Mountain snowpack response to different levels of warming

Laurie S. Huning1,2 and Amir AghaKouchak1,3

1Department of Civil and Environmental Engineering, University of California, Irvine, CA 92697; and 2Department of Earth System Science, University of California, Irvine, CA 92697

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Temperature variability impacts the distribution and persistence of the mountain snowpack, which critically provides snowmelt-derived water resources to large populations worldwide. Warmer temperatures decrease the amount of montane snow water equivalent (SWE), forcing its center of mass to higher elevations. We use a unique multivariate probabilistic framework to quantify the response of the 1 April SWE volume and its centroid to a 1.0 to 2.0 °C increase in winter air temperature across the Sierra Nevada (United States). A 1.0 °C increase reduces the probability of exceeding the long-term average (1985–2016) average rangewide SWE volume (15.7 km$^3$) by 20.7%. It correspondingly is 60.6% more likely for the centroid to be higher than its long-term average (2,540 m). We further show that a 1.5 and 2.0 °C increase in the winter temperature reduces the probability of exceeding the long-term average SWE volume by 31.0% and 41.1%, respectively, whereas it becomes 79.3% and 89.8% more likely that the centroid will be higher than 2,540 m for those respective temperature changes. We also characterize regional variability across the Sierra Nevada and show that the northwestern and southeastern regions of the mountain range are 30.3% and 14.0% less likely to have 1 April SWE volumes exceed their long-term average for a 1.0 °C increase about their respective average winter temperatures. Overall, the SWE in the northern Sierra Nevada exhibits higher hydrologic vulnerability to warming than in the southern region. Given the expected increases in mountain temperatures, the observed rates of change in SWE are expected to intensify in the future.

Significance

Across the world, the seasonal montane snowpack stores and releases substantial amounts of water annually. As the global temperature is projected to rise, it becomes increasingly important to assess the vulnerability of the mountain snowpack. We therefore turn to the historical record to understand the extent to which snow water equivalent (SWE) and its centroid respond to different levels of warming. Using a probabilistic framework, we show that even a 1.0 or 2.0 °C increase in average temperature leads to approximately a 20 to 40% increase in the likelihood of below average SWE. We also quantify changes in the distribution of the amount of SWE and where it is stored elevationally across the mountain range given warmer winters.

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warming is warranted, since the former condition has been less widely examined (22). Such discussions motivate our study, where we characterize the vulnerability of SWE (i.e., amount and elevation of its centroid) to temperature variability across the Sierra Nevada over a historical period. Our analysis uses a historical spatially distributed snow data set and while it may provide insight into possible future SWE and temperature relationships, analysis of such relationships is left for forthcoming research.

We characterize the extent to which hydrologic variables respond to different levels of warming. We use the terms vulnerability or hydrologic “risk” to characterize changes in the likelihood that the long-term average SWE volume (SWE) will be exceeded (i.e., exceedance probability or \( P_e \)) for various winter temperature conditions. The terms are also used to quantify changes in the nonexceedance probability (\( P_{nc} \)) or probability that the SWE centroid, \( z_c \), will be lower than its long-term average value (\( z_c \)) for those same temperatures. Herein, greater risk corresponds to a higher sensitivity of the snowpack to warming.

The driving question of this study is, To what extent does the hydrologic risk associated with the SWE volume vary range wide and spatially across the Sierra Nevada (e.g., windward vs. leeward side, northern vs. southern basins, etc.) given a 1.0–2.0 °C increase in temperature? Using a conditional multivariate approach (Materials and Methods), we examine changes in the distribution of the SWE volume and centroid to break down the overarching question as follows: (i) What is the likelihood that the 1 April SWE volume will exceed its long-term average value given different average winter air temperatures across this maritime mountain range? (ii) What is the likelihood that the SWE centroid will occur at elevations lower than its long-term mean given an increase in temperature?

**Sierra Nevada**

We use the 90-m (gridded), daily Sierra Nevada snow reanalysis [described briefly in Materials and Methods and in detail by Margulis et al. (23)] to estimate the 1 April SWE volume and centroid. The average November–March (winter) air temperatures are also derived from this data set, providing physical consistency. In situ snow sensor observations were not used to derive the snow reanalysis, but rather for independent verification (10, 23). The reanalysis spans 32 water years (WYs: October–September) 1985–2016. The SWE centroid presented herein represents the centroid above 1,500 m. This elevation is the lowest provided by this data set as it is typically the lowest seasonally snow-covered elevation in the Sierra Nevada (24). During times when the snow line extends below 1,500 m, the centroid may be lower than presented here.

Across the Sierra Nevada, SWE and snowfall have strong regional and elevational signatures (refs. 2, 10, 25, and 26, etc.). To better understand the spatial variability of the hydrologic risk for various precipitation regimes in the Sierra Nevada [e.g., windward (western) vs. leeward (eastern) sides, higher (southern) vs. lower (northern) elevations, etc.], we divided the 20 basins out of the Sierra Nevada into four study domains: northwest (NW), southwest (SW), northeast (NE), and southeast (SE). For these observations. For additional perspective, we consider the most densely sampled elevations across the Sierra Nevada based on the California Department of Water Resources in situ observations. Within this network, the average snow pillow elevation is ∼2,300 m, and these observations serve as an indicator of the amount of SWE across the range, rather than a direct measure of the SWE volume. Over 60% of the sensor measurements occur below 2,540 m, which is the average elevation of \( z_c \) on 1 April (Figs. 1C and 2). Snow courses in the Sierra Nevada have a similar elevational distribution. Thus, on average, about half of the SWE across the range is located at elevations above the majority of the sampling network. Also, for the basins in Fig. 4A, we have observations.

Undersampling the highest elevations with the current in situ network can misrepresent the amount of SWE stored and where its center of mass is located in space and time (Fig. 1C). Although high elevations make up a smaller fraction of the total area than lower elevations (Fig. 1B), they will play an increasingly important role in a warmer climate since warmer temperatures generally melt SWE and are SWE centroids lower elevations resulting in a higher snow line and SWE centroid (24). Thus, the northern
Sierra Nevada and in particular the NW, with the lowest winter SWE centroid (Fig. 1C), are likely most susceptible to warming. Also, the strongest correlations between winter temperature and both 1 April SWE and $z_c$ occur in the NW (SI Appendix, Fig. S3). Not only do warmer temperatures shift the partitioning of total precipitation from snowfall toward rainfall, but also snow that occurs at these elevations would likely melt sooner under warmer conditions. While other hydrometeorological drivers beyond temperature (e.g., precipitation) impact SWE, the focus of this study is on understanding SWE distributions conditioned on temperature.

Although 1 April is often taken to represent the end of the accumulation season, the 32-y average day-of-peak SWE across each region occurs earlier (9–16 March) with individual regions yielding extreme early (i.e., 21 December) to late (i.e., 9 May) dates for a given year. Hence, the melt season often begins before April. While our focus is on the accumulation season, other environmental controls impact the SWE distribution and melt rate and their relative importance fluctuates across seasons, mountain ranges, etc. For instance, Painter et al. (27) found that the radiative forcing by dust was a stronger control on snowmelt than temperature in the Upper Colorado River Basin.

With the western side of the mountain range facing into the prevailing winds, the NW and SW have larger average SWE volumes (dashed vertical lines in Fig. 2) than the eastern basins in the rain shadow. Corresponding to the higher mean elevation in the eastern basins (relative to the western basins, Fig. 1B), the NE has a higher average centroid than the NW on 1 April (Figs. 1C and 2). The same relationship is observed between the SE and SW. Also, the western Sierra Nevada has greater interannual variability of SWE and centroid values than the eastern regions (Fig. 2). In all regions, the extremely warm 2015 winter was the warmest winter season, which corresponded to the highest SWE centroid in the Sierra Nevada during this record. However, the coolest winter (WY 1985) neither corresponded to the largest SWE nor lowest $z_c$ in any of the regions.

SWE Volume, Centroid, and Temperature Characterization

Fig. 2 presents the regional climatology and interannual variability of the 1 April SWE volume and centroid and average winter temperature. Strong, statistically significant ($P < 0.05$) negative correlations exist between the SWE volume and $z_c$ with the regional correlation coefficients ranging from $-0.66$ (NW) to $-0.80$ (SE). A weaker range-averaged correlation exists ($r = -0.53$) due to differences among the regions (e.g., elevation) that greatly contrast between the northern and southern Sierra Nevada and degrade its strength relative to the individual regions. Nonetheless, a smaller SWE volume tends to correspond to a higher centroid elevation than when a larger SWE volume occurs.

The peak elevation of a region physically constrains the maximum possible elevation of $z_c$. As such, it is expected that $z_c$ will often be lower in the northern Sierra Nevada. Warmer temperatures reduce the SWE volume, thereby increasing the height of its centroid (Fig. 2 and SI Appendix, Fig. S3). Stronger correlations exist between temperature and $z_c$ than between temperature and SWE (SI Appendix, Fig. S3). Approximately 38% (SE) to 69% (NW) of the variance in $z_c$ is explained by temperature variability, whereas temperature only explains $\sim 14\%$ (NW) of the variance in SWE. These relationships are consistent with Mote et al. (6), who found strong correlations between the intermittent melt and the accumulated 1 April SWE in the Sierra Nevada. Regional differences in intermittent melt rates/patterns contribute to variability in the strength of the correlations. Using the Theil–Sen trend estimator, a decreasing SWE trend from WY 1985–2015 of $\sim -22\ km^3$ SWE per century is found, which agrees well with that of $\sim -23$ and $-16\ km^2$ per century from Wang et al. (4) (estimated using the data sets with the highest and lowest average SWE volumes from figure S7 in ref. 4 for these years, respectively).

Fig. 2 (Bottom Right) summarizes the interannual variability of the average winter temperature. Only the NW has a positive long-term average temperature (i.e., 0.6 °C), while the other basins have subzero average temperatures ($T_a$; “x” symbols), with the lowest occurring in the SW at $-0.9$ °C. The difference in $T_a$ values between the NW and SW is $\sim -1.6$ °C, which is 5.4 times larger than the difference between the NE and SE. While the rangewide temperatures span more than 2 °C about its mean value, this is not the case for all of the regions. Therefore, we explore the risk associated with a 1.0–2.0 °C temperature change around the rangewide average air temperature, but only consider a 1.0 °C change for the subregions.

Rangewide SWE Vulnerability to 1.0–2.0 °C Increase

Fig. 3 (Top Left) presents the rangewide SWE distribution sampled for various temperatures including $\pm 0.5$, $\pm 0.75$, and $\pm 1.0$ °C about the mean. These temperatures correspond to 1.0, 1.5, and 2.0 °C changes centered on $T_a$, respectively. The

Fig. 2. Scatterplots of annual SWE volume and $z_c$ values on 1 April where the shading of the circles represents the average winter temperature for each of the 32 y. Correlation coefficients (and P values) between the SWE volume and centroid are shown. Plus signs demarcate the 25th, 50th, and 75th quartiles along the respective axes. Dashed lines demarcate the long-term average values. (Bottom Right) Average winter temperature distribution for each region. Whiskers span the range of the data. Long-term averages are indicated with “x” symbols.
SWE distributions that are generated for cooler (warmer) temperatures than the 32-y average are blue (red), while the black curve denotes the SWE distribution corresponding to \( T_a \). The probability density functions (PDFs) become more strongly skewed toward smaller SWE values with increasing temperatures, indicating that less SWE is more probable with warmer temperatures (Fig. 3, Top Left). The likelihood that the long-term average SWE volume (dashed line) will be exceeded decreases with warming as Fig. 3 (Bottom Left) summarizes.

For a 1.0 °C change from 0.5 °C below to 0.5 °C above the mean value, it becomes 20.7% less likely that the SWE volume will be larger than its long-term average value \( (SWE) \), which corresponds to exceedance probabilities of 54.3% at –0.6 °C and 33.7% at 0.4 °C. As the temperature change about the mean increases to 1.5 and 2.0 °C, the likelihood of exceeding the average SWE further decreases. For a 1.5 °C increase (from –0.9 to 0.6 °C), it is 31.0% less likely that the long-term SWE will be exceeded, with 0.6 °C corresponding to an exceedance probability of 30.4%. Similarly for a 2.0 °C change, it is 41.1% less likely that the SWE volume will be larger than \( (SWE) \) when the temperature changes from –1.1 °C \( (P_e = 68.4\%) \) to 0.9 °C \( (P_e = 27.3\%) \). Therefore, the change in the exceedance probability for 2.0 °C is ~1.3 and 2.0 times larger than for the 1.5 and 1.0 °C changes, respectively.

We similarly assess the vulnerability of the SWE centroid in Fig. 3 (Right) for the same temperatures. As evident in Fig. 3 (Top Right), the distribution of \( z_c \) shifts toward higher elevations when warmer winters occur. This shift is consistent with the inverse relationship observed in Fig. 2 between the SWE volume and its centroid, causing the PDFs in Fig. 3 (Top Left) to shift toward lower SWE values and those in Fig. 3 (Top Right) to shift toward higher elevations under warmer conditions. As a result, Fig. 3 (Bottom Right) shows that for the colder than average temperatures considered, the probability that the SWE centroid is lower than its 32-y average value ranges from 98.3% (at \( < T_a > - 1.0 °C \)) to 82.8% (at \( < T_a > - 0.5 °C \)). It drastically decreases to 22.1% at \( < T_a > + 0.5 °C \) and 8.5% at \( < T_a > + 1.0 °C \) for warmer than average temperatures. A temperature 1.0 °C above \( < T_a > \) is 5.8% and 13.7% less likely to have a lower than average centroid than when the winter temperature is 0.75 and 0.5 °C above \( < T_a > \), respectively. Overall, increases in the winter temperature of 1.0, 1.5, and 2.0 °C about \( < T_a > \) result in changes in the exceedance probabilities of ~60.6%, ~79.3%, and ~89.8%, respectively (Fig. 3, Right).

Under warmer atmospheric conditions, it is highly probable that the centroid will be forced to higher elevations than its long-term historical location. Also, less of the snowpack will be monitored within the existing in situ network since the centroid will likely reside above the majority of in situ sites, sampling less of the 1 April SWE distribution. Changes in the distribution of montane SWE will present new challenges for monitoring the SWE storage and forecasting the potential spring/summer runoff. These findings emphasize the importance of generating, maintaining, and improving near-real-time–distributed SWE data.

Regional Analysis
Hereafter, we consider an increase of 1.0 °C about \( < T_a > \) for each region, which represents an overall warming accounting for spatial variability. It facilitates a comparison of the vulnerability of each region to the same amount of warming by identifying areas that are the most susceptible to increased temperature and quantifying associated changes in the SWE distributions.

**Regional SWE Volume Vulnerability to 1.0 °C Increase**

Fig. 4 (Left, rows 1–4) shows the regional SWE volume distributions for the mean winter temperature (black) and 0.5 °C above (red) and below (blue) \( < T_a > \). Similar to the rangewide SWE patterns in Fig. 3 (Top Left), the positively skewed SWE distributions in Fig. 4 (Left, rows 1–4) indicate that warmer temperatures result in a higher probability of having smaller SWE volumes. For 1.0 °C of warming about the mean, the exceedance probability (Fig. 4, Bottom Left) decreases from 58.5% (at \( < T_a > - 0.5 °C \)) to 28.2% (at \( < T_a > + 0.5 °C \)) in the NW, a reduction in the likelihood of exceedance of 30.3%. For comparison, the rangewide decrease in \( P_e \) is from 54.3% to 33.7% for 1.0 °C of warming about its mean (Bottom Left, Figs. 3 and 4).

As shown in Fig. 4 (Bottom Left), 1.0 °C of warming reduces the likelihood of above average SWE in the SW and SE, which have the coldest winters on average, by 17.6% and 14.0%, respectively. However, at temperatures 0.5 °C below \( < T_a > \), the SW and SE have the lowest \( P_e \) values at 53.1% and 48.2%, respectively. Overall, with warmer temperatures it becomes less probable that larger than average SWE volumes will accumulate. Consistent with previous studies (e.g., refs. 28–30), we find that the spring snowpack in the northern Sierra Nevada is more vulnerable to warming given its larger changes in exceedance probabilities than in the southern region. With lower elevations and typically warmer winters, the NW and NE, respectively, undergo changes in the exceedance probabilities of ~30.3% and ~28.8% highlighting their greater sensitivity to temperature. This \( P_e \) reduction from 0.5 °C below to 0.5 °C above \( < T_a > \) is also more severe along the western slope than on the eastern side (i.e., NW vs. NE and SW vs. SE).

Since all regions have average winter temperatures spanning –0.5 to +0.5 °C (Fig. 2), we also investigate the SWE response to warming across this 1.0 °C range in SI Appendix, Text SI.

Regional SWE Centroid Vulnerability to 1.0 °C Increase

As the winter temperature increases from 0.5 °C below (blue) to 0.5 °C above (red) the mean in Fig. 4 (Right, rows 1–4), the distribution of centroid values shifts toward the right. A shift toward higher elevations was also shown at the mountain range scale (Fig. 3, Top Right). Alike at the range scale, the order of the temperature-conditioned PDFs for the centroid is reversed.
average winter temperature is 0.1 °C (i.e., 0.5 °C below \(\langle T_a \rangle\)) in the NW and only a 22.0% chance at 1.1 °C, which amounts to a decrease in the \(P_{ne}\) of 70.3% for 1.0 °C of warming. As mentioned above, the change in the rangewide nonexceedance probability is also large (i.e., \(-60.6\%\)) for a 1.0 °C increase from \(-0.6\ °C\). Both the NW and rangewide changes in the \(P_{ne}\) values subject to 1.0 °C of warming are substantial given the lower risks in the NE, SW, and SE, where the changes in nonexceedance probabilities are \(-52.8\%, -45.6\%, \) and \(-33.0\%, \) respectively.

Alike the analysis for the SWE volume, we also consider a 1.0 °C change about 0 °C for the centroid in SI Appendix, Text S2.

**Conclusion**

As temperatures are projected to rise across California, a key question emerges: To what extent do hydrologic variables respond to different levels of warming? Hence, we characterize the range of historical snowpack responses given 1.0–2.0 °C of warming across the Sierra Nevada. The response is magnified as the amount of warming increases, which is demonstrated by it becoming less likely for the SWE volume (centroid) to be larger (lower) than its long-term average value for a 2.0 °C versus 1.5 or 1.0 °C change about the long-term mean temperature. We show that the change in the likelihood of above average SWE for a 2.0 °C change is twice as large as that for a 1.0 °C change, whereas the change in the likelihood of a lower than average SWE centroid for a 2.0 °C change is \(-1.5\) times larger than for a 1.0 °C change. Although we do not use climate projections, results highlight the significance of even small changes in temperature (e.g., 1.5 °C vs. 2.0 °C of warming). Also, point-scale measurements alone cannot yield robust estimates of the montane SWE centroid as done here, which provide valuable information for water managers.

Using a multivariate approach that is adaptable to other SWE characteristics and hydrometeorological forcings, we probabilistically identify water resources vulnerabilities to provide insight into plausible SWE responses to climate change. The northern Sierra Nevada exhibits a greater susceptibility to warming than the southern portion, where the change in the likelihood of above average SWE given 1.0 °C of warming is twice as large in the NW as in the SE. The larger northern response poses risk for increased future wildfire activity given that the region has historically been vulnerable to wildfires with shifts in snowmelt timing (31). Warmer winters reduce the 1 April SWE and force its centroid to higher elevations above the majority of the in situ network, which can have major implications in water resources management, flood control, hydropower generation, etc. Given the generality of our framework, our model can be applied to other snow-covered mountain ranges across the globe.

**Materials and Methods**

**Snow and Temperature Data.** We use the SWE and air temperature maps from the Sierra Nevada snow reanalysis (23), which was generated by assimilating Landsat fractional snow-covered area images within a Bayesian framework (32) across the range. To generate the reanalysis, an ensemble of meteorological fields (e.g., air temperature, humidity, precipitation, etc.), derived from the North American Land Data Assimilation System phase 2 (NLDAS-2, ref. 33), forced the forward land surface model runs. As shown by Walton and Hall (34), the NLDAS-2 minimum and maximum temperature climatologies are biased relative to station observations. However, our modeling framework relies on relative relationships between temperature and SWE (see Conditional Multivariate Model below).

The posterior SWE from the snow reanalysis has been highly verified against snow pillows and courses since these observations were not assimilated (10, 23). Margulis et al. (23) found that the 1 April SWE has a mean difference (MD) and root-mean-squared difference (RMSD) less than 3 and 13 cm, respectively, relative to collocated snow pillows and courses. Huning and Margulis (10) further demonstrated that the winter cumulative snowfall derived from this data set has a MD and RMSD of \(-4\) and 12 cm, respectively, relative to collocated snow pillows.
Conditional Multivariate Model. We use a probability risk model, similar to that described by Madadgar et al. (35), to compute the likelihood that the 1 April SWE volume exceeds its long-term average value (SWE), i.e., SWE > \( \text{SWE} \). Similarly, the elevation of the 1 April SWE volume centroid (\( z_c \)) is also examined. However, given the negative correlation between the SWE volume and \( z_c \) (discussed above), the exceedance and nonexceedance probabilities are computed for SWE and \( z_c \), respectively, to maintain physical consistency.

Therefore, the model computes the probability that the SWE volume will be larger than SWE, whereas it quantifies the likelihood that the centroid of the SWE volume will be located at an elevation lower than the long-term average SWE centroid (\( z_c \)). The model utilizes region-specific thresholds to account for the various regional physiographic features (e.g., elevation) that contribute to variability of the SWE volume and \( z_c \).

We describe the joint probability distribution between temperature \( T_a \) and the response variable \( Y \) (i.e., SWE volume or centroid) using a bivariate copula function as follows:

\[
F_{TV}(t_a, y) = C_{FT}(F_{Ta}(t_a), F_{Y}(y)),
\]

where \( C \) is the cumulative distribution function (CDF) of the bivariate copula and \( F_{Ta} \) and \( F_{Y} \) are marginal CDFs of \( T_a \) and \( Y \), respectively. The copula joins multiple random variables (\( T_a \) and Y) through their marginal distributions. The conditional PDF is given by

\[
f_{TV|Y}(y|y_a) = C_{FT}(t_a, y) \cdot \frac{f_{y}(y)}{F_Y(y)},
\]

where \( C \) is the PDF of the bivariate copula function and \( f_{y} \) is the marginal PDF of Y. Our multivariate model depends on individual ranks of each data point (i.e., relative relationships). Copulas provide a framework for examining the underlying dependence structure of multiple variables. They serve as a mapping tool from the variable space into another space \([0,1]\), where the dependence structure is determined and the joint probabilities are built with the parameter values corresponding to the maximum likelihood, Akaike and Bayesian information criteria, Nash–Sutcliff efficiency, and RMSD. The selected copulas (SI Appendix, Table S1) yield the most optimal values of the original variable space (36).

We consider commonly used copula functions including Gaussian, Frank, and Clayton (36) for describing the correlation structure between variables: (i) SWE and \( T_a \) and (ii) \( z_c \) and \( T_a \). We use a Markov chain Monte Carlo (MCMC) sampling approach to select the model parameters following Sadegh et al. (36) for each region and pair of variables. Using this approach, we compute the maximum likelihood, Akaike and Bayesian information criteria, Nash–Sutcliff efficiency, and RMSD. The selected copulas (SI Appendix, Table S1) yield the most optimal values of the original variable space (36).

SI Appendix, Fig. S1 shows the posterior distribution of parameter values for the fitted copulas from the MCMC simulations, which includes uncertainty from the number of years used here. Our multivariate model is built with the parameter values corresponding to the maximum likelihood from the MCMC simulations (black line). SI Appendix, Fig. S2 indicates that uncertainty associated with the copula parameters (SI Appendix, Fig. S1) results in low uncertainty in the derived conditional PDFs and probabilities for all regions. SI Appendix, Fig. S3 shows the data (red dots) with the conditional \( P_L \) and \( P_{sw} \) values (shading) for SWE (Left) and \( z_c \) (Right), respectively.

The snow reanalysis can be obtained from https://margulis-group.github.io/data.

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