

# Melt trends portend widespread declines in snow water resources

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## Article

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# Abstract

In many mountainous regions, winter precipitation accumulates as snow that melts in spring and summer providing water to one billion people globally. As the climate warms and snowmelt occurs earlier, this natural water storage is compromised. While snowpack trend analyses commonly focus on snow water equivalent (SWE), we propose that trends in accumulation season snowmelt serve as a critical indicator of hydrologic change. We compare long-term changes in snowmelt and SWE from snow monitoring stations in western North America. Nearly four-times more stations have increasing winter snowmelt trends than SWE declines; significant ( $p < 0.05$ ) at 42% vs. 12% of stations, respectively. Snowmelt trends are highly sensitive to temperature and an underlying warming signal, while SWE trends are more sensitive to precipitation variability. Thus, continental-scale snow-water resources are in steeper decline than is inferred from widely reported SWE trends alone. More winter snowmelt will complicate future water resources planning and management efforts.

## Main Text

Snow is the primary source of water and streamflow in western North America (Li et al., 2017) and supports the water supply for more than one billion people globally (Barnett et al., 2005). In mountainous regions, accumulated snow extends the downstream delivery of meltwater through the spring and summer when human and ecosystem demands are greatest. For over a century, hydrologists have used mountain snowpack observations to make spring and summer runoff forecasts (Church, 1933; Garen, 1992), which help farmers plan irrigation, water managers operate reservoirs, communities protect against floods, and energy companies manage hydropower assets and set annual prices (Abramovich, 2007; Anghileri et al., 2016; Pagano, 2010; Palmer, 1988).

It is well established that climate change is expected to shift melt earlier and reduce snow water resources (Barnett et al., 2005; Nijssen et al., 2001) with broad impacts on ecosystem productivity (Boisvenue & Running, 2006), winter flood risk (Musselman et al., 2018), groundwater recharge (Ford et al., 2020), agriculture and food security (Immerzeel et al., 2010; Qin et al., 2020; Shindell et al., 2012), and wildfire hazard (Westerling, 2016). Water resource management in snow-dominated regions rely on distinctly separate snow accumulation and snowmelt seasons such that annual river flows can be predicted based on the quantity of maximum snow accumulation. The occurrence of substantial snowmelt and streamflow prior to maximum SWE reduces streamflow and drought forecast accuracy (Livneh & Badger, 2020) and complicates the management of dams and reservoirs. How warming has and will continue to impact these diverse socio-environmental systems is a critical research question in light of model projections that snowpack will decline and winter melt will increase this century (Addor et al., 2014; Musselman, Clark, et al., 2017; Thackeray et al., 2019; Vano et al., 2010). Ground-based snowpack observation networks offer critical monitoring capacity to assess current conditions and long-term trends in a manner unsurpassed by current remote sensing techniques (Lievens et al., 2019) or models alone (Giroto et al., 2020).

The western U.S. has extensive networks of long-running manual and automated snow observations. Here, manual snow measurement records have facilitated historical trend analyses extending back to the 1950s (Mote et al., 2005; Mote et al., 2018), with a recent study reporting declines in early spring SWE at 33% of >600 sites (Mote et al., 2018). Decadal variability in precipitation and long-term warming codetermine SWE trends in the western U.S. (Mote et al., 2005; Pierce et al., 2008). The high sensitivity of SWE to long-term precipitation trends complicates assessments of snowpack response to warming, particularly as future precipitation changes are much less certain than warming (Pendergrass et al., 2017). Conversely, winter snowmelt may be more sensitive to warming than to changes in precipitation. While (monthly) manual snow survey SWE data (Mote et al., 2005; Mote et al., 2018) do not resolve melt, automated snow station observations of SWE, measured using a weighing device to relate snowpack mass to the equivalent water depth, facilitate long-term melt trend analysis. As a hydrologic flux, snowmelt trends can serve as an insightful indicator of shifts in snow water resources relevant to global water assessments (Oki & Kanae, 2006).

To date, no study has conducted long-term trend analyses of melt from SWE measurements made at the >1,000 automated stations located across western North America. Only recently has the automated station record become sufficiently long (30 to 40+ years) to permit robust trend analysis. We present an empirical study of daily melt and SWE from 1,065 automated snowpack monitoring stations in the western U.S. and Canada. For each station and year, we compute the cumulative annual daily melt, the date of maximum SWE, and April 1<sup>st</sup> SWE. The date of April 1<sup>st</sup> is commonly used in water supply management to divide winter snow accumulation and spring melt and as a proxy for the date of maximum annual SWE (Pagano et al., 2004). We report the cumulative annual melt as the fraction of total annual melt (fraction of melt; FM) on the date of maximum SWE ( $FM_{max}$ ) or April 1<sup>st</sup> ( $FM_{Apr1}$ ). We introduce the FM metric to characterize the mobilization of snow water resources during what is traditionally considered to be the accumulation period before spring melt and use it to assess historical snowpack response to climate variability.

We conduct trend analyses of  $FM_{Apr1}$ , April 1<sup>st</sup> SWE, and the date of maximum SWE using a Mann-Kendall test and the Theil-Sen slope estimator on data records 30 yrs. and present trends with statistical significance at the 95% confidence level. We relate interannual anomalies in these measured snow metrics to observation-based long-term and interannual variability in temperature and precipitation. Finally, to assess the climatological drivers of observed trends in melt, SWE and date of maximum SWE, we constrain our trend analysis to stations with long (40+ yr.) records coincident with the observation-based Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (Daly et al., 1994). We used these stations and climate data to conduct a controlled assessment of how decadal variability and long-term trends in temperature and precipitation impact our reported melt and SWE trends. See the Methods Section for details.

## Melt and Snowpack Baseline Conditions

To evaluate trends in melt before the date of maximum SWE, we first assess the long-term average date of maximum SWE and the fraction of melt occurring before this date. The average date of maximum SWE computed on all stations for the full period of record is within one day of April 1<sup>st</sup> (Figure 1a); however, there is much geographic variability (Figure 1b). On average, the snowpack of the Sierra Nevada and inter-continental regions peaks within ~10 days of April 1<sup>st</sup>, while the snowpack in the U.S. Pacific Northwest and Southwest peaks around the first week of March. In interior Alaska, the date of maximum SWE occurs in mid- to late-April. In cold, continental regions including Colorado, Wyoming, Montana, the Canadian Rockies, and interior British Columbia, maximum SWE occurs closer to May 1<sup>st</sup>.

On average at western North American stations, 88% of snow remains available to melt on the date of maximum SWE. Figure 1c indicates that the average  $FM_{max}$  is 0.12 (see vertical line) with a mean range (computed on all years) of 0 to 0.4. Similar to the date of maximum SWE,  $FM_{max}$  exhibits substantial geographic variability (Figure 1d) with proportionately more winter melt in warmer regions such as the U.S. Pacific Northwest and Southwest, where >20% of annual snow water resources melt before the date of maximum SWE (Figure 1c). By comparison, <5% of annual snow water resources mobilizes as melt before maximum SWE in places like the Rocky Mountains, interior British Columbia, and interior Alaska (Figure 1d). Similarly, the average  $FM_{Apr1}$  is 0.21, indicating that 79% of snow water resources monitored at North American stations has yet to mobilize as melt on the regional average date of maximum SWE (not shown). For controlled assessments between sites and over time, we use April 1<sup>st</sup> to assess long-term changes in melt and SWE. We also assess changes in the date of maximum SWE.

## Melt and Snowpack Trends

Melt occurring before April 1<sup>st</sup> has increased at 42% of 634 stations with long records in western North America (Figure 2a; red markers) at an average rate of 3.5% 3.3% per decade (Figure 2b; green markers) compared to <10% of stations with earlier maximum SWE (Figure 2c; red markers) and 12% of stations with lower April 1<sup>st</sup> SWE (Figure 2d; red markers). Figure 2a shows that stations with statistically significant ( $p < 0.05$ ) trends toward proportionately more melt before April 1<sup>st</sup> cover all regions of western North America. Only seven stations had reductions in  $FM_{Apr1}$  (i.e., less melt before April 1<sup>st</sup>). Importantly, melt before April 1<sup>st</sup> has increased at 4.2-times the number of stations with trends toward earlier maximum SWE and 3.5-times the number of stations with less April 1<sup>st</sup> SWE (Figure 2; compare red markers in panel a to those in panels c and d, respectively).

Melt is increasing in all snow-dominated months before April 1<sup>st</sup> (i.e., ONDJFM) with the greatest rate of change in November and March. Median monthly melt, presented as the fraction of total annual melt occurring in a given month, has increased by ~0.5% decade<sup>-1</sup> in the months of ONDJF and ~1.3% decade<sup>-1</sup> in March (Figure S2a). Notably, 9% to 24% of stations with long records (30+ years) have statistically significant ( $p < 0.05$ ) melt increases in snow-dominated months before April 1<sup>st</sup> (Figure S2b). Figure S3

shows that the number of stations with monthly trends is greatest in November and March (24% and 22% of stations with long records, respectively) and least in February (9%) followed by October and January (13%) and December (16%). These results indicate that while proportionately more melt is shifting from post-April 1<sup>st</sup> into March, the increase in  $FM_{Apr1}$  is most extensive during the late-fall and late-winter and significant in all cold season months (October to March).

## Melt and Snowpack Sensitivities to Climate

To evaluate the sensitivities of the snow metrics to interannual variations in air temperature and precipitation during the accumulation season, we assess anomalies in the snow metrics as a function of NDJFM (1979-2019) precipitation and temperature anomalies. Figure 3a-c show data markers for each station-year (n 29,700) and precipitation and temperature anomaly colored by annual anomaly (in percentile units) in the respective snowpack metric. The structure of the data clouds in Figures 3a-c is the same; the shape indicates that drier years tend to be warmer than wetter years, a weak but significant (p 0.05) negative correlation ( $r=-0.24$ ), supporting previous work on the topic (Lehner et al., 2017; Luce et al., 2014). Importantly, the colors of the data points in Figure 3a-c are stratified uniquely across the precipitation-temperature anomaly space for the three different snow metrics, suggesting different primary drivers of variability.

To characterize the relative influence of precipitation and temperature on the snow indices across the percentile space, the data were divided into six percentile bins (see colors in Figures 3abc) and a centroid (mean temperature and precipitation anomaly) was computed for each group. The slope of the lines connecting the centroids in Figure 4d indicates the relative influence of temperature and precipitation on the snow metric. The more horizontal the line, the stronger the temperature influence. The centroid line for  $FM_{Apr1}$  is more horizontal than for the SWE metrics, showing that  $FM_{Apr1}$  is more strongly influenced by temperature. In contrast, for the SWE metrics, the centroid line is steeper, indicating a stronger control of precipitation and a weaker sensitivity to the temperature signal. The curved shapes of the April 1<sup>st</sup> SWE and date of maximum SWE lines suggest that precipitation plays a dominant role in determining late and high maximum SWE (upper left part of the curve) compared to early and lower maximum SWE (lower right part of the curve), which are more driven by temperature. Simply put, it takes an unusually warm winter to cause very early and/or low maximum SWE, while very late and/or high maximum SWE typically results from unusually wet winters. In contrast, the linear shape of the  $FM_{Apr1}$  centroid line indicates that seasonal temperature reliably controls snowmelt.

To connect results from the interannual sensitivity of melt and SWE (Figure 3) to the climatic drivers behind the long-term historical trends shown in Figure 2, we conduct a trend analysis on 173 snow stations that had longer records (1979-2019) (see Methods Section and Supplemental Figure S4). To isolate the effects of trends in temperature and precipitation on the snow indices, we created two subsamples of stations: those with drying trends and those with warming trends. Stations with warming trends were more likely to have melt increases than declines in April 1<sup>st</sup> SWE (compare red lines in Figure

4a), emphasizing again the greater sensitivity of  $FM_{APR1}$  to temperature, but this time at the decadal time scale. Stations with a drying trend have substantial changes in April 1<sup>st</sup> SWE (Figure 4b).

The number of U.S. stations with significant ( $p \leq 0.05$ ) warming has quadrupled from 21 (12%) in 2009 to 80 (46%) in 2019 (Figure 4a; black line) and cover much of the western U.S. as of 2019 (Figure S4a). Conversely, fewer stations (<26 or <15%) exhibit drying trends (Figure S4b) and the number has not varied in the recent decade to the same degree as warming (Figure 4; compare the black lines in panels a and b, noting different y-axis scales). A majority of the stations with warming trends also have melt increases (Figure 4c; see purple line calculated as the ratio of the data shown by the red line in Figure 4a to that of the black line in Figure 4a). The same is not true for April 1<sup>st</sup> SWE, where most stations with warming have no trends in April 1<sup>st</sup> SWE (Figure 4b; inferred from the difference between the black and dashed red lines). Generally, stations with long-term precipitation declines (i.e., drying) also have decreasing trends in April 1<sup>st</sup> SWE (Figure 4b; see orange line calculated as the ratio of the data shown by the dashed red line to that by the black line in Figure 4b). Thus, melt is much more sensitive to long-term warming than April 1<sup>st</sup> SWE (inferred from the purple line plotting above orange line in Figure 4c), which itself is more sensitive to precipitation variability (Figure 4d).

## Summary And Discussion

We assess historical daily melt using automated SWE measurements from 1,065 remote telemetry stations that span mountainous regions of western North America. We show that snowmelt is increasing during the snow accumulation season at 42% of North American stations. This is evidence that the seasonal distinction between accumulation and melt is becoming increasingly blurred. The melt increases are 3.5-times more widespread than changes in April 1st SWE and are driven by a long-term warming trend whereas commonly reported April 1st SWE declines are less sensitive to temperature than precipitation declines. Precipitation variability is shown to drive trends in the April 1st SWE record whereas melt trends are more temperature-dependent, although mechanistically determined by the snowpack energy balance including net radiation and turbulent transfer (Cline et al., 1998); the date of maximum SWE is moderately sensitive to both precipitation and temperature trends. Thus, changes in April 1st SWE are more difficult to detect than snowmelt due to the weaker climate change signal in precipitation than in temperature. Widespread melt increases across western North America despite lesser change in commonly used snow metrics indicates that this critical water resource is in steeper decline than is inferred from SWE trends alone.

We show that snowpack magnitude has declined at only 12% of 634 stations with long records in western North America. The result appears at odds with recently reported more widespread (33%) declines in April 1st SWE observations from manual snow courses in the western U.S. (Mote et al., 2018); however, our results are consistent (33% using 2016 as the end date; see green line in Fig. 4c) when restricted to western U.S. stations with long records. Since manual snow courses are generally conducted at lower elevations than automated stations (Dressler et al., 2006) and snowpack at lower elevations is

more sensitive to warming (Mote, 2006; Mote et al., 2005; Musselman, Molotch, et al., 2017), direct comparisons of trend assessments on manual vs. automated snow observations, particularly over different time periods, should be made with care. Our results illustrate the benefit of using snow observations from automated stations to monitor melt trends as an insightful indicator of warming-induced changes in snow water resources.

More snowmelt mobilizing earlier in the year has important hydrological and ecological implications. Hydrologically, this melt water readily enters the soil system (Harpold et al., 2015), reducing the buffering capacity of soils and heightening flood risk in response to rain-on-snow (Henn et al., 2020; Musselman et al., 2018) and spring melt (Berghuijs et al., 2016). Increased soil moisture during the snow-covered season sustains microbial activity in soils beneath snow (Brooks et al., 1996), facilitating the production of carbon dioxide (CO<sub>2</sub>) and making nutrients readily available for transport (Edwards et al., 2007). The melt trends we present likely have implications on nutrient cycling and functioning of headwater ecosystems. Hydrologic and streamflow prediction models require accurate characterization of soil moisture (Harpold et al., 2017; Shukla & Lettenmaier, 2011). Given the challenges of hydrologic models to accurately represent soil moisture (Koch et al., 2016), snowpack (Günther et al., 2019) and winter melt fluxes (Pflug et al., 2019), together with the needs to better understand the impact of climate change on water resources, the carbon cycle, and ecosystem productivity, future studies are needed to address the coupled hydrological and ecological consequences of the shift to more winter melt.

We show that the percentage of annual melt occurring before April 1st is increasing by 3.5% per decade at 42% of available stations. This substantial and widespread rate of change implies a loss of seasonal storage of snow water resources in North American mountain water towers (Immerzeel et al., 2020). Over the recent decade, the expansion of stations exhibiting long-term increases in melt corresponds with the sharp increase in stations with warming trends (Fig. 4a). The magnitude of the melt increases (Fig. 2b), in many regions, remains orders of magnitude less than maximum annual SWE such that a significant increase in melt may not yet yield significant declines in SWE at many sites. Rather, the observed widespread melt trends we report likely serve as a harbinger of snowpack response to global warming, consistent with future model projections of earlier melt (Musselman, Clark, et al., 2017). We conclude that long-term melt trends are an overlooked and important indicator of change in western North America's primary water supply that supports some of the world's largest agricultural and forest product industries and more than 85 million people.

## Methods

### Snowpack telemetry station observations

Snowpack telemetry stations measure SWE using a metal, fluid-filled snow "pillow" constructed on the ground and a pressure transducer to relate measurements of the overlying snowpack mass to water depth equivalent. Daily SWE observations for the historical record to September 2019 at 1,065 stations in

Loading [MathJax]/jax/output/CommonHTML/jax.js obtained from the Natural Resources Conservation Service,

the California Department of Water Resources, Alberta Environment, the British Columbia Ministry of Environment, and the Yukon Government Water Resources Branch. The earliest record dates to 1963. There were nearly 70 stations operating by 1975 and by 1980 there were 230. The data were visually inspected by individual water year (Oct. 1 – Sep. 30) for erroneous and missing data that would adversely affect the estimation of the timing and magnitude of maximum SWE and accumulation season dynamics. The visual assessment permitted flexibility to include snow-years with substantial missing data after maximum SWE that might otherwise have been excluded with an algorithm (e.g., Serreze et al., 1999), as data after peak-SWE were not used in this analysis. In the case of missing summer data, a zero SWE value was prescribed on August 1st to best estimate total annual melt (see *Calculation of Snow Metrics*). The manual inspection procedure identified 1,280 station-years (< 4%) in which stations recorded data but were excluded from analysis. An additional 142 station-years were manually corrected to remove erroneous spikes. The quality control procedure left 31,343 station-years for analysis. This data set is publicly available in netCDF format (see Data Availability) including level 1 (raw; formatted) and level 2 (QA/QC) products required for reproducibility.

## Calculation of snow metrics

Figure S1 demonstrates three snow metrics derived from the historical daily SWE observations and provides examples of how those metrics vary between a continental (Figure S1a) and maritime (Figure S1b) snow regime. First, the date and magnitude of maximum SWE (dashed vertical lines in Figure S1) were calculated for each snow season and station. The date of maximum SWE is defined as the day, relative to October 1st, on which the annual maximum SWE value occurred; in cases of multiple maxima, the later date is used (Trujillo & Molotch, 2014).

We introduce a metric derived from daily SWE observations that complements the date of maximum SWE and provides additional hydrologic information. The fraction of cumulative annual snow water resources that has melted before a given date  $i$ ,  $FM_i$ , was computed for each station-year. This daily metric was computed in three steps for each of two dates: 1) the date of maximum SWE and 2) April 1st. First, daily melt (Figure S1; blue bars) was computed as the daily decrease in SWE, presented as positive values. Second, cumulative daily melt (Figure S1; red hashed line) was computed as the cumulative sum of daily melt from October 1st to August 1st. Third, the cumulative sum of daily melt was normalized by the total annual melt (on August 1st) to estimate the (daily) fraction of cumulative annual melt, which was then sampled on the dates of maximum SWE ( $FM_{max}$ ) and April 1st ( $FM_{Apr1}$ ). The August 1st end date was chosen to avoid rare cases where early-season (i.e., September) snowfall could impact estimates of the total annual melt and to ensure that any late-lying snow (almost always gone by August at sensor locations) was recorded as annual melt.

The complement '1- $FM_i$ ' is the fraction of annual snow water resources that remains to be melted on day of water year,  $i$  (the North American water year begins on October 1st). In the idealized case of snowpack as a fully efficient water tower with distinct accumulation and melt seasons delineated by the date of maximum SWE,  $FM = 0.0$  on the date of maximum SWE when no snowfall has melted to date and no



snowfall will occur after that date. In all cases,  $FM = 1.0$  occurs on the last date of snow disappearance. The snow metrics date of maximum SWE, magnitude of maximum SWE,  $FM_{max}$ , and  $FM_{Apr1}$  were computed for each year of record for all stations.

## Historical trend analysis

To assess long-term trends in the snowpack observations, linear trend analysis and a Mann-Kendall test (Gilbert, 1987) were conducted on each snow metric. The non-parametric Mann-Kendall (MK) (Kendall, 1948; Mann, 1945) test was chosen over slope-based alternatives, such as the parametric t-test, as MK performs optimally with non-normally distributed data such as time series (Yue & Pilon, 2004). This approach is similar to a recent snowpack trend assessment by Mote et al. (2018). Only stations with at least 30 years of record were assessed and only trends with statistical significance at the 95% confidence level ( $p \leq 0.05$ ) are reported. Slopes of linear fits to the data were calculated using the Theil-Sen estimator method (Sen, 1968), which is the median of the slopes computed over pair-wise data points, and has been used in the hydrologic (Lettenmaier et al., 1994) and climate trend analyses (Martel et al., 2018).

## Relationships of snowpack trends with precipitation and temperature

We investigate the roles of cold season (i.e., NDJFM) temperature and precipitation in influencing interannual variations in  $FM_{Apr1}$  and the date and magnitude of maximum SWE. Monthly air temperature and precipitation were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) for 1979–2019 (PRISM Climate Group, Oregon State University, <http://prism.oregonstate.edu>, last accessed 10 June 2020). The gridded PRISM data are produced at 800 m resolution and upscaled to and provided at 4 km. Monthly temperature and precipitation data were extracted for all snow telemetry stations in the contiguous U.S. For each station and year, average air temperature and total precipitation were calculated for the months of NDJFM and presented as anomalies relative to the long-term (1979–2019) mean NDJFM values. Similarly, anomalies in the  $FM_{Apr1}$  and the date and magnitude of maximum SWE were computed for each station-year. In this way, air temperature and precipitation anomalies were plotted against anomalies in snow metrics for each year and station for which snowpack data were available.

## Controlled snow metric sensitivity and trend assessment

To assess the climatological drivers of observed trends in melt, SWE and the date of maximum SWE, we constrain our trend analysis to stations with long (40 + yr.) records coincident with the observation-based Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (Daly et al., 1994). We sampled historical monthly temperature and precipitation at the station locations and iteratively modified the end-year of our trend analysis from 2009 (30 + yr. record) to 2019 (40 + yr. record). In this way, we mimic the result of conducting the trend analysis on the record available to date, every year for a decade. We used these stations and climate data to conduct a controlled assessment of how decadal variability

and long-term trends in temperature and precipitation impact our reported melt and SWE trends. We evaluated the number of stations with trends in temperature or precipitation and, for these specific station subsets, assessed trends in the snowpack response (melt, SWE and the date of maximum SWE). We thus evaluated how the snowpack trends and drivers have changed over recent decades of this relatively short observation record.

## Declarations

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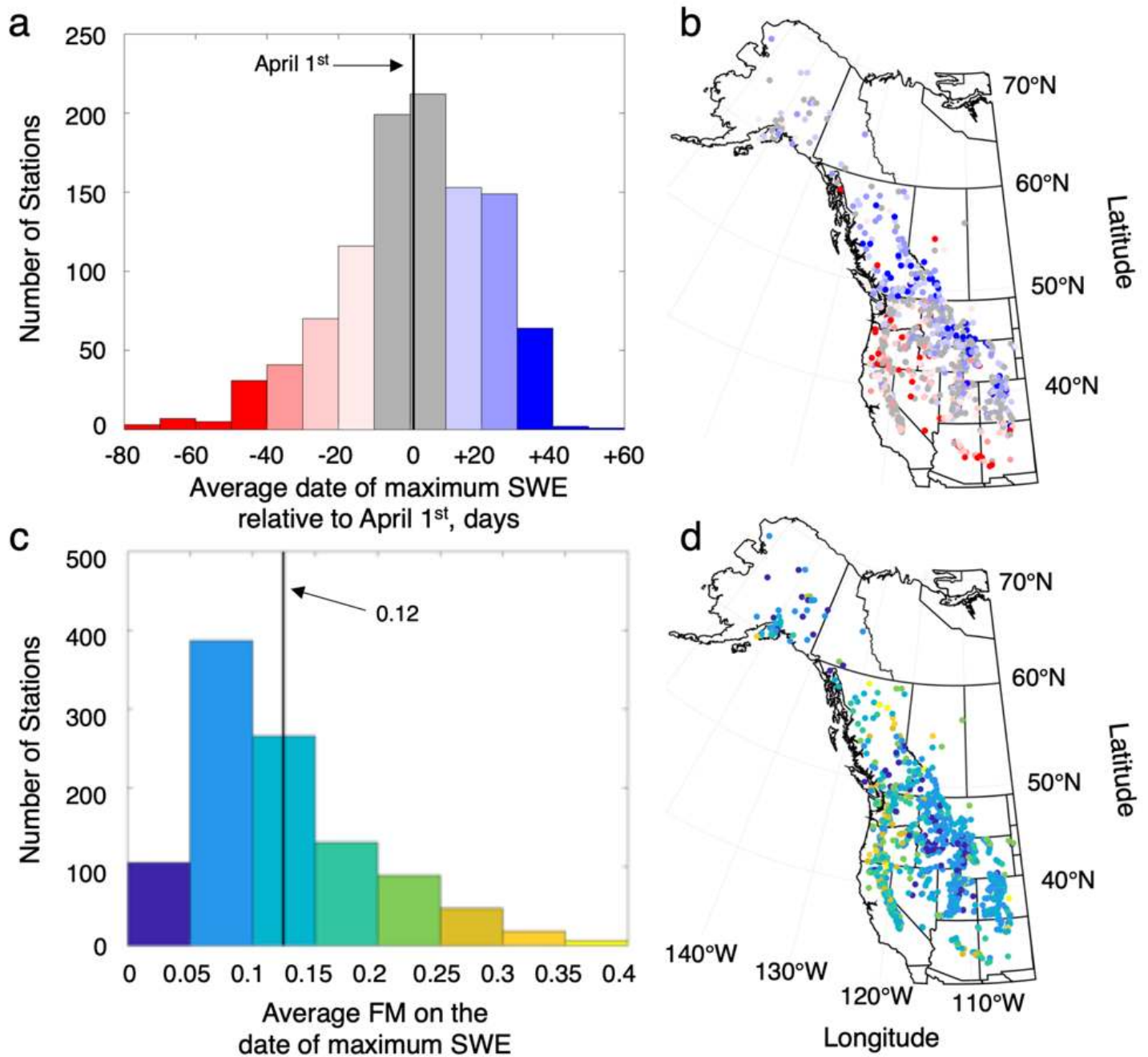
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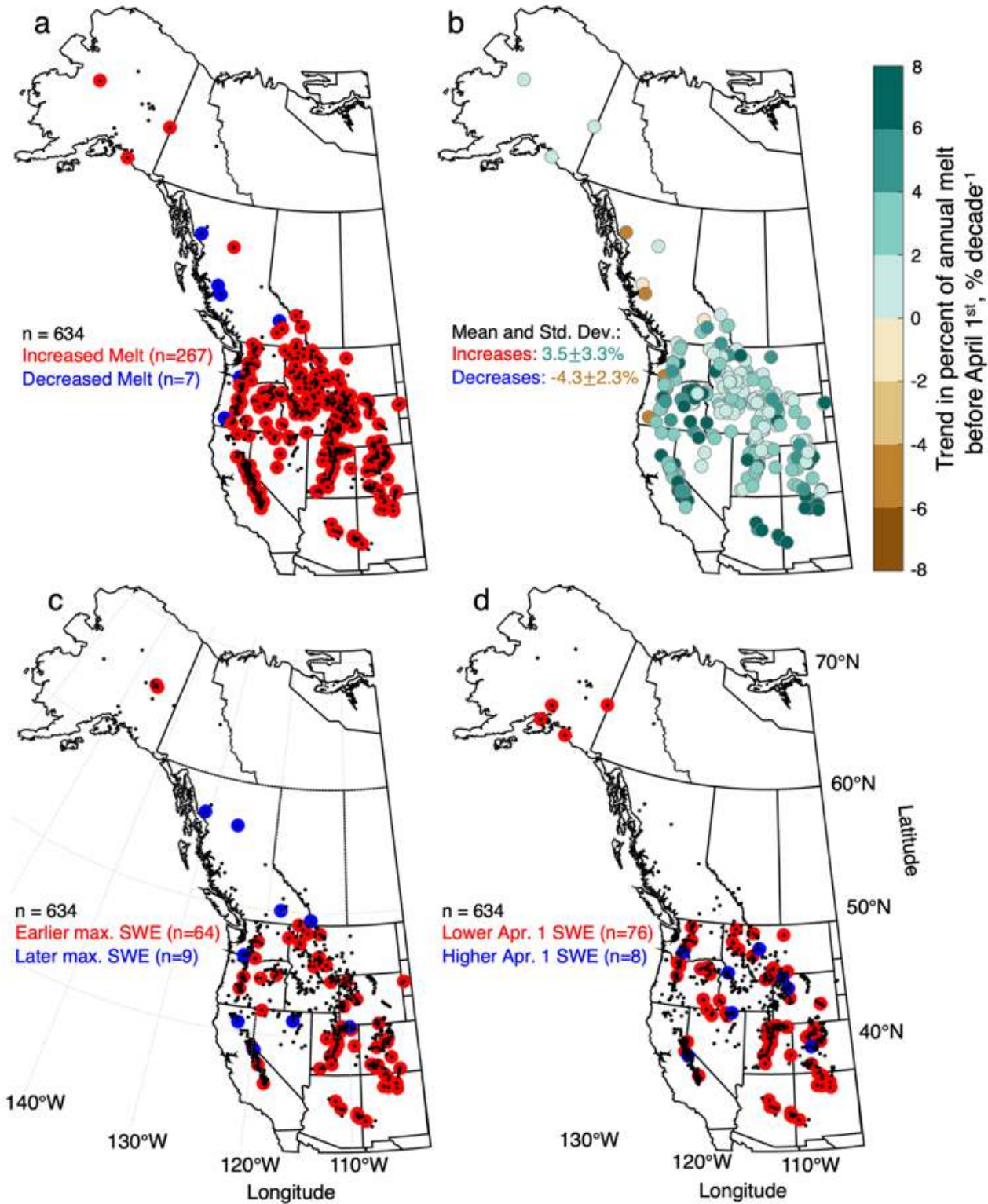
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## Figures



**Figure 1**

On average across western North America, snowpack reaches an annual maximum on April 1st when 88% of annual snow has yet to melt. A (a) histogram and (b) map of the average (Oct. 1960 – Sep. 2019) date of maximum SWE relative to April 1st as measured at 1,065 snowpack telemetry stations (circle symbols) in western North America. The symbol colors in (b) correspond to the values shown in the x-axis of the histogram in (a). (c) and (d) show the average fraction of cumulative annual melt on the date of maximum SWE as in (a) and (b), respectively. The average values of all sites and station-years is indicated in (a) and (c) by the vertical line.

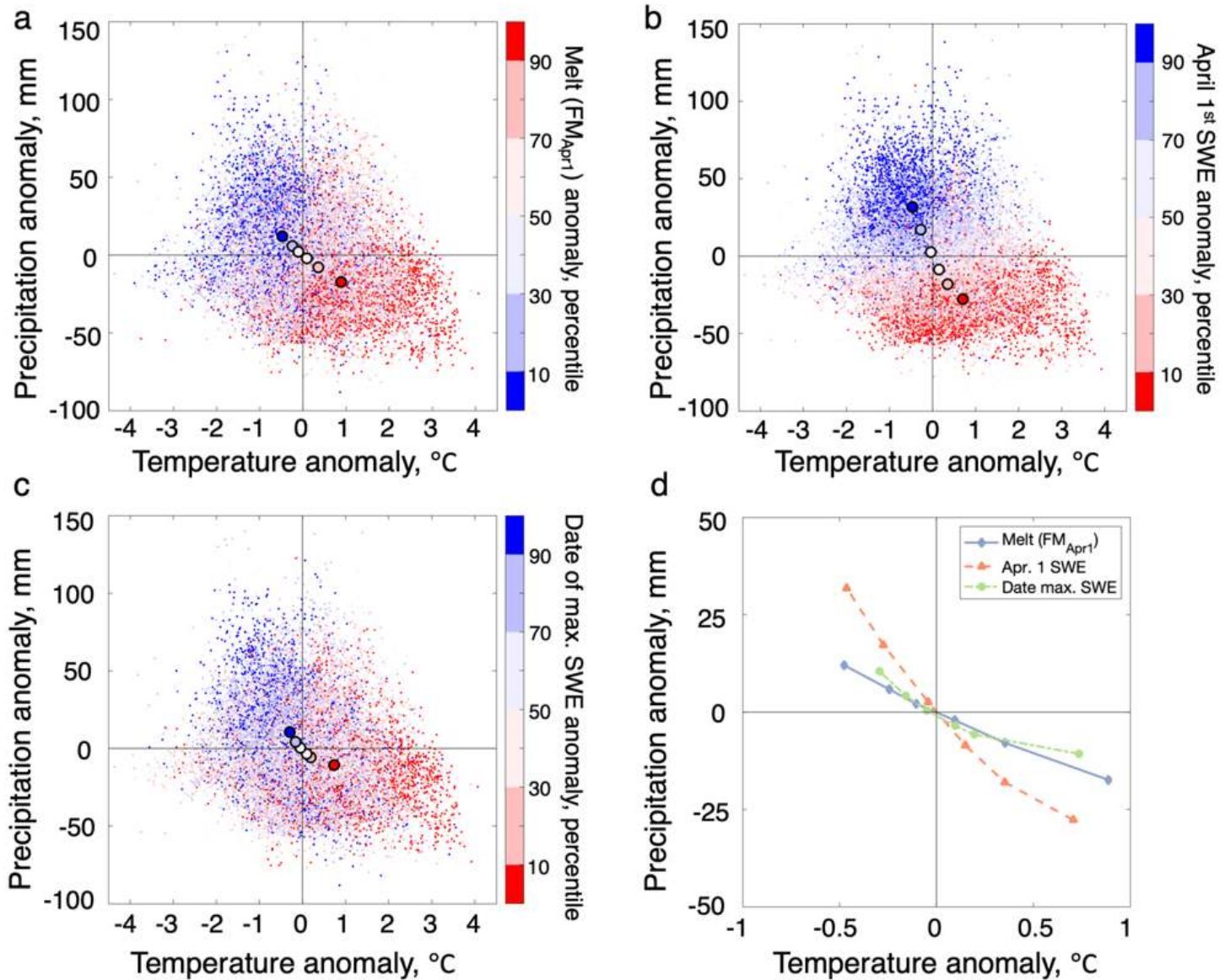


**Figure 2**

Trends toward more melt before April 1st are about four-times more widespread than trends toward earlier maximum or lower April 1st SWE. Snowpack telemetry stations with data records  $\geq 30$  years (small points; n=634) that have statistically significant ( $p \leq 0.05$ ; colored circles) historical trends (see text color in legends) in (a) the fraction of cumulative annual melt that has occurred by April 1st (the



corresponding rate of melt change is mapped in (b)), (c) the date of maximum SWE, and (d) the magnitude of April 1st SWE.



**Figure 3**

Snowmelt is more sensitive to temperature whereas SWE is more influenced by precipitation. The axes of each panel indicate anomalies in NDJFM precipitation (y-axis) and temperature (x-axis) from PRISM at U.S. snowpack telemetry sites relative to the long-term (1979 to 2019) mean values. The anomalies in (a) FM on April 1st, (b) April 1st SWE, and (c) date of maximum SWE are shown as percentiles using colors. Larger circles indicate the centroid for the percentile classes for each of six color categories (see color bars). (d) Centroids for each snow metric (from a-c; see legend).

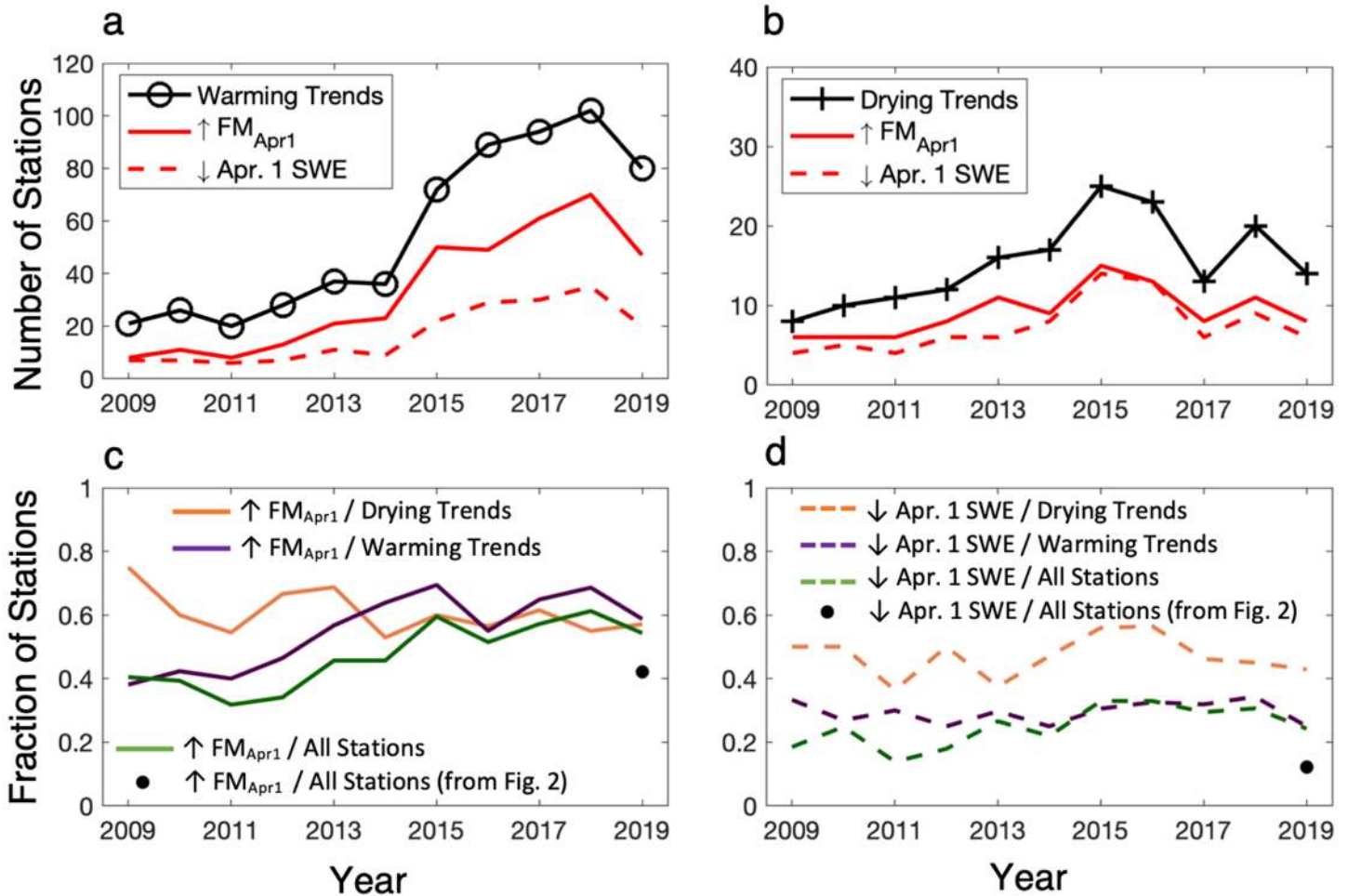


Figure 4

The increasing number of stations with melt is explained by widespread, long-term warming while SWE declines are more sensitive to precipitation variability. Historical trend analyses conducted each year based on information to date showing the number of long-term (40+ yr.) stations with significant ( $p \leq 0.05$ ) a) warming and b) drying trends from PRISM (NDJFM averages) and, of those subset stations, the corresponding number of stations with trends in melt and April 1st SWE (see legends). Note the scale difference in y-axes. The number of stations with decreases in melt or increases in April 1st SWE is negligible; stations with no trends can be inferred from the difference between the black and red lines. The fraction of stations with warming and drying trends that also have trends in c) melt and d) April 1st SWE trends. Also plotted are the fractions of stations with snow trends relative to all subset stations (green lines) and all North American stations as of 2019 shown in Fig. 2 (black circles).

## Supplementary Files

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