in all streams except Sagehen.

We set the stepwise linear model algorithm to initiate with a model using Qmin and the previous week's mean air temperature as predictors (the two variables that most consistently had significant and large correlations with peak water temperature). The stepwise algorithm then added or removed variables from this initial model depending on multiple measures of fit (as described in Section 2.4). Using this method, we retained both Qmin and air temperature as predictors only for Sagehen, whereas Qmin alone was retained as a predictor of peak temperature in the Merced River, and only air temperature for Cedar River (Figure 3c; Table S6). For Donner und Blitzen, this method added aridity to the model, but aridity and low flows are highly negatively correlated ($r = -0.6$); removing aridity as a candidate variable led the algorithm to select a model with only Qmin as a predictor for Donner und Blitzen's peak water temperature (including air temperature slightly reduced the R^2 value). According to these models, a 1°C increase in air temperature was associated with a 0.3–

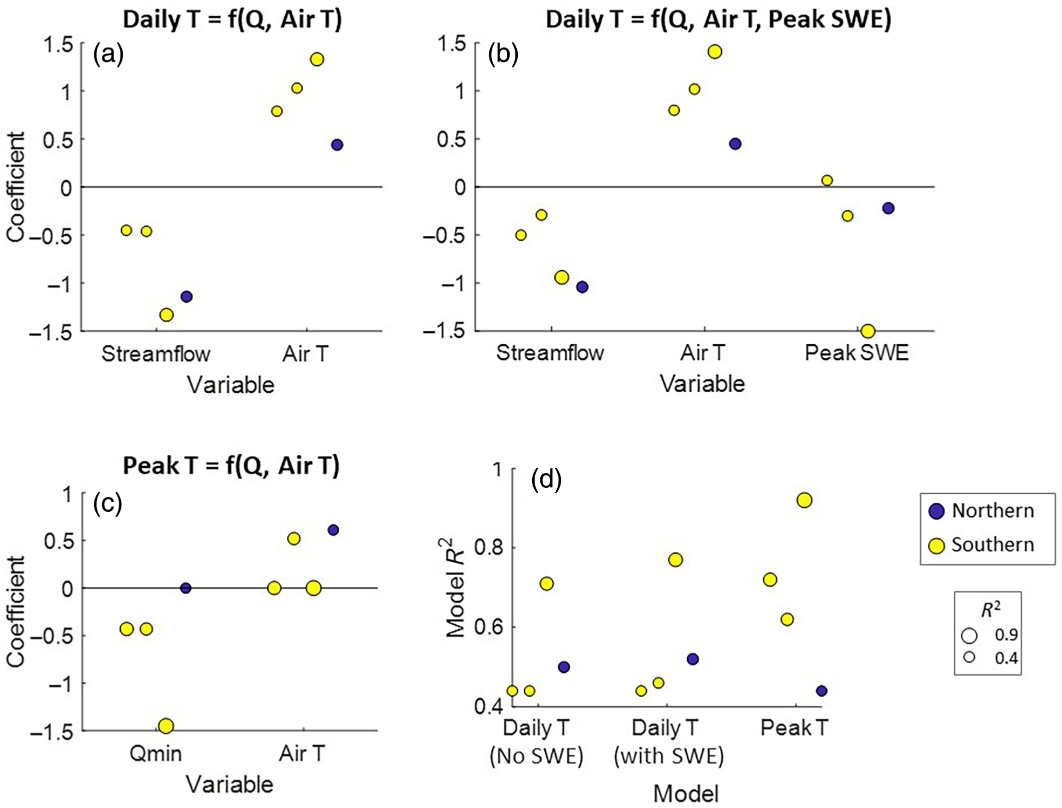

FIGURE 3 Coefficients for water temperature models, as described in Equation (1). Watersheds are ordered from more southern on the left to more northern on the right (same order as Table 2). The three most arid watersheds (Merced, Sagehen, Donner und Blitzen) are shown in yellow while Cedar River is shown in blue. Circle size is proportional to the R^2 value for each model (also shown in Panel d). The three models shown include models of daily water temperature either with (b) or without (a) peak SWE as a predictor, and a model of peak annual 7-day mean water temperature (c).

0.4°C increase in peak water temperature for Sagehen and Cedar, while a given percent decrease in Qmin had the strongest influence on peak water temperatures at Donner und Blitzen (Figure B3).

Since higher Qmin values were associated with lower water temperatures for all streams studied (according to correlation analyses, linear models or both) we study drivers of Qmin to expand our sample size by using streamflow data instead of relying on sites with long water temperature records. Higher streamflow being associated with decreased water temperature is consistent with a larger mass of water for incoming energy to warm.

3.3 | Qmin volume relationship to precipitation, water storage and demand

For all locations, peak SWE was positively correlated with Qmin (Table 3) and had a positive linear regression coefficient in the simplest linear models (Figure 4a; Table S2), showing that higher peak SWE is generally associated with greater Qmins. Qmin Prior had either positive or very weakly negative relationship with Qmin for all locations in all models (Figure 4, Tables 3 and S1–S3). Mean correlation between peak SWE and Qmin Prior across all watersheds was only 0.06, with a maximum of 0.18, suggesting these predictors are sufficiently independent for a meaningful multiple linear regression. Linear model coefficients and relative sensitivity values were usually larger for Peak SWE than Qmin Prior (Figures 4a and B1).

Higher Aridity or PET predicted lower Qmin volumes in models which included these variables (Figure 4c, Tables S1 and S3), consistent with these variables' negative correlation with Qmin (Table 3; Figure S1). The only exception was Thunder Creek, where Summer PET had a small but positive coefficient (Figure 4c). The Storage + Demand model had a higher R^2 value than the Storage model for most watersheds and a lower AIC for all watersheds (Figure 4b; Tables S2 and S3). These measures of fit indicate that including demand terms leads to more accurate prediction of Qmin, even when using AIC to account for the fact that the Supply + Demand models include a greater number of predictors. Relative sensitivity had a greater magnitude for PET than for Peak SWE or Qmin Prior (Figure B1).

Qmin values in the southern, more arid watersheds were fit much better using linear models compared with the more northern watersheds (Figure 4b, Tables S1–S3). Qualitatively, Figure 5 also shows that the lowest flows usually occur in years with lower peak SWE and smaller previous year Qmin for more southern sites (a–d) but this relationship is weaker or non-existent in the more northern sites (g–i). The relationship between SWE and Qmin appears slightly non-linear in some watersheds (e.g., Figure 5c), but fitting models to the log or

TABLE 2 Correlation coefficients of annual peak 7-day mean water temperature with multiple variables describing snow water equivalent (SWE), streamflow (Q), precipitation (P) and air temperature (T).

	Merced River	Sagehen Creek	Donner und Blitzen	Cedar River
Qmin	**−0.84**	**−0.51**	**−0.87**	**−0.48**
Air T (same day)	−0.40	**0.53**	0.33	0.40
Air T (previous week mean)	0.10	**0.60**	**0.74**	**0.66**
Air T (previous 2 weeks mean)	−0.11	**0.70**	0.63	**0.53**
Peak SWE	−0.68	**−0.65**	−0.67	0.07
Qmin Prior	0.55	−0.15	−0.05	**0.48**
Summer PET	0.00	0.31	0.50	0.36
Aridity	0.62	**0.47**	0.20	−0.06
Runoff Ratio	−0.53	**−0.55**	**−0.92**	0.07
Peak Flow	−0.74	**−0.53**	−0.68	−0.20
Q50	−0.54	**−0.55**	−0.65	−0.16
P80	**0.86**	0.21	0.02	−0.17
SWE Fraction	−0.31	−0.44	−0.50	0.12
Winter P	−0.76	**−0.49**	−0.32	0.00
Summer P	−0.70	0.11	0.18	−0.38
Water Year P	−0.77	**−0.50**	−0.42	−0.13
Previous 2 weeks' P	−0.47	0.37	0.42	−0.10
Previous 4 weeks' P	−0.50	0.08	0.57	−0.36
Previous Week's Mean Flow	−0.77	−0.27	−0.56	−0.19

Note: Blue colours indicate that a higher value of that variable leads to lower peak water temperatures (negative correlation) while red indicates a variable associated with higher peak water temperatures. Bold numbers indicate a statistically significant correlation ($p < 0.05$).

square root of flows led to only very small improvements in model fit and did not change our interpretation of variable importance (results not shown) so we chose to maintain purely linear models for ease of interpretation.

The stepwise linear model tested all variables defined in Section 2.4 as candidate predictors. Previous years' Qmin was selected by the stepwise linear regression algorithm for 4/9 watersheds (the 4 with mean annual aridity index >1). These same four watersheds all either had Peak SWE or Water Year P selected. Aridity (PET/P) was selected as a predictor for three of the more northern watersheds. Summer precipitation or the 8 weeks of precipitation leading up to Qmin were selected for four watersheds, suggesting that recent summer rains have a noticeable impact on these streams' low flows. (Table S1).

3.4 | Qmin timing

Higher peak SWE and summer precipitation values were always positively correlated with later Qmin timing. In contrast, high summer PET was associated with earlier Qmin dates, especially in the four most southern watersheds (Table 4).

Linear models were not able to predict Qmin timing as well as volume (R^2 < 0.7 for all models tested). While these low model fits suggest that linear modelling is not able to adequately capture the factors driving low flow timing, in general model coefficients mirrored the correlation analysis results in that Peak SWE was a more important predictor than Qmin Prior, and higher Summer P was associated with later minimum flows (results not shown). Part of the poor model fit may be due to the strong correlation between DOY Q Rise and Qmin timing in most watersheds (Table 4), which suggests that the timing of minimum flows are often dictated by the onset of late summer and fall rains.

4 | DISCUSSION

4.1 | Water temperature

Unsurprisingly, high air temperatures were strong predictors of high summer water temperatures. Water temperatures are therefore expected to rise in response to the increased air temperatures that are predicted across our entire study region in coming decades (Figure C1). However, Qmin was also strongly correlated with peak water temperature (especially in Donner und Blitzen, the most eastern watershed; Table 2). For two of our study watersheds (Merced and Donner und Blitzen), a linear model with Qmin gave the most accurate prediction of peak annual water temperature of all linear models tested (Figure 3; Table S6). This shows that despite peak water temperatures nearly always occurring before Qmin is reached, years with

TABLE 3 Correlation coefficient of each variable with the given river's annual Qmin.

	Merced R., CA	Galena Crk., NV	Sagehen Creek, CA	Donner und Blitzen, OR	Sandy R., OR	American R., WA	Cedar R., WA	Stehekin R., WA	Thunder Creek, WA
Peak SWE	**0.57**	**0.83**	**0.66**	**0.80**	**0.38**	**0.54**	0.14	**0.38**	0.21
Winter P	**0.59**	**0.82**	**0.69**	**0.69**	0.22	**0.54**	0.14	**0.29**	0.09
Water Year P	**0.63**	**0.85**	**0.72**	**0.73**	0.20	**0.55**	0.21	**0.31**	0.23
SWE fraction	**0.29**	**0.35**	0.10	**0.31**	0.15	**0.29**	0.07	0.18	0.08
Qmin Prior	**0.28**	**0.48**	**0.48**	**0.45**	−0.01	0.15	0.16	0.05	0.04
Qmin Prev. 2 Years Mean	**0.29**	**0.48**	**0.45**	**0.44**	−0.03	0.17	0.13	0.04	0.00
Qmin Prev. 3 Years Mean	**0.25**	0.34	**0.36**	**0.34**	−0.01	0.18	0.14	0.10	−0.01
Summer PET	**−0.57**	−0.35	**−0.51**	**−0.58**	−0.27	−0.24	**−0.44**	**−0.25**	−0.04
Aridity (PET/P)	**−0.59**	**−0.76**	**−0.68**	**−0.67**	−0.28	**−0.59**	**−0.49**	**−0.37**	−0.21
Runoff Ratio (Q/P)	**0.51**	**0.41**	**0.83**	**0.79**	0.05	**0.56**	0.12	0.17	−0.04
Peak Flow	**0.58**	**0.60**	**0.81**	**0.81**	**0.31**	**0.47**	**0.33**	0.16	0.10
Q50 (Date of 50% annual flow)	**0.44**	**0.44**	**0.53**	**0.35**	0.13	**0.40**	0.20	**0.23**	0.05
P80 (Date of 80% annual P)	−0.11	−0.23	−0.24	0.12	**−0.45**	−0.13	**0.34**	−0.04	−0.02
Summer P	**0.41**	**0.62**	**0.61**	**0.47**	−0.10	0.11	0.20	0.09	**0.35**
Prev. 2 weeks P	0.03	−0.17	0.18	−0.06	−0.17	−0.11	−0.09	−0.10	0.06
Prev. 4 weeks P	0.06	0.10	**0.31**	−0.02	−0.22	−0.03	−0.06	0.09	**0.25**
Prev. 8 weeks P	**0.30**	0.23	**0.27**	0.12	−0.17	0.04	0.02	0.05	**0.34**
Qmin timing	0.03	**0.63**	**0.59**	**0.60**	**−0.40**	0.03	**−0.36**	**−0.35**	**−0.28**
DOY Q Rise	−0.06	**0.52**	**−0.32**	−0.04	**−0.48**	−0.08	**−0.44**	**−0.33**	**−0.35**

Note: Numbers in bold indicate statistically significant correlations ($p < 0.05$). Numbers in grey indicate highly non-significant correlations ($p > 0.50$). Watersheds are ordered from most southern on the left to most northern on the right. Blue indicates a positive correlation, red a negative correlation and white a near-zero correlation.

low baseflows are generally associated with warmer water temperatures. This relationship could be attributable to various causes such as shallower streams warming more quickly than deep water and/or higher Qmin values indicating more contribution from cold groundwater flowpaths (Tague et al., 2007). Although part of this correlation may simply be due to the fact that warmer air temperatures lead to higher evaporative demand and thus lower streamflows, the importance of Qmin in addition to air temperature in our models for most watersheds suggests that flow itself contributes to stream temperatures.

Peak SWE only had a significant correlation ($p < 0.05$) with peak temperature for Sagehen, although the p value was still <0.15 for the three other streams. For Sagehen, the correlation of water temperature with peak SWE was stronger than the correlation with Qmin, suggesting that snowpack variation may play an important role in the variability of water temperature. Previous work has shown that the timing of snowmelt recession has a strong impact on the amount of time that water temperatures remain elevated, and only a small impact on peak water temperatures (Null et al., 2013). Although we focused on magnitude of stream temperature correlations with flow volume, future work should explore temporal patterns in more detail as well.

Air temperature in the week prior was significantly correlated with peak water temperature in every stream except the Merced River (Table 2), and air temperature was not selected as a predictor in the linear model of peak water temperature for Merced (Table S6). It may be that Merced River temperature is less sensitive to air temperature since it has the highest maximum elevation of the watersheds analysed for temperature, and therefore much of its water comes directly from cold snowmelt for more of the year. This is consistent with other studies showing colder summer water temperatures in streams that are more snow-dominated compared with rain-dominated (McGill et al., 2023; Siegel et al., 2022) and suggests that snowpack (which is highly sensitive to climate change) may be an important regulator of stream temperatures.

Increased peak SWE and increased daily streamflows were both associated with colder daily water temperatures (Table 2). Disaggregating the individual effects of these two related values would require a process-based model, which is beyond the scope of the current study.

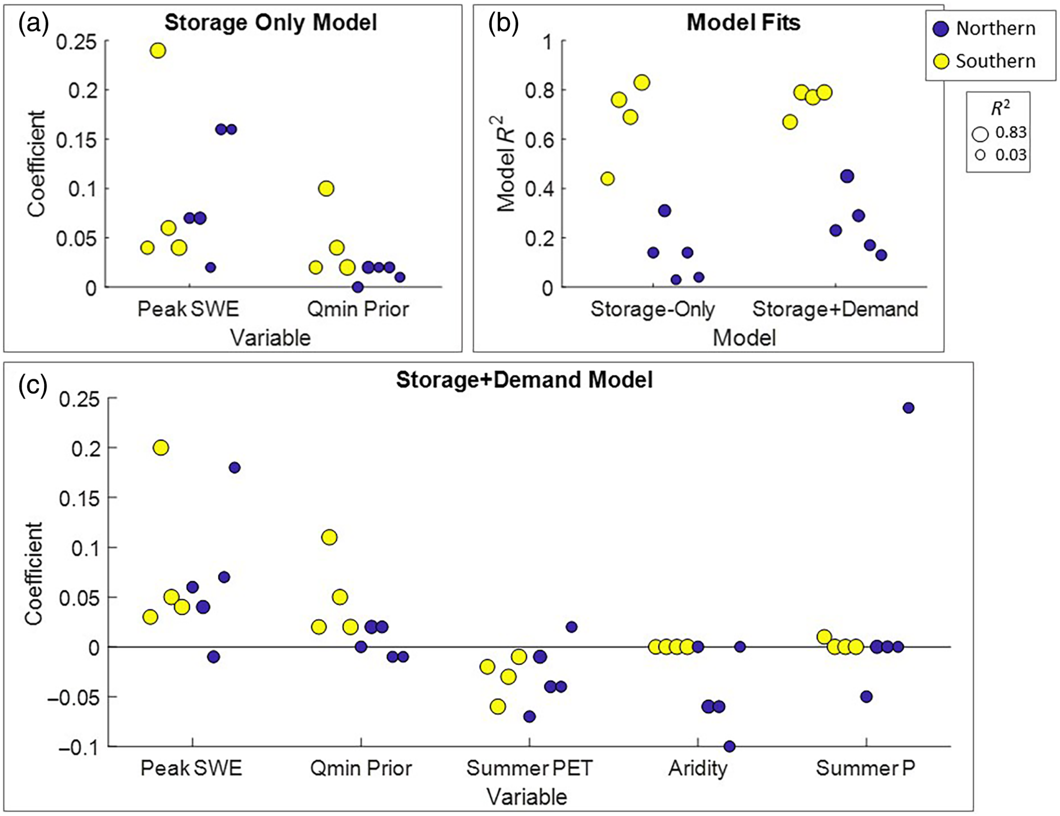

FIGURE 4 Coefficients for the Storage-Only model (a) and Storage+Demand model (c) for Qmin in each watershed, as described in Equation (1). Watersheds are ordered from more southern on the left to more northern on the right (same order as Table 1). The four most arid watersheds are shown in yellow while the remainder are shown in blue. Circle size is proportional to the R^2 value for each model (also shown in Panel b).

4.2 | Qmin volume

Deeper peak snowpack and greater precipitation were associated with higher Qmin values and lower stream water temperatures under most of our statistical analyses. In the drier southern watersheds, a positive relationship between Qmin and the prior years' low flows indicates that subsurface water storage may provide a buffer to interannual SWE variations (which could also make these watersheds more sensitive to multi-year drought). The importance of prior years' Qmin in predicting the current year's low flow in Sagehen is consistent with Godsey et al. (2014) finding that annual low flows in this watershed were highly sensitive to the previous year's snowpack. While some watersheds were modelled well using only storage metrics, adding evapotranspiration increased model accuracy. The influence of water year P, Peak SWE and Summer PET are illustrated in Figures S2 and S3, demonstrating that higher Qmin values happen in years with lower PET, but that low PET years also often have high P and SWE which makes attribution of causality difficult. In Sagehen, Qmin is generally lower in more recent years regardless of SWE (Figure 5C). This can partly be explained by a trend towards higher summer PET over time (Figure S4).

While peak SWE generally had the greatest magnitude coefficient in our linear models (indicating that the interannual variability of peak SWE had a proportionally larger impact on the interannual variability of Qmin) it should be noted that the relative sensitivity was generally largest for summer PET (Figures 4a,c and B1). While a 10% increase in peak SWE or Winter P was found to increase Qmin by up to 8% or 9%, respectively (depending on the watershed and model chosen), a 10% increase in summer PET would decrease Qmin by up to 50% (Figures B1 and B2). Cooper et al. (2018) used a larger number of watersheds but only considered each variable independently; they found 10% increases in SWE or Winter P to raise Qmin 4% or 5% (respectively) and a 10% PET increase to reduce Qmin 21%.

The stepwise linear regression algorithm for Qmin selected Peak SWE as a predictor variable for three of the watersheds (Merced, Donner und Blitzen and Sandy) and Water Year (WY) P (which is correlated with peak SWE) was selected for three of the remaining seven watersheds (Table S1). Winter P was not selected by the algorithm for any watersheds and had a slightly smaller correlation with Qmin than Peak SWE for most watersheds (Table 2). In contrast, Cooper et al. (2018) found that Qmin was slightly more responsive to Winter P compared with Peak SWE. A variation on the storage-only model using Winter P instead of Peak SWE to predict Qmin gave slightly better model fits for 4/9 of our study watersheds, but usually SWE was a better or equal predictor (Table S2). The positive correlation of SWE Fraction (the ratio of Peak SWE to Water Year P) with Qmin in

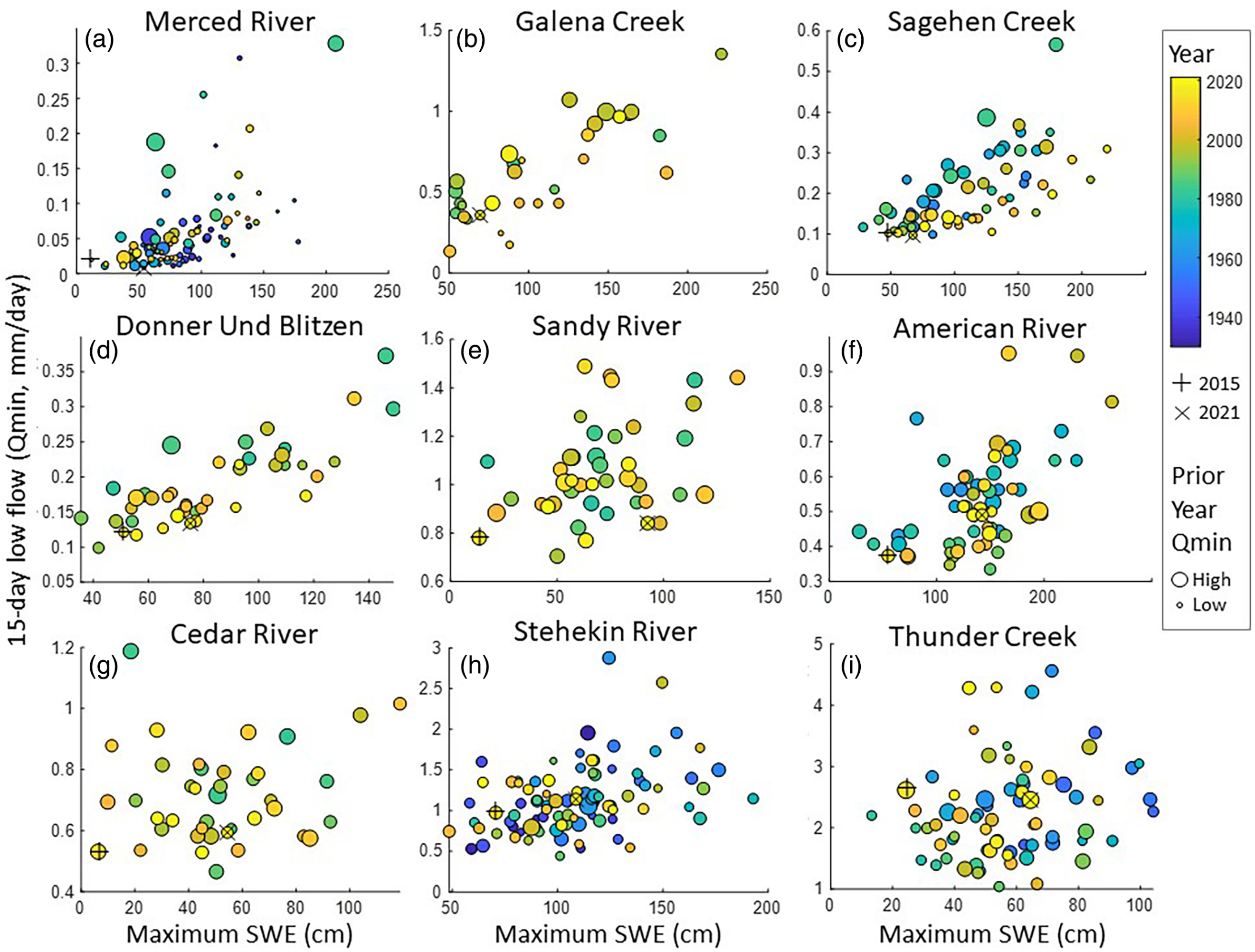

FIGURE 5 Relationship between 15-day low flow (Qmin), snow and storage. Plots give annual minimum 15-day flow plotted against the previous winter's peak SWE. Colours denote water year, and size of circle is proportional to the previous year's Qmin (a surrogate for subsurface water storage). For the more southern sites, the lowest flows appear to occur in years with lower peak SWE and smaller previous year Qmin (a–d) but this relationship is weaker or nonexistent in the more northern sites (g–i). An 'X' denotes data from 2021, the lowest Qmin in our study period for Merced and Sagehen. A '+' denotes data from 2015, which had the lowest peak SWE since year 2000 for most watersheds.

all watersheds also suggests that snowpack storage is important for summer low flows independently of precipitation volumes (Table 3). Figure S5 demonstrates that Winter P does not explain much of the variation in Qmin that is not predictable by peak SWE and carryover storage (years with low peak SWE but relatively high Qmin do not regularly have high winter P). Nonetheless Peak SWE, Winter P and WY P are highly correlated with each other and it is likely that P alone, whether rain or snow, is a significant control on Qmin. Our analyses do suggest that total annual precipitation and the amount stored as snowpack are slightly more important to determining low flow than the volume of precipitation during winter months. Watersheds such as Donner und Blitzen where Peak SWE is a more important predictor than WY P (Table S1) may be more hydrologically sensitive to a warmer future when precipitation is more likely to fall as rain.

Future climates are likely to increase factors associated with lower minimum flows. According to downscaled global climate models (GCMs) from the Coupled Model Inter-Comparison Project 5 (CMIP5; Pierce et al., 2014, 2015; Taylor et al., 2012), across the entire region of study water storage in soils and snow are expected to decrease, summer PET to increase and mean annual precipitation is projected to either remain the same or increase slightly (Figures C1–C3). All of these changes, except for precipitation, are likely to decrease low flows. Looking more closely at our four most southern watersheds, individual GCMs' projections are mixed in terms of whether annual precipitation or the 20th percentile of annual precipitation (an indicator of drought severity) are likely to increase or decrease by the end of the century (Figures C3 and C4), but most models predict that peak SWE will decrease (Figure C5). It is possible that higher annual precipitation might help increase Qmin even if SWE decreases. However, simulations from a continent-wide application of the Variable Infiltration Capacity (VIC) model (Vano et al., 2020) predict future decreases in August and September streamflow for all of the southern study watersheds using forcings from most climate models (Figures C6 and C7). Donner und Blitzen shows the most models

TABLE 4 Correlation of various climate and flow metrics with the date of annual Qmin.

	Merced R., CA	Galena Crk., NV	Sagehen Creek, CA	Donner und Blitzen, OR	Sandy R., OR	American R., WA	Cedar R., WA	Stehekin R., WA	Thunder Creek, WA
Peak SWE	**0.28**	**0.64**	**0.70**	**0.62**	0.05	**0.31**	**0.36**	0.15	0.03
Winter P	**0.40**	**0.63**	**0.64**	**0.40**	−0.19	**0.32**	−0.03	0.08	0.18
WY P	**0.40**	**0.66**	**0.67**	**0.59**	−0.15	**0.41**	0.13	0.19	0.22
SWE Fraction	−0.11	0.29	**0.28**	0.24	0.17	0.18	**0.32**	0.06	−0.06
Low Flow Prior	−0.06	0.24	0.14	0.02	0.05	0.00	0.11	−0.04	0.13
Summer PET	**−0.31**	−0.31	**−0.36**	**−0.59**	−0.02	−0.06	−0.06	−0.10	0.02
Aridity	−0.22	**−0.43**	**−0.58**	**−0.40**	0.23	**−0.32**	0.13	−0.08	−0.14
Runoff Ratio	0.22	0.25	**0.61**	**0.53**	0.18	0.16	0.16	0.02	0.17
Peak Flow	**0.39**	**0.36**	**0.72**	**0.64**	−0.13	**0.32**	0.05	**0.31**	0.13
Q50	**0.32**	**0.48**	**0.71**	**0.53**	0.09	0.18	0.24	0.19	0.02
P80	−0.11	−0.29	−0.16	0.08	0.24	**−0.38**	−0.06	−0.19	−0.15
Summer P	0.11	**0.54**	**0.56**	**0.66**	0.23	**0.36**	**0.42**	**0.30**	0.13
P2w	−0.08	−0.25	0.07	0.22	0.26	0.05	0.19	−0.07	−0.08
P4w	−0.07	0.09	0.19	0.30	**0.33**	0.01	0.26	0.08	−0.04
P8w	0.03	0.14	**0.26**	**0.47**	**0.38**	0.12	**0.32**	0.17	0.17
DOY Q Rise	**0.77**	**0.58**	−0.08	−0.13	**0.95**	**0.79**	**0.96**	**0.96**	**0.96**

Note: Numbers in bold indicate statistically significant correlations ($p < 0.05$). Watersheds are ordered from most southern on the left to most northern on the right. Blue indicates a positive correlation, red a negative correlation and white a near-zero correlation.

predicting higher August and September flows in the future, which may be due to its relatively low projected increases in summer PET (Figure C2), relatively low Qmin sensitivity to PET (Figure B1), and slight increase in projected precipitation even during relatively dry years (Figure C4).

4.2.1 | Regional variations

The more southern watersheds in our study had the highest R^2 values for models predicting Qmin using the annual-scale climate variables tested in this study (Figure 4). Cooper et al. (2018) also found that low flows in southern watersheds were more sensitive to annual sums of precipitation and PET compared with northern watersheds. These southern watersheds also had the highest mean elevations, and observations in Switzerland found that low flows in late summer were more directly affected by snowpack in watersheds above 2000 m elevation (Jenicek et al., 2016). The four northern-most catchments in this study (American, Cedar, Stehekin and Thunder) are all relatively slow-draining and storage-dominated with long baseflow recessions (Cooper et al., 2018). Previous work has shown that low flows in slower-draining watersheds with later snowmelt dates (such as the more northern sites in our study) may actually be more sensitive to changing snowpack than faster draining watersheds (Tague & Grant, 2009). This sensitivity may be difficult to observe with the methods used here due to multiple factors, however. One such factor is demonstrated by the fact that in Cedar, Stehekin, Sandy and Thunder Creek Qmin volume is negatively correlated with both Qmin date and DOY Q Rise (Table 2). In these watersheds streamflow would likely keep decreasing throughout the summer until fall rains began raising water levels (see hydrographs with a dashed line in Figure 2), so a later Qmin date means more time for flow to recede before the wet season and thus a greater chance of a small Qmin value regardless of other variables. This is supported by the fact that streamflow in these watersheds generally begins to rise within a few days of Qmin being reached (Figure S6), suggesting that Qmin generally occurs just before late summer or fall rains cause an end to summer recession. In the faster-draining basins, on the other hand, streamflow levels bottom out at a relatively constant level earlier in the summer (solid lines in Figure 2), and earlier Qmin dates would reflect drier conditions and thus a lower summer baseflow (positive correlation between Qmin timing and volume; Table 2). Geological differences such as these are important to keep in mind when assessing watersheds' sensitivities to future climate, as both Qmin timing and magnitude have strong impacts on aquatic ecology.

The Thunder Creek watershed contains glaciers, which likely have a strong influence on summer low flows since warmer temperatures can lead to greater glacier melt and therefore increase summer streamflows compared with what would be expected in response to lower precipitation and higher temperatures in an unglaciated basin (Pelto, 2008). These glacial impacts may contribute to the poor ability of our simple linear models to predict low flows in Thunder Creek. Stehekin has a very small amount of glacier coverage, and none of the other watersheds contain any glaciers (CEC, 2010).

Relatively low snow fractions for Sandy River (0.32) and Cedar River (0.34) may be part of the reason that peak SWE was a poor predictor of Qmin in those catchments. Both of these watersheds did have significant positive correlations between Q50 and Qmin, however, suggesting that the timing of snowmelt may still be an important driver of summer flow volumes. Sandy River had a negative relationship between P80 and Qmin, whereas American River had positive relationships between these variables (Table 3, Table S1). This suggests that spring and summer rainstorms (including rain on snow events) may be strongly influencing summer flows in these watersheds with opposite effects.

4.2.2 | Importance of multi-year droughts

Our analyses demonstrate the importance of considering flow drivers at multi-year timescales. The proportion of precipitation allocated to streamflow is reduced during extended droughts since partitioning of local precipitation to streamflow is minor until subsurface saturation is reached, and extensive droughts leave a large subsurface storage deficit that needs to be met in order to reach saturation (Bales et al., 2018; Flint et al., 2018; Hahm et al., 2022). This impact of multi-year drought is reflected in the fact that the four most arid watersheds in our study had positive relationships between previous years' Qmin (up to 3 years prior) and summer low flows in every linear model tested (Tables 3, S1 and S2). In wetter watersheds, such as the more northern watersheds in our study, soils might be less likely to remain unsaturated and therefore the impact of previous year's level of drought would be lower. This is supported by the poor ability of previous year's Qmin to predict Qmin for the more northern watersheds (Figure 4) and low correlation (Table 3).

The summer of 2021 provided a good example of multiple dry years in a row causing exceptionally low flows due to an accumulated deficit in subsurface water storage (Lapides et al., 2022). Water Year (WY) 2021 (denoted with an X in Figure 5) had the lowest Qmin in our study period for Sagehen and Merced. The storage-only model (Figure 4A) predicted 2021 Qmin almost perfectly in both of those watersheds (overpredicted by <0.01 mm/day). High model accuracy for 2021 suggests that the record low flows were due to exceptional multi-year drought conditions (and the resulting storage deficits, as suggested by Lapides et al., [2022]) rather than by a new emerging behaviour. Peak SWE and total precipitation for WY 2021 were low in these watersheds (bottom 25th and 10th percentiles for SWE and WY P, respectively), but not the lowest on record. The previous year's minimum flows were also low (bottom 10th percentile for Merced and 20th percentile for Sagehen). WY 2021 also had summer PET in the top 95th percentile for both Sagehen and Merced, and was the second year in a row with PET/P >1. In the other study watersheds, behaviour in 2021 was mixed. In Thunder Creek and Stehekin, 2021 had near-average SWE and Qmin, and the storage-only model fit it well (error <0.1 mm/day and <3%). For comparison, WY 2015 (denoted with a + in Figure 5) had the lowest peak SWE since the year 2000 for most of our study watersheds, and followed three previous dry years (including WY 2014 which had Qmin in the bottom 10th percentile for both Merced and Sagehen) but observed 2015 Qmin was slightly higher than 2021 for Sagehen and Merced, and the storage-only model underpredicted 2015 Qmin by ~0.03 mm/day in both watersheds. This is possibly due to slightly lower summer PET and higher WY P in 2015 compared with 2021 for those watersheds. A widespread spring heat wave also led to record-breaking snowmelt rates in April of 2021 across the Western United States which may have further exacerbated drought conditions (McEvoy & Hatchett, 2023). A linear model using Water Year P was better able to predict 2015 low flows than a model using Peak SWE (which underpredicted 2015 Qmin), suggesting that the 2015 summer water balance was more controlled by total precipitation rather than snowpack storage (results not shown). This could indicate that during exceptional drought periods—when snow melts too early to fully perform its usual function as a reservoir slowly releasing water during the dry season, and subsurface storage is sufficiently depleted that it has the capacity to hold much of the precipitation inputs even if they come as winter rain—the total amount of precipitation is more important than snowpack levels for replenishing subsurface storage and maintaining baseflows.

4.3 | Qmin timing

Interestingly the timing of Qmin is more challenging to predict from the simple climate metrics used in our study. Timing of Qmin can be ecologically very important, and we found some evidence that Peak SWE affected this timing. Peak SWE was positively correlated with the date of Qmin for all watersheds, and this correlation was statistically significant ($p < 0.05$) for 6/9 watersheds (Table 4). Godsey et al. (2014) also found that greater peak SWE generally led to later onset of low flows. Summer precipitation may also be important in delaying the timing of minimum flows, as summer P was significantly positively correlated with Qmin date for 6/9 watersheds, while higher summer PET can advance the timing (Table 4). Since summers with higher PET generally have lower P, however, it is hard to disentangle the independent impacts of these two drivers. Prior years' Qmin was not significantly correlated with date of Qmin in any watersheds, suggesting that carryover storage is more important for summer flow volume than it is for timing.

4.4 | Study limitations and opportunities for further work

Our water temperature analyses are limited by the fact that we only had sufficient data at four locations, and these sites only represent temperature in the main stem of their respective rivers. Individual stream reaches within each of these watersheds may show varying sensitivities to snowpack, groundwater storage and so on, depending on local geologic variations (Tague et al., 2007). Other watersheds may also exhibit very different relationships between air temperature and water temperature depending on local non-climatic factors (Arismendi et al., 2012). Our analyses did not account for potential impacts of changing vegetation cover on low flows or water temperature, which could be an important mechanism especially if a multi-year drought causes increased tree mortality from water stress and wildfire (Bales et al., 2018; Chen & Chang, 2023) or warming climates lead to vegetation expansion into higher elevations (Goulden & Bales, 2014). However, since satellite data are not available for the entire period of record for all watersheds such an analysis would involve high levels of uncertainty. It is possible that reduced vegetation cover could increase annual minimum flow volumes, especially in less water-limited catchments, by reducing losses to evapotranspiration and/or increasing snowpack storage (Goeking & Tarboton, 2020; Roche et al., 2018). However, reduced vegetation cover in riparian areas can lead to higher stream temperatures (Arismendi et al., 2012; Caissie, 2006; LeBlanc & Brown, 2000; Webb et al., 2008) as well as greater evaporation losses. Understanding these trade-offs will be vital to future climate mitigation efforts.

While the linear models and correlations shown here provide valuable insights into the sensitivity of flow volumes and stream temperatures to variations in climate and precipitation, such statistical methods cannot identify direct causal explanations for these sensitivities. The collinearity of many different predictor variables shows the danger of implying that any of our variables is directly causing changes in flows. Figure 4 shows that the relative importance of different variables can depend greatly on the chosen linear model. For example, in Cedar River peak SWE either had a slightly positive coefficient (0.02) or slightly negative (−0.01) depending on whether demand-related variables were included in the model. It should be noted, however, that these coefficients only represent a 0.06% to −0.02% change in Qmin for a 1% change in peak SWE. In general, the influence of Peak SWE on Qmin was more sensitive to the model structure than previous year's Qmin or summer PET (Figure B1). While stepwise linear regression provides a useful way to examine the parameter space, this method can give potentially misleading results and does not necessarily separate predictors with a causal relationship from those that are only related coincidentally (Smith, 2018). The stepwise regression's variable selection was very sensitive to which other variables were supplied and what starting model was chosen. Therefore, while the results of our stepwise regressions can provide helpful insights into the relationships between different variables, these results should not be interpreted as the one 'best' model.

Our findings are limited by the fact that precipitation, snowpack and air temperature in mountain environments can be highly spatially variable and sparsely measured. It is therefore possible that the measurements available to us do not always represent the mean conditions upstream of the stream gage (Hatchett et al., 2022a). In low snow years, it might be especially hard to capture representative snowpack measurements if most snowpack is in the highest watershed elevations which are also the least likely to be measured. New methods such as lidar measurements of snowpack can help address this issue for recent years, but do not cover long enough time periods for the present study.

One of the central findings of our work is that year to year carryover subsurface storage may be important for low flows and consequently summer stream temperature, particularly for the more arid watersheds. Our chosen proxy for storage, Qmin Prior, does have limitations. For example, it gives little information about storage deficits in the unsaturated zone, since this water does not directly produce streamflow. However, assuming that groundwater (saturated) storage makes up the majority of subsurface water storage, that Qmin is a monotonically increasing function of the saturated storage at the end of that year's dry season, and that storage does not continue to deplete significantly after Qmin is reached, we expect Qmin to be highly correlated with subsurface water storage. If actual ET data were available, a simple water balance approximation using P-ET-Q might be a better indicator of storage carryover. Although models could provide estimates of ET, in this study we chose not to use reanalysis products but focused on observed data.

Future climates with less snowpack may not continue to follow trends observed from historical data. Less data from low elevation snow observation stations, as well as changes to streamflow generation efficiency, could lead to future relationships between snowpack and streamflow that are very different from what has been observed to date (Livneh & Badger, 2020). Studies such as ours can help inform which areas are already sensitive to variations in snowpack (and thus are clearly at high risk), but may not identify locations that will become more sensitive in the future.

4.5 | Implications for watershed management

For Sierra Nevada watersheds, our linear models show that increasing peak SWE by 1% relative to the mean would increase that summer's minimum flow volume by approximately 0.7%–0.8% relative to the mean (Figure B1). In turn, each 10% increase in Qmin would be expected to decrease peak stream temperature by up to 0.4°C depending on the watershed (Figure B3). Each 1° increase in air temperature would lead to a 0.3°–0.4° increase in peak water temperature for Sagehen Creek and Cedar River (Figure B3). These results suggest that forest management actions to promote deeper snowpack may increase summer flow volumes in arid mountain watersheds of California, Nevada and Oregon, and these streamflow increases may partly counteract the water temperature increases from warming air temperatures. In the Pacific Northwest, the relationship between snowpack and low flows is more complex and the potential impacts of increasing snowpack water storage are unclear.

The strong relationship between previous years' low flows and current year's low flow in our more arid watersheds demonstrates the role of carryover water storage from year to year. Efforts to increase subsurface water storage—such as wetland restoration (Melesse et al., 2007; Ohara et al., 2013; Tague et al., 2008), creation of infiltration basins and/or vegetation management to reduce transpiration losses—may help reduce the drought sensitivity of low flows. This analysis also shows the importance of including metrics of subsurface water storage when predicting streamflow behaviour in arid watersheds. Managers may overpredict summer streamflows (and thus underestimate summer water temperatures) if they rely only on historical relationships between a given year's precipitation and streamflow volume.

5 | CONCLUSIONS

This study presents an empirical analysis of the predictability of summer stream temperature from multiple climate and streamflow metrics for a range of watersheds in the mountain western US. Reductions in summer low flows generally translated into higher summer stream temperatures. While we did not find strong correlations between peak snowpack and summer stream temperatures, the links between snowpack (and other storage metrics) and summer flow volumes suggest at least an indirect effect of these storage terms on summer stream temperatures through low flow volumes. Annual peak summer stream temperatures were also highly correlated with summer air temperatures, generally within the week of the maximum temperature. Thus, warmer summer air temperatures and lower future flow volumes may combine to create much warmer summer water temperatures.

Our study also focused on predictors of minimum flow volumes as a useful proxy for stream temperature since daily streamflow records are much more common and because we find that minimum flow volumes are often an important predictor of summer stream temperature (meaning that manipulating flow volumes may be a useful management tool for lowering water temperatures). Our goal was to assess the extent to which both short term storage of water as snowpacks and multi-year carryover storage as groundwater influence streams during the summer. Our results show a mix of controls on low flows and associated water temperature. Snowpack depth is a strong predictor of summer low flows in the more arid mountain regions of the western states, but less so for more northern sites. Although much of this effect is related to the total precipitation and the strong correlation between snowpack depth and precipitation, there is some evidence that snowpack depth is a slightly stronger predictor for the more arid watersheds. One exception may be during multi-year droughts, when precipitation in any form is valuable for refilling depleted subsurface water stores and therefore snowpack levels may be less important than overall precipitation in predicting summer low flows. The importance of year to year carryover of subsurface water storage also varies across watersheds, but was clearly important for the more arid watersheds in our set. These relationships are also mediated by atmospheric water demand. Taken together our results suggest that a warmer future with lower snow water storage, greater PET and longer droughts is likely to lead to lower summer streamflows and earlier dates of minimum flow with warmer water temperatures. This effect will likely be stronger in more arid watersheds, whereas wetter watersheds may not see as much impact of snowpack change on their minimum flows.

Our results suggest that climate (e.g., changes in precipitation and air temperature) and geology (e.g., groundwater drainage rates) will determine much of future streams' characteristics during the summer months that can be ecologically stressful. However, land management activities that increase water storage as snow and groundwater while decreasing evapotranspiration may help mitigate some of the effects of climate change, especially in more arid watersheds.

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DATA AVAILABILITY STATEMENT

The data used here are publicly available from the following sources: Daily Streamflow–usgs.gov; Snow Water Equivalent-https://wcc.sc.egov.usda.gov/reportGenerator/; Air Temperature-wrcc.dri.edu/cgi-bin/rawMAIN.pl?casagh; ncdc.noaa.gov; PRISM downloaded from climateengine.org; Precipitation and PET–TerraClimate data were downloaded from climateengine.org.

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REFERENCES

Abatzoglou, J. T., Dobrowski, S., Parks, S. A., & Hegewisch, K. C. (2018). Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data*, *5*, 170191. https://doi.org/10.1038/sdata.2017.191

Addor, N., Newman, A. J., Mizukami, N., & Clark, M. P. (2017). *The CAMELS data set: Catchment attributes and meteorology for large-sample studies, hydrology and earth system sciences*. UCAR/NCAR. https://doi.org/10.5065/D6G73C3Q

Arismendi, I., Johnson, S. L., Dunham, J. B., Haggerty, R., & Hockman-Wert, D. (2012). The paradox of cooling streams in a warming world: Regional climate trends do not parallel variable local trends in stream temperature in the Pacific continental United States. *Geophysical Research Letters*, *39*(10), L10401. https://doi.org/10.1029/2012GL051448

Bales, R. C., Goulden, M. L., Hunsaker, C. T., Conklin, M. H., Hartsough, P. C., O'Geen, A. T., Hopmans, J. W., & Safeeq, M. (2018). Mechanisms controlling the impact of multi-year drought on mountain hydrology. *Scientific Reports*, *8*(1), 690. https://doi.org/10.1038/s41598-017-19007-0

Brutsaert, W. (2005). *Hydrology: An Introduction*. Cambridge University Press. ISBN-10 0-521-82479-6.

Caissie, D. (2006). The thermal regime of rivers: A review. *Freshwater Biology*, *51*(8), 1389–1406. https://doi.org/10.1111/J.1365-2427.2006.01597.X

Chen, J., & Chang, H. (2023). A review of wildfire impacts on stream temperature and turbidity across scales. *Progress in Physical Geography: Earth and Environment*, *47*(3), 369–394. https://doi.org/10.1177/03091333221118363

Commission for Environmental Cooperation (CEC). (2010). *North American Glaciers and Sea Ice, 2004. Ed. 2.0*. Natural Resources Canada (NRCan), Instituto Nacional de Estadística y Geografía (INEGI), U.S. Geological Survey (USGS). cec.org

Cooper, M. G., Schaperow, J. R., Cooley, S. W., Alam, S., Smith, L. C., & Lettenmaier, D. P. (2018). Climate elasticity of low flows in the Maritime Western U.S. Mountains. *Water Resources Research*, *54*(8), 5602–5619. https://doi.org/10.1029/2018WR022816

Flint, L. E., Flint, A. L., Mendoza, J., Kalansky, J., & Ralph, F. M. (2018). Characterizing drought in California: New drought indices and scenario-testing in support of resource management. *Ecological Processes*, *7*(1), 13. https://doi.org/10.1186/s13717-017-0112-6

Fuller, M. R., Leinenbach, P., Detenbeck, N. E., Labiosa, R., & Isaak, D. J. (2022). Riparian vegetation shade restoration and loss effects on recent and future stream temperatures. *Restoration Ecology*, *30*(7), e13626.

Godsey, S. E., Kirchner, J. W., & Tague, C. L. (2014). Effects of changes in winter snowpacks on summer low flows: Case studies in the Sierra Nevada, California, USA. *Hydrological Processes*, *28*(19), 5048–5064. https://doi.org/10.1002/hyp.9943

Goeking, S. A., & Tarboton, D. G. (2020). Forests and water yield: A synthesis of disturbance effects on streamflow and snowpack in Western coniferous forests. *Journal of Forestry*, *118*(2), 172–192. Oxford University Press. https://doi.org/10.1093/jofore/fvz069

Gordon, B. L., Brooks, P. D., Krogh, S. A., Boisrame, G. F. S., Carroll, R. W. H., McNamara, J. P., & Harpold, A. A. (2022). Why does snowmelt-driven streamflow response to warming vary? A data-driven review and predictive framework. *Environmental Research Letters*, *17*(5), 053004. https://doi.org/10.1088/1748-9326/ac64b4

Goulden, M. L., & Bales, R. C. (2014). Mountain runoff vulnerability to increased evapotranspiration with vegetation expansion. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(39), 14071–14075. https://doi.org/10.1073/pnas.1319316111

Hahm, W. J., Dralle, D. N., Sanders, M., Bryk, A. B., Fauria, K. E., Huang, M. H., Hudson-Rasmussen, B., Nelson, M. D., Pedrazas, M. A., Schmidt, L., Whiting, J., Dietrich, W. E., & Rempe, D. M. (2022). Bedrock vadose zone storage dynamics under extreme drought: Consequences for plant water availability, recharge, and runoff. *Water Resources Research*, *58*(4), e2021WR031781. https://doi.org/10.1029/2021WR031781

Hatchett, B. J., Rhoades, A. M., & McEvoy, D. J. (2022a). Monitoring the daily evolution and extent of snow drought. *Natural Hazards and Earth System Sciences*, *22*(3), 869–890. https://doi.org/10.5194/NHESS-22-869-2022

Hatchett, B. J., Rhoades, A. M., & McEvoy, D. J. (2022b). Decline in seasonal snow during a projected 20-year dry spell. *Hydrology*, *9*(9), 155. https://doi.org/10.3390/HYDROLOGY9090155

Heinze, G., Wallisch, C., & Dunkler, D. (2018). Variable selection–A review and recommendations for the practicing statistician. *Biometrical Journal*, *60*(3), 431–449. https://doi.org/10.1002/BIMJ.201700067

Huntington, J. L., Hegewisch, K. C., Daudert, B., Morton, C. G., Abatzoglou, J. T., McEvoy, D. J., & Erickson, T. (2017). Climate engine: Cloud computing and visualization of climate and remote sensing data for advanced natural resource monitoring and process understanding. *Bulletin of the American Meteorological Society*, *98*(11), 2397–2410. https://doi.org/10.1175/BAMS-D-15-00324.1

Huntington, J. L., & Niswonger, R. G. (2012). Role of surface-water and groundwater interactions on projected summertime streamflow in snow dominated regions: An integrated modeling approach. *Water Resources Research*, *48*(11), 20. https://doi.org/10.1029/2012WR012319

Isaak, D. J., Luce, C. H., Horan, D. L., Chandler, G. L., Wollrab, S. P., & Nagel, D. E. (2018). Global warming of Salmon and Trout Rivers in the Northwestern U.S.: Road to ruin or path through purgatory? *Transactions of the American Fisheries Society*, *147*(3), 566–587. https://doi.org/10.1002/TAFS.10059

Isaak, D. J., Wollrab, S., Horan, D., & Chandler, G. (2012). Climate change effects on stream and river temperatures across the northwest U.S. from 1980-2009 and implications for salmonid fishes. *Climatic Change*, *113*(2), 499–524. https://doi.org/10.1007/S10584-011-0326-Z/TABLES/1

Jenicek, M., Seibert, J., Zappa, M., Staudinger, M., & Jonas, T. (2016). Importance of maximum snow accumulation for summer low flows in humid catchments. *Hydrology and Earth System Sciences*, *20*(2), 859–874. https://doi.org/10.5194/hess-20-859-2016

Kinnard, C., Bzeouich, G., & Assani, A. (2022). Impacts of summer and winter conditions on summer river low flows in low elevation, snow-affected catchments. *Journal of Hydrology*, *605*, 127393. https://doi.org/10.1016/j.jhydrol.2021.127393

Knowles, N., Dettinger, M. D., & Cayan, D. R. (2006). Trends in snowfall versus rainfall in the Western United States. *Journal of Climate*, *19*(18), 4545–4559. https://doi.org/10.1175/JCLI3850.1

Lapides, D., Hahm, J., Rempe, D., & Dralle, D. (2022). Causes of missing snowmelt following drought. *Geophysical Research Letters*, *49*(19), e2022GL100505. https://doi.org/10.1029/2022GL100505

LeBlanc, R. T., & Brown, R. D. (2000). The use of riparian vegetation in stream-temperature modification. *Water and Environment Journal*, *14*(4), 297–303. https://doi.org/10.1111/J.1747-6593.2000.TB00264.X

Li, D., Wrzesien, M. L., Durand, M., Adam, J., & Lettenmaier, D. P. (2017). How much runoff originates as snow in the western United States, and how will that change in the future? *Geophysical Research Letters*, *44*(12), 6163–6172. https://doi.org/10.1002/2017GL073551

Livneh, B., & Badger, A. M. (2020). Drought less predictable under declining future snowpack. *Nature Climate Change*, *10*(5), 452–458. https://doi.org/10.1038/s41558-020-0754-8

McEvoy, D. J., & Hatchett, B. J. (2023). Spring heat waves drive record western United States snow melt in 2021. *Environmental Research Letters*, *18*, 10. https://doi.org/10.1088/1748-9326/aca8bd

McEvoy, D. J., Pierce, D. W., Kalansky, J. F., Cayan, D. R., & Abatzoglou, J. T. (2020). Projected changes in reference evapotranspiration in California and Nevada: Implications for drought and wildland fire danger. *Earth's Futures*, *8*(11), 17. https://doi.org/10.1029/2020EF001736

McGill, L. M., Steel, E. A., & Fullterton, A. H. (2023). Empirical stream thermal sensitivities cluster on the landscape according to geology and climate. *Hydrology and Earth System Sciences Discussions*, *2023*, 1–38. https://hess.copernicus.org/preprints/hess-2022-428/

Meixner, T., Manning, A. H., Stonestrom, D. A., Allen, D. M., Ajami, H., Blasch, K. W., Brookfield, A. E., Castro, C. L., Clark, J. F., Gochis, D. J., Flint, A. L., Neff, K. L., Niraula, R., Rodell, M., Scanlon, B. R., Singha, K., & Walvoord, M. A. (2016). Implications of projected climate change for groundwater recharge in the western United States. In *Journal of hydrology* (Vol. 534, pp. 124–138). Elsevier B.V. https://doi.org/10.1016/j.jhydrol.2015.12.027

Melesse, A., Nangia, V., Wang, X., & McClain, M. (2007). Wetland restoration response analysis using MODIS and groundwater data. *Sensors*, *7*(9), 1916–1933. https://doi.org/10.3390/s7091916

Mote, P. W., Hamlet, A. F., Clark, M. P., & Lettenmaier, D. P. (2005). Declining mountain snowpack in Western North America. *Bulletin of the American Meteorological Society*, *86*(1), 39–50. https://doi.org/10.1175/BAMS-86-1-39

Mote, P. W., Li, S., Lettenmaier, D. P., Xiao, M., & Engel, R. (2018). Dramatic declines in snowpack in the western US. *Npj Climate and Atmospheric Science*, *1*(1), 1–6. https://doi.org/10.1038/s41612-018-0012-1

Newman, A. J., Clark, M. P., Sampson, K., Wood, A., Hay, L. E., Bock, A., Viger, R. J., Blodgett, D., Brekke, L., Arnold, J. R., Hopson, T., & Duan, Q. (2015). Development of a large-sample watershed-scale hydrometeorological data set for the contiguous USA: Data set characteristics and assessment of regional variability in hydrologic model performance. *Hydrology and Earth System Sciences*, *19*, 209–223. https://doi.org/10.5194/hess-19-209-2015

Null, S. E., Viers, J. H., Deas, M. L., Tanaka, S. K., & Mount, J. F. (2013). Stream temperature sensitivity to climate warming in California's Sierra Nevada: Impacts to coldwater habitat. *Climatic Change*, *116*(1), 149–170. https://doi.org/10.1007/s10584-012-0459-8

Ohara, N., Kavvas, M. L., Chen, Z. Q., Liang, L., Anderson, M., Wilcox, J., & Mink, L. (2013). Modelling atmospheric and hydrologic processes for assessment of meadow restoration impact on flow and sediment in a sparsely gauged California watershed. *Hydrological Processes*, *28*(7), 3053–3066. https://doi.org/10.1002/hyp.9821

Pelto, M. S. (2008). Impact of climate change on North Cascade alpine glaciers, and alpine runoff. *Northwest Science*, *82*(1), 65–75. https://doi.org/10.3955/0029-344X-82.1.65

Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., & Hegewisch, K. C. (2015). Improved bias correction techniques for hydrological simulations of climate change. *Journal of Hydrometeorology*, *16*(6), 2421–2442. https://doi.org/10.1175/JHM-D-14-0236.1

Pierce, D. W., Cayan, D. R., & Thrasher, B. L. (2014). Statistical downscaling using localized constructed analogs (LOCA). *Journal of Hydrometeorology*, *15*(6), 2558–2585. https://doi.org/10.1175/JHM-D-14-0082.1

Poff, N. L. R., Allan, J. D., Bain, M. B., Karr, J. R., Prestegaard, K. L., Richter, B. D., Sparks, R. E., & Stromberg, J. C. (1997). The natural flow regime: A paradigm for river conservation and restoration. *Bioscience*, *47*(11), 769–784. https://doi.org/10.2307/1313099

Roche, J. W., Goulden, M. L., & Bales, R. C. (2018). Estimating evapotranspiration change due to forest treatment and fire at the basin scale in the Sierra Nevada, California. *Ecohydrology*, *11*(7), e1978. https://doi.org/10.1002/eco.1978

Siegel, J. E., Fullerton, A. H., & Jordan, C. E. (2022). Accounting for snowpack and time-varying lags in statistical models of stream temperature. *Journal of Hydrology X*, *17*, 100136. https://doi.org/10.1016/J.HYDROA.2022.100136

Smith, G. (2018). Step away from stepwise. *Journal of Big Data*, *5*(1), 1–12. https://doi.org/10.1186/S40537-018-0143-6/FIGURES/1

Tague, C. L., Farrell, M., Grant, G., Lewis, S., & Rey, S. (2007). Hydrogeologic controls on summer stream temperatures in the McKenzie River basin, Oregon. *Hydrological Processes*, *21*(24), 3288–3300. https://doi.org/10.1002/HYP.6538

Tague, C. L., & Grant, G. E. (2009). Groundwater dynamics mediate low-flow response to global warming in snow-dominated alpine regions. *Water Resources Research*, *45*(7), 7421. https://doi.org/10.1029/2008WR007179

Tague, C. L., Valentine, S., & Kotchen, M. (2008). Effect of geomorphic channel restoration on streamflow and groundwater in a snowmelt-dominated watershed. *Water Resources Research*, *44*(10), 10. https://doi.org/10.1029/2007WR006418

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

USDA. (2022). Snow and climate monitoring: Snowpack. Natural Resources Conservation Service National Water and Climate Center. https://www.nrcs.usda.gov/wps/portal/wcc/home/snowClimateMonitoring/

USGS. (2022). USGS water data for the nation. National Water Information System: Web Interface. https://waterdata.usgs.gov/nwis

Vano, J., Hamman, J., Gutmann, E., Wood, A., Mizukami, N., Clark, M., Pierce, D. W., Cayan, D. R., Wobus, C., Nowak, K., & Arnold, J. (2020). Comparing Downscaled LOCA and BCSD CMIP5 Climate and Hydrology Projections-Release of Downscaled LOCA CMIP5 Hydrology. https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/techmemo/LOCA_BCSD_hydrology_tech_memo.pdf

Webb, B. W., Hannah, D. M., Moore, R. D., Brown, L. E., & Nobilis, F. (2008). Recent advances in stream and river temperature research. *Hydrological Processes*, *22*(7), 902–918. https://doi.org/10.1002/HYP.6994

Wolf, M. A., Jamison, L. R., Solomon, D. K., Strong, C., & Brooks, P. D. (2023). Multi-year controls on groundwater storage in seasonally snow-covered headwater catchments. *Water Resources Research*, *59*(6), e2022WR033394. https://doi.org/10.1029/2022WR033394

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A: ADDITIONAL DETAILS REGARDING DATA SOURCES

TABLE A1 Site details.

Gage number	Site name	Gage longitude	Gage latitude	In Cooper et al?	SNOTEL ID (s)	Snow course name (s)	Air T data source
10343500	Sagehen C near Truckee CA	−120.238	39.43157	Yes	539-541	Independence Creek	wrcc.dri.edu/cgi-bin/rawMAIN.pl?casagh
12175500	Thunder Ck near Newhalem WA	−121.0717	48.67278	Yes	711, 817	Thunder Basin	PRISM Daily Data
12451000	Stehekin River AT Stehekin, WA	−120.6906	48.32972	Yes	681, 606, 711	Rainy Pass	PRISM Daily Data
12115000	Cedar R near Cedar Falls WA	−121.6239	47.37028	Yes	420	N/A	NOAA, Fire Training Academy (USR0000WFTA)
12488500	American R near Nile WA	−121.1675	46.97778	Yes	642	Bumping Lake	PRISM Daily Data
10348850	Galena Creek at Galena Creek State Park, NV	−119.8575	39.35444	No	652	Mount Rose	PRISM Daily Data
14137000	Sandy River near Marmot, OR	−122.1361	45.39972	No	655	N/A	PRISM Daily Data
10396000	Donner und Blitzen River near Frenchglen OR	−118.8675	42.79083	No	477	N/A	PRISM Daily Data
11264500	Merced R A Happy Isles Bridge, Yosemite CA	−119.5591	37.73131	No	N/A	Gin Flat, Peregoy Meadows	NOAA, Yosemite Park HQ

Note: List of USGS streamflow gages used along with their locations, SNOTEL sites and snow courses used for peak snow water equivalent, and source of air temperature (T) data. We also note whether the site was included in Cooper et al. (2018) to assist with comparisons between our findings.

APPENDIX B: RELATIVE SENSITIVITY

We define relative sensitivity as the ratio of changes relative to the mean:

$$\text{Relative Sensitivity} = \left(\frac{\Delta y/\bar{y}}{\Delta x_i/\bar{x_i}}\right) = \frac{c_i \bar{x_i}}{\sigma_{x_i}\bar{y}},$$

where y and $\bar{y}$ represent the independent variable (Qmin or temperature) and its mean overall years; x_i, $\bar{x_i}$ and σ_{x_i} represent a single predictor variable and its mean and standard deviation, respectively; and c_i represents the linear model coefficient of the normalized version of x_i from Equation (1). If relative sensitivity is greater than 1, then a given percent change in x will lead to a higher percent change in y.

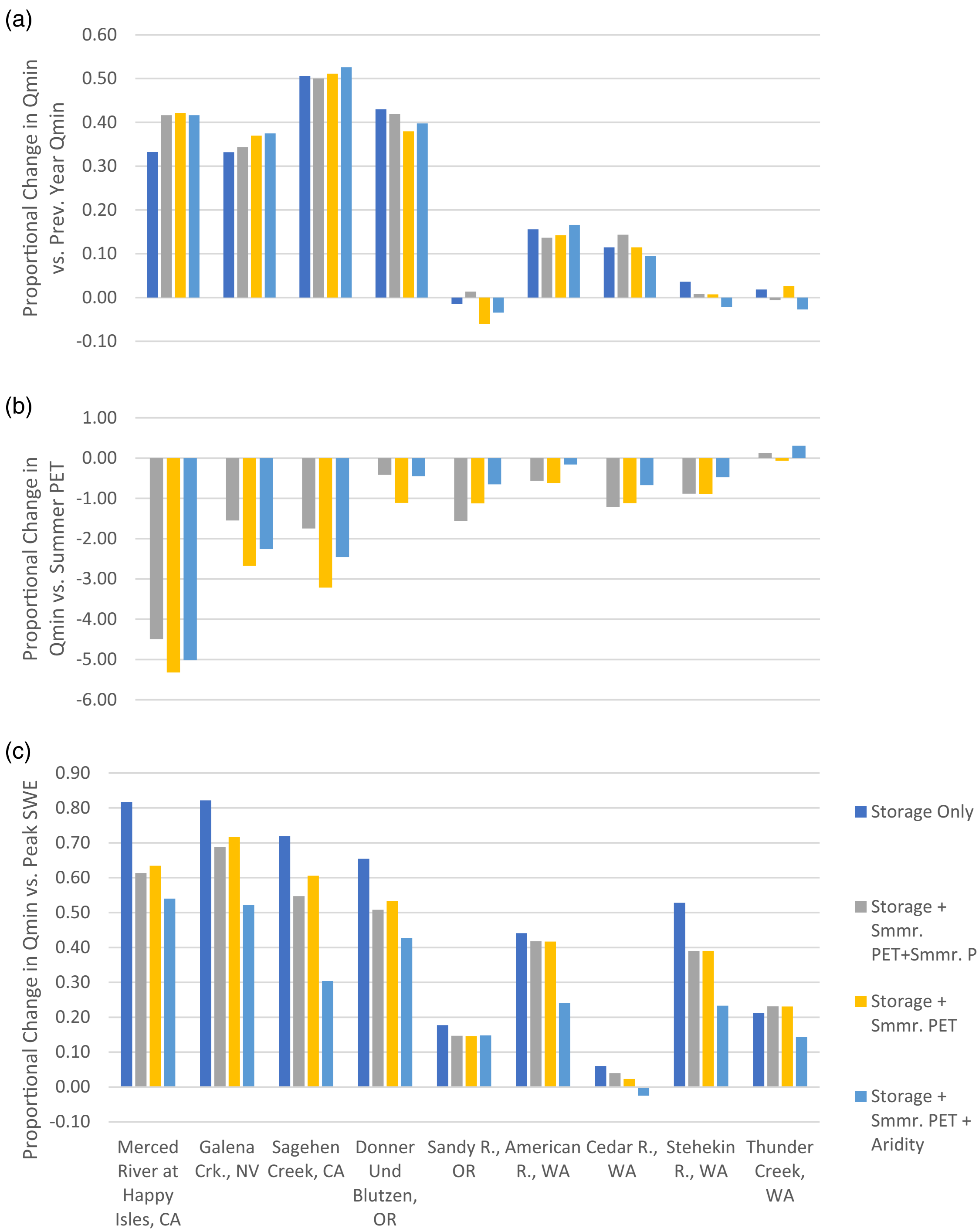

FIGURE B1 Relative sensitivity of Qmin to Previous year's Qmin (a), Summer PET (b) and Peak SWE (c) using linear models with different predictor variables. The storage-only model includes only Peak SWE and prior year's Qmin as predictors. The other three models are variations on the Storage+Demand model which use Peak SWE, Qmin Prior, Summer (Smmr.) PET, Summer Precipitation (P) and/or Aridity as predictors. Note that high correlations between predictor variables may cause misleading values for some models.

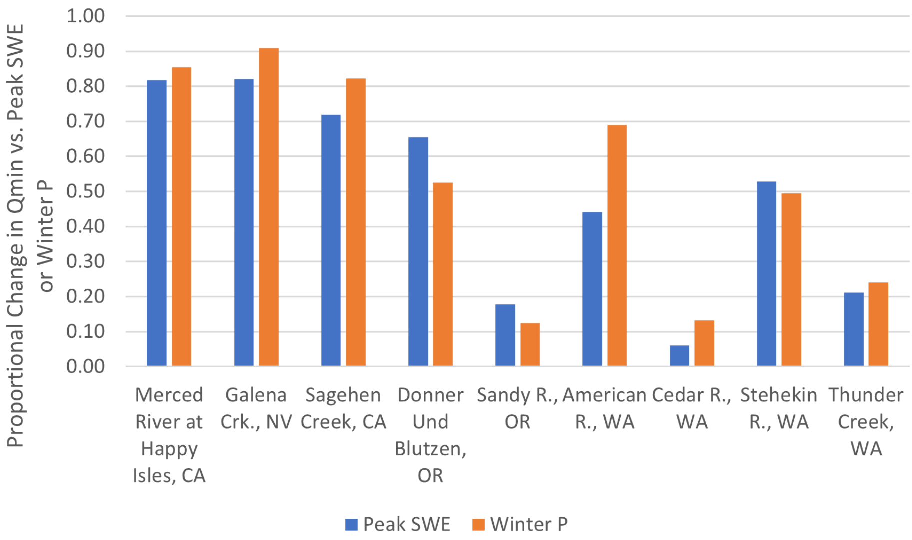

FIGURE B2 Relative sensitivity of Qmin to Peak SWE according to the original Storage Model (Qmin as a linear combination of Peak SWE and Qmin Prior) and relative sensitivity to Winter P according to a variation of the Storage Model using Winter P and Qmin Prior as predictor variables. A relative sensitivity of 1 would mean that a 1% increase in the given variable would cause a 1% increase in Qmin.

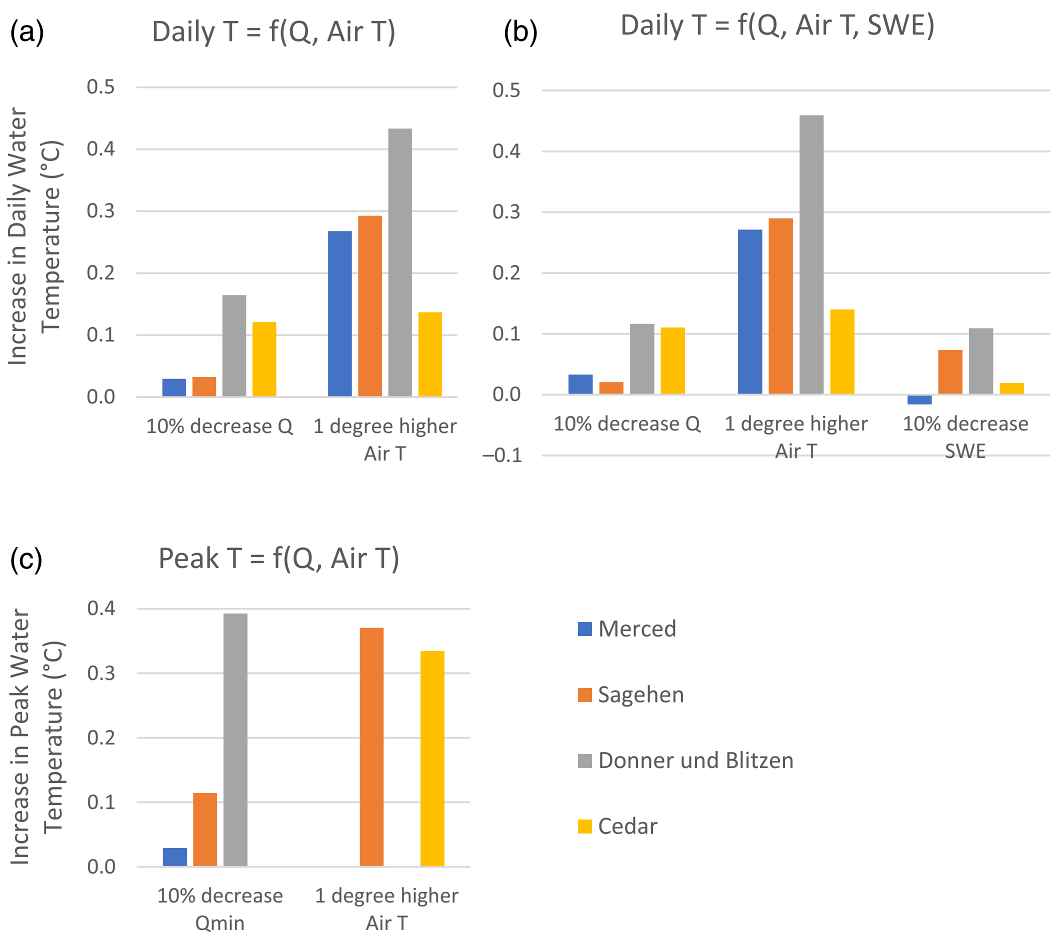

FIGURE B3 (a, b) Increases in daily peak water temperature for every 10% decrease in daily streamflow (Q), 1°C increase in daily air temperature, or 10% decrease in peak SWE. (c): Increase in annual peak water temperature for every 10% decrease in Qmin or 1°C increase in mean daily air temperature for the week preceding peak water temperature. Values are calculated from the linear models described in Figure 3.

APPENDIX C: CLIMATE CHANGE CONTEXT

We explored projections of climate and hydrology from other studies in order to provide context for our analyses in terms of projected changes. Mountain areas are especially likely to experience future warming as well as decreases in snowpack and soil water storage (Figure C1).

While the mean projected changes were similar across our study watersheds, we also wanted to know the levels of uncertainty in climate projections at our four most sensitive watersheds. We therefore downloaded projections at each of the more southern watersheds for 32 different GCMs. These projections were downscaled using the Localized Constructed Analogs (LOCA) methodology (Pierce et al., 2014, 2015), and hydrologic variables were then calculated using the Variable Infiltration Capacity (VIC) model (Vano et al., 2020). We chose to look only at changes for the end of the century (2070–2099) under the RCP 8.5 scenario. Proportional changes are calculated as the difference between the median values for 2070–2099 and the median values for a historical reference period (1971–2000), divided by the mean historical value. All climate projections and their associated hydrologic model outputs were downloaded from the 'Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections' archive at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ using the tributary area selection method. These data are summarized in Figures C2–C7.

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups for producing and making available their model output. For CMIP the US Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

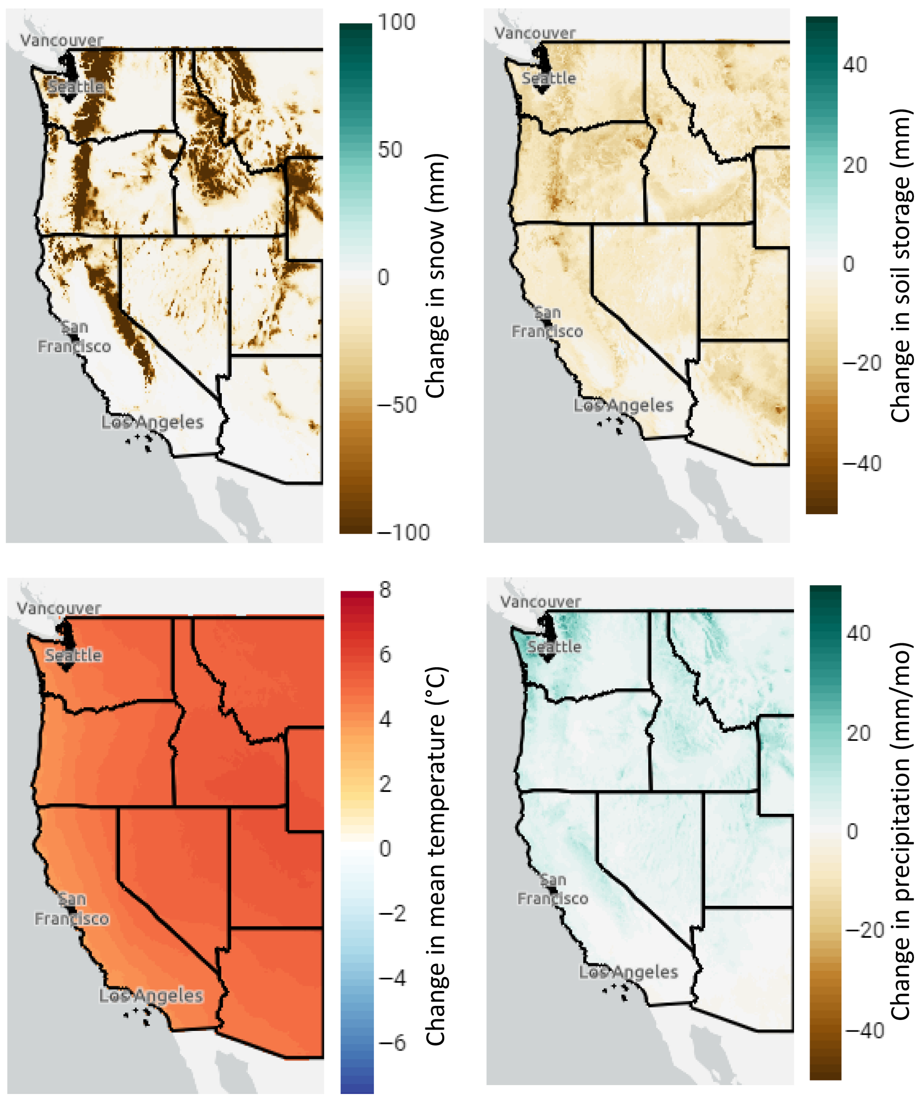

FIGURE C1 Maps of projected changes in snow, soil water storage, mean air temperature and annual precipitation for the 2075–2099 period compared with a 1981–2010 reference. Values are an average over 20 GCM from the CMIP5 Project. Source: https://apps.usgs.gov/nccv/maca2/.

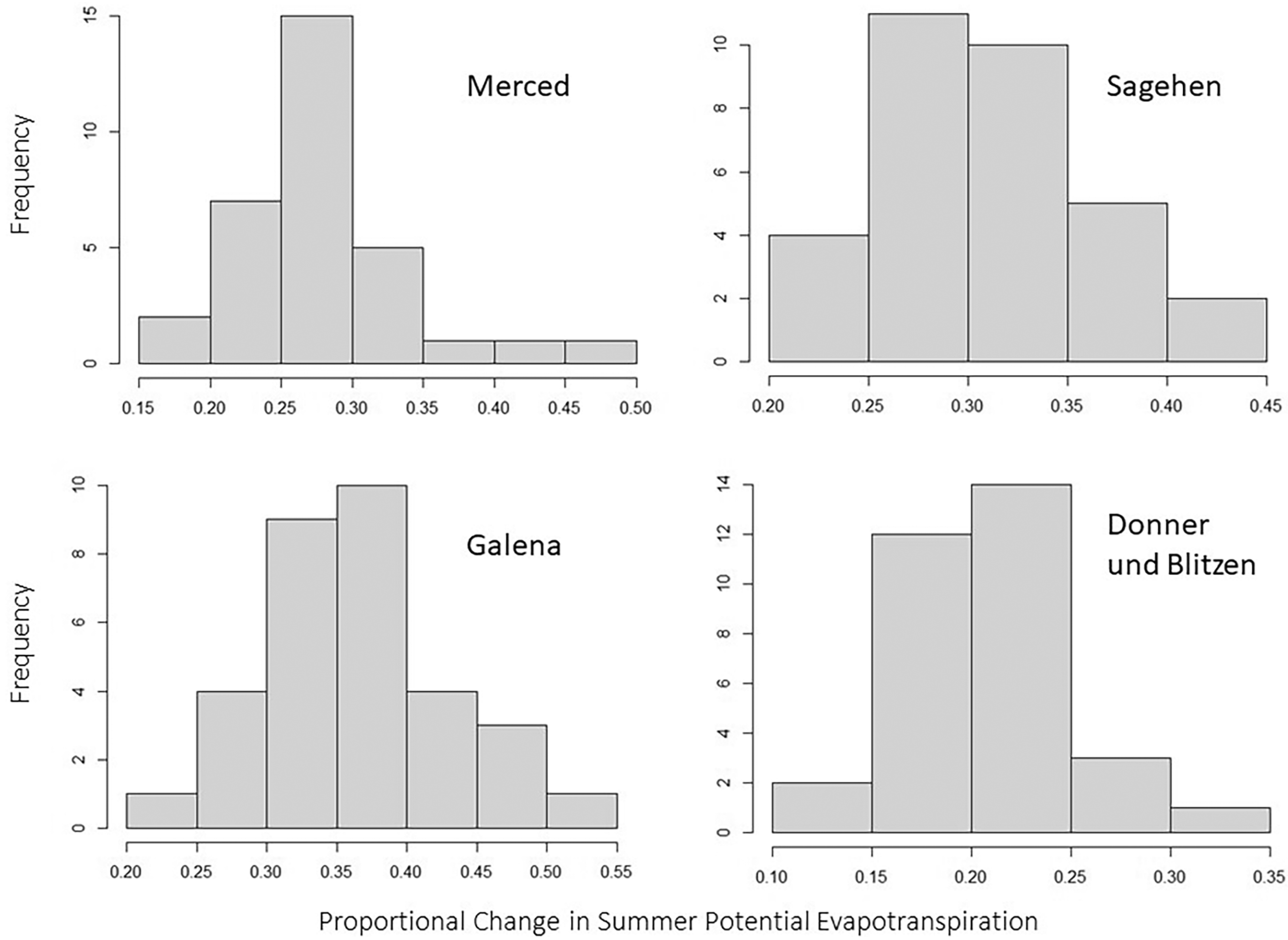

FIGURE C2 Projected change in median summer potential evapotranspiration (PET) across 32 GCMs (2070–2099 versus 1971–2000).

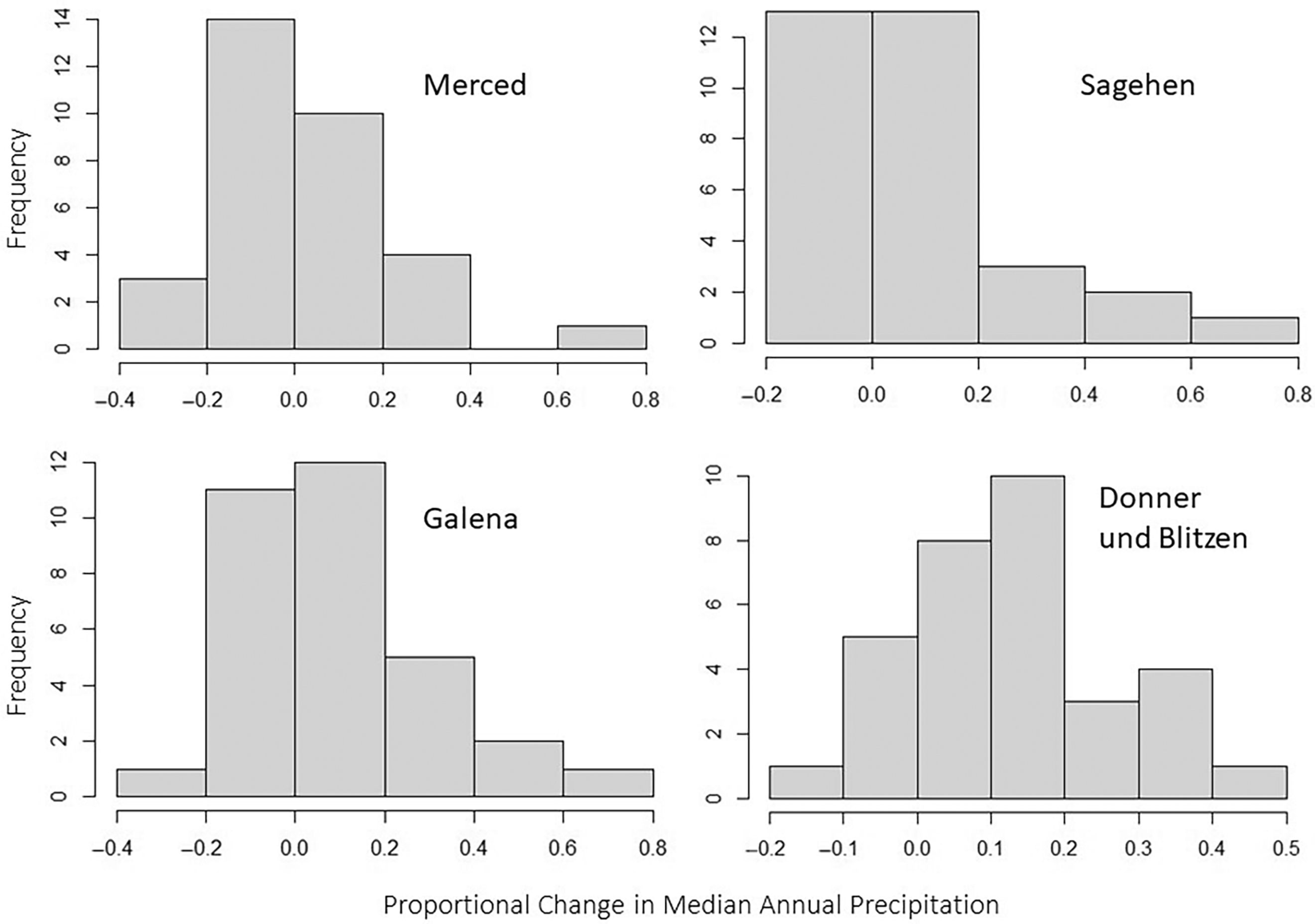

FIGURE C3 Projected proportional changes in median annual precipitation across 32 GCMs (2070–2099 versus 1971–2000).

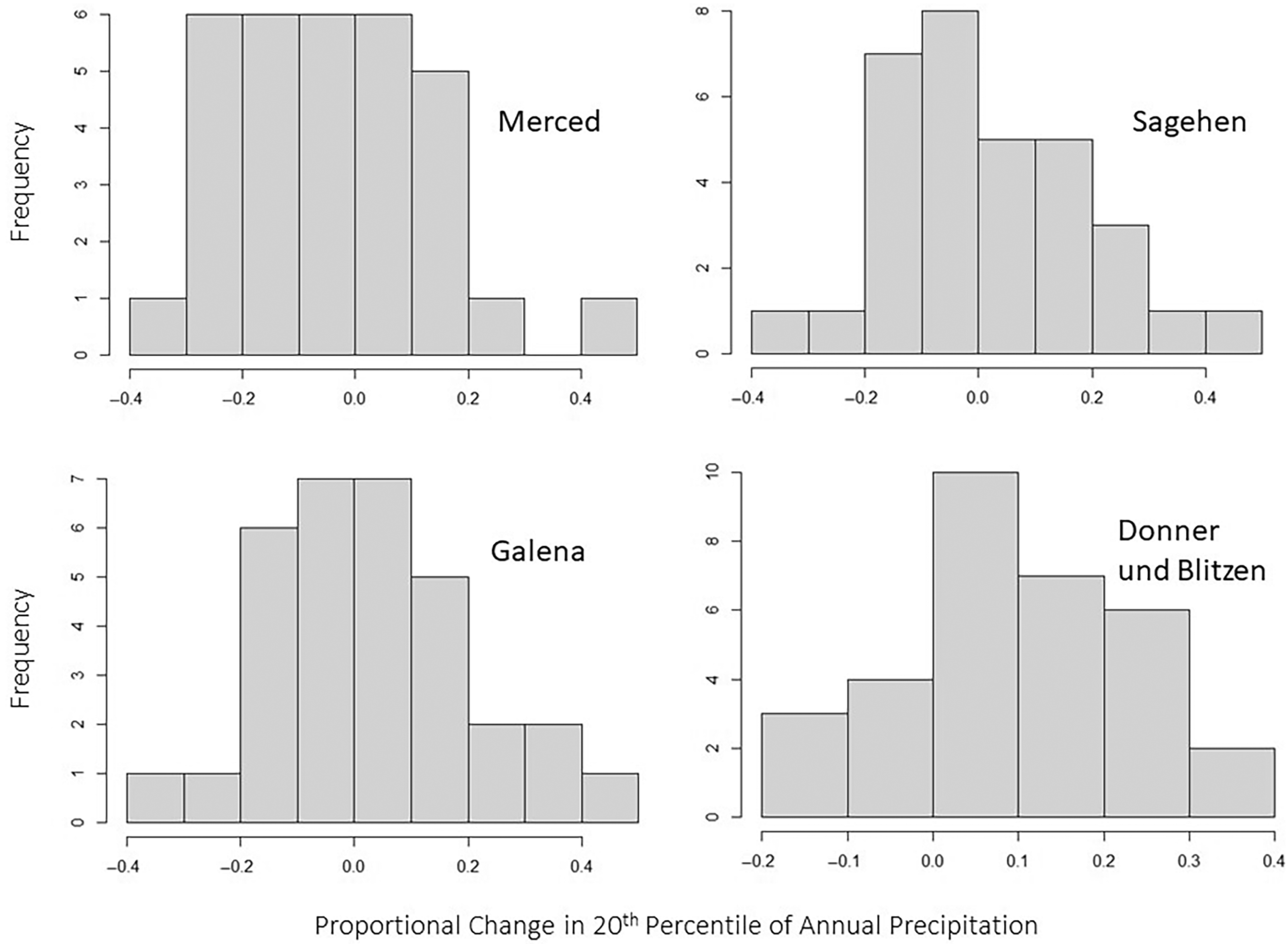

FIGURE C4 Projected proportional changes in the 20th percentile of annual precipitation (2070–2099 versus 1971–2000). A negative number indicates that drought years may be more extreme in future periods.

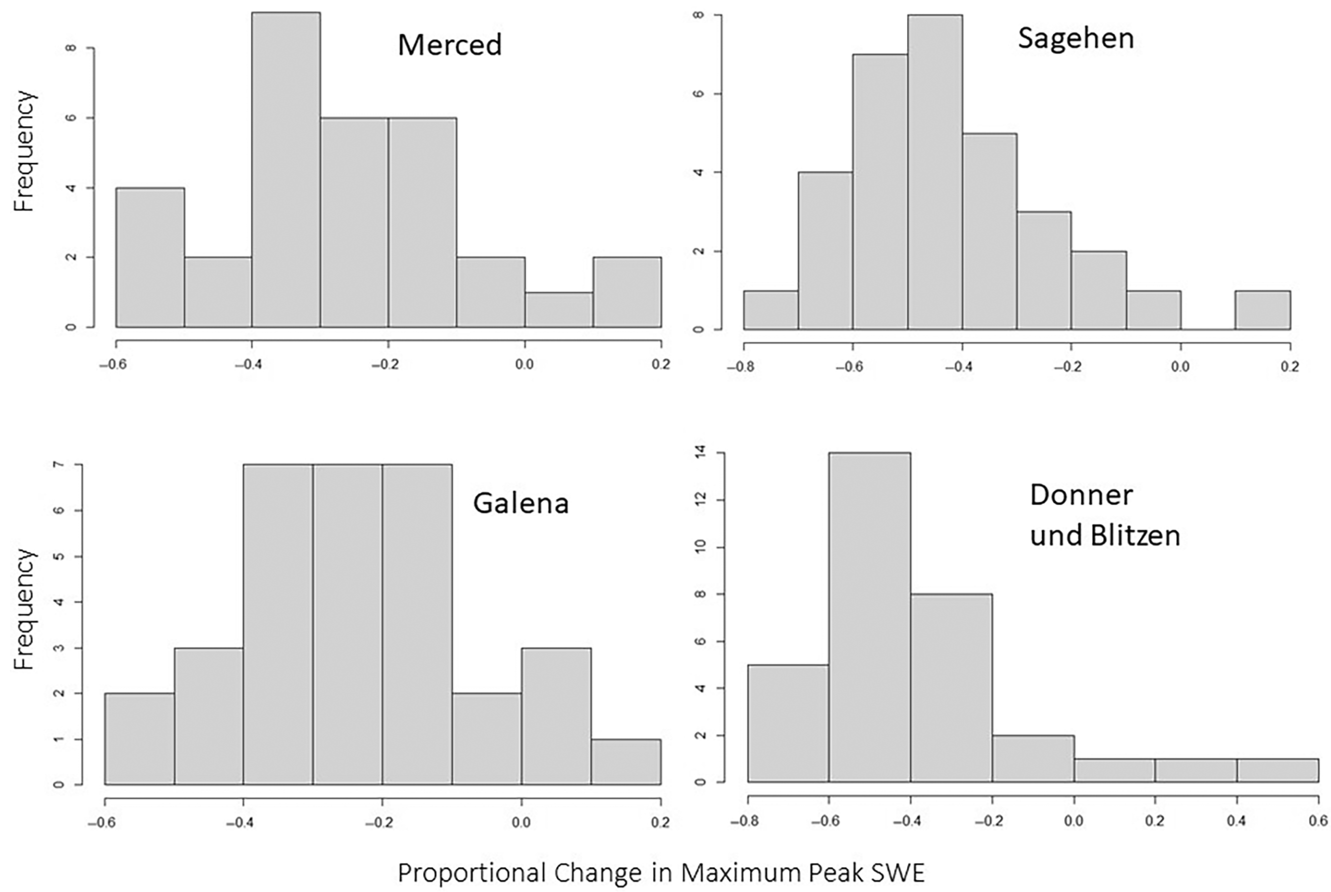

FIGURE C5 Change in maximum annual peak snow water equivalent (SWE). A positive value means that at least 1 year in the projection had a higher peak SWE than was seen during the historic period; median peak SWE may still decline in those models. (Changes are for 2070–2099 versus 1971–2000).

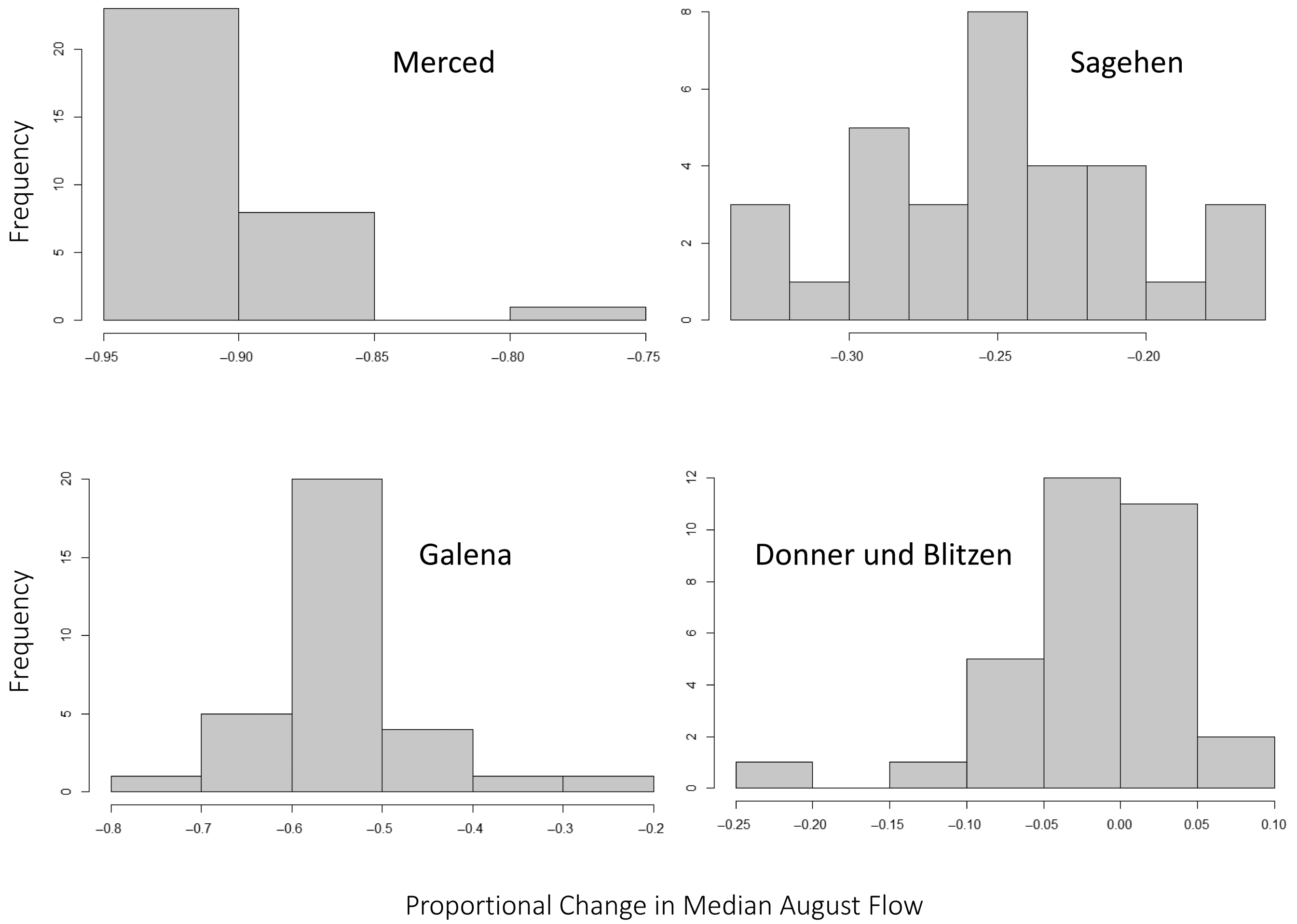

FIGURE C6 Modelled change in August streamflow (2070–2099 versus 1971–2000). Streamflow is calculated as baseflow plus runoff from the VIC model across the entire watershed. Note that this estimate of streamflow does not account for any flow routing, and comes from a model that is not specifically calibrated for the local watersheds studied here.

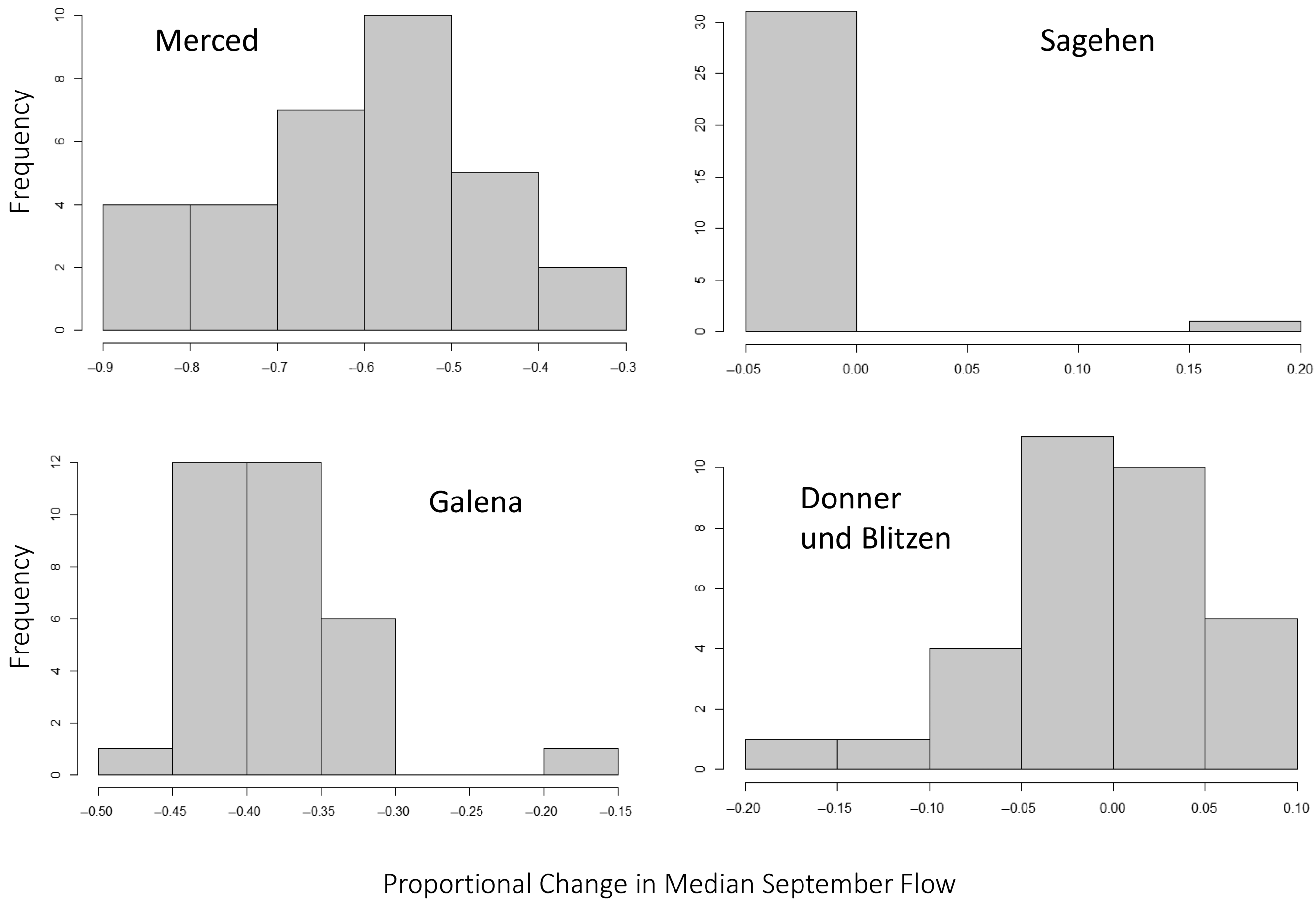

FIGURE C7 Modelled changes in September streamflow (2070–2099 versus 1971–2000). Streamflow is calculated as baseflow plus runoff from the VIC model across the entire watershed. Note that this estimate of streamflow does not account for any flow routing, and comes from a model that is not specifically calibrated for the local watersheds studied here.