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Key Points:
- Interannual variability of peak snowpack amount in the western United States will decrease in regions transitioning from snow to rain
- Peak snowpack timing will become more interannually variable and occur across a broader range of months
- Consecutive snow droughts will become much more common across mountains of the western United States

Supporting Information:
- Supporting Information S1

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Projected Changes in Interannual Variability of Peak Snowpack Amount and Timing in the Western United States

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Abstract Interannual variability of mountain snowpack has important consequences for ecological and socioeconomic systems, yet changes in variability have not been widely examined under future climates. Physically based snowpack simulations for historical (1970–1999) and high-emission scenario (RCP 8.5) mid-21st century (2050–2079) periods were used to assess changes in the variability of annual maximum snow water equivalent (SWE_{max}) and SWE_{max} timing across the western United States. Models show robust declines in the interannual variability of SWE_{max} in regions where precipitation is projected to increasingly fall as rain. The average frequency of consecutive snow drought years (SWE_{max} < historical 25th percentile) is projected to increase from 6.6% to 42.2% of years. Models also project increases in the variability of SWE_{max} timing, suggesting reduced reliability of when SWE_{max} occurs. Differences in physiography and regional climate create distinct spatial patterns of change in snowpack variability that will require adaptive strategies for environmental resource management.

Plain Language Summary A wealth of research has established that warming temperatures associated with climate change in the western United States will generally reduce snowpack accumulation and result in earlier snowmelt timing, with important consequences for water resources and ecosystems. However, changes in the variability of snowpack conditions between years have not been well established. We analyze simulated snowpack data for historical and future climate scenarios and find that changes in variability differ across the western United States. Variability of annual maximum snowpack between years decreases while the timing of peak snow accumulation becomes more variable, particularly in areas transitioning from snow- to rain-dominated precipitation. We also find that consecutive years with very low or early snowpack will become much more frequent. These findings highlight the need to consider changes in snowpack variability in climate change impact assessments and adaptation planning.

1. Introduction

Anthropogenic climate change is altering water resources in the western United States, with decreasing mountain snowpack across the region (Mote et al., 2018; Pierce et al., 2008) and earlier runoff timing in basins that supply water to humans and ecosystems (Barnett et al., 2008). The effects of warming on changes in average snowpack conditions are well characterized for historical (Hamlet & Lettenmaier, 2007; Knowles et al., 2006; Mote, 2006; Pierce et al., 2008; Siler et al., 2019) and future conditions (Fyfe & etal, 2017; Gergel et al., 2017; Hamlet et al., 2005; Kapnick & Delworth, 2013; Klos et al., 2014; Rhoades, Ullrich, & Zarzycki, 2018), but there is a relative paucity of information on how the interannual variability of snowpack amount and timing might shift as the climate changes.

Changes in interannual variability of snowpack amount and timing would impact ecological, socioeconomic, and coupled social-ecological systems that rely on snow cover and melt, although these impacts are not as well established as the impact of changes in mean conditions. For example, the magnitude of interannual variability affects the reliability of reservoir inflows (Rhoades, Jones, & Ullrich, 2018), hydroelectric power generation (Fleming & Weber, 2012), and tourism (Scott et al., 2008). For each of these cases, low interannual variability may be associated with greater reliability, whereas high variability may increase the potential for high snowfall and runoff years to offset the negative consequences of drought years. High interannual precipitation variability has been associated with reduced groundwater depletion because occasional high precipitation years can break a positive feedback between groundwater pumping and reservoir depletion (Apurv et al., 2017), though the contribution of variability in snow-related patterns, processes, and fluxes to surface and groundwater withdrawals is not as well documented.

One dimension of variability that may be particularly important is the degree of change between consecutive years. Precipitation whiplash—the occurrence of an extremely dry winter immediately followed by or preceding an extremely wet winter—is projected to increase in California (Swain et al., 2018), though snowfall patterns will not reflect those of overall precipitation due to increasing temperatures. Recent multiyear snow droughts in the western United States, whether caused by unusually warm winters and/or low winter precipitation, have drawn attention to the causes and impacts of chronic snow droughts (Cooper et al., 2016; Hatchett & McEvoy, 2018; Ullrich et al., 2018). While studies of snow droughts have predominantly addressed snowpack amounts, consecutive years with early snow accumulation and ablation may also impact water resources (Jefferson et al., 2008). Current flood operations are guided by static rule curves that require reservoir drawdowns during fall months and neglect antecedent moisture conditions beyond the current season (Willis et al., 2011). The combination of required drawdowns and the potential for multiyear snow drought is a widespread threat to water availability from managed reservoirs.

Snowpack variability also affects ecological processes. For example, snow is important for threatened wildlife, such as wolverine (Copeland et al., 2010), and vegetation dynamics, such as timing of forest greenness (Trujillo et al., 2012). Earlier snow melt timing advances peak soil moisture timing (Harpold & Molotch, 2015) and flowering plant phenology (Dunne et al., 2003), increases vegetation water stress (Harpold et al., 2015), and is associated with increased wildfire activity (Westerling, 2016). While the importance of interannual variability and consecutive years with early snowmelt timing has not been formally established in this context, they may exacerbate stress on vegetation or affect plant community composition and productivity.

Previous studies have examined projected changes in interannual variability of temperature, precipitation, and snowpack across portions of the western United States. For example, in the Columbia River Basin, interannual temperature variability is projected to increase during summer and decrease in winter (Rupp et al., 2016). Interannual precipitation variability in the western United States is projected to increase, especially toward the end of the 21st century (Berg & Hall, 2015; Swain et al., 2018). Snowfall accumulation variability is projected to decrease in warmer-maritime regions and increase in colder continental regions (Lute et al., 2015). However, spatially explicit assessments of changes in the interannual variability of snowpack magnitude and timing are limited. These changes in snowpack variability may vary spatially in both direction and magnitude over relatively fine scales.

In this study, we assess projected changes in interannual variability of snowpack magnitude and timing, measured as annual maximum snow water equivalent (SWE_{max}) and date of SWE_{max} (DMS), across the western United States. These variables are selected to characterize the total amount of snow available to contribute to spring-summer runoff (SWE_{max}) and the timing of the snow accumulation season (DMS). We also assess the frequency of consecutive years with very early or low SWE_{max} occurring before or below the historical 25th percentile. Finally, we conduct a spatially explicit assessment of the frequency with which DMS occurred in specific months. This study is the first to assess how the magnitude and direction of change in variability are expected to vary spatially and differ between SWE_{max} and DMS across the western United States. These findings provide important information for improving assessments of climate change impacts on water resources for socioeconomic, ecological, and coupled social-ecological systems.

2. Methods

Daily SWE data for the western United States were obtained from the Variable Infiltration Capacity (VIC) model (Liang et al., 1994) forced with downscaled climate model outputs. Ten global climate models (GCMs) from the Fifth Climate Model Intercomparison Project (CMIP5; Taylor et al., 2011) were selected based on their ability to credibly simulate temperature and precipitation patterns and variability across the northwestern United States (Abatzoglou & Rupp, 2017; Rupp et al., 2013). Many of these models also performed well in California (Pierce et al., 2018). While historical performance may not predict future accuracy, culling of models is often used to guide impact-based modeling (e.g., Vano et al., 2015). Projected changes in seasonal temperature and precipitation for the subset of 10 models were largely consistent with a broader sample of GCM outputs for the region.

Data from each GCM was acquired for historical (1950–2005) and high-emissions representative concentration pathway (RCP) 8.5 (2006–2099) climate forcings. Daily GCM outputs were statistically downscaled to (1/16th)° resolution using multivariate adaptive constructed analogs (Abatzoglou & Brown, 2012) with the training data set of Livneh et al. (2013) and used to drive VIC. Comparisons of VIC simulations with observed SWE from the SNOTEL network showed good agreement, particularly with respect to interannual variability (Gergel et al., 2017) and have been widely used in hydroclimate research (e.g., Li et al., 2017). Study area maps are provided in the supporting information (Figures S1 and S2).

For each GCM, water year, and grid cell, annual SWE_{max} and DMS were calculated from daily SWE for the water year beginning on 1 October for historical (1970–1999) and future (2050–2079) periods. When multiple days had the same value of SWE_{max}, the last occurrence was recorded as DMS. The data were subset to grid cells where historical mean SWE_{max} was greater than 100 mm; all subsequent calculations were conducted using this spatial domain. The interquartile range (IQR; 75th minus 25th percentile) of SWE_{max} and DMS was calculated over the 30-year periods for the historical and future time periods for each GCM and grid cell. Mean values of SWE_{max} and DMS are presented in the supporting information (Figures S3–S5).

We calculated changes in the frequency of consecutive low SWE snow drought, defined as years for which both the current and antecedent year had SWE_{max} below the historic 25th percentile. Similarly, we calculated changes in the frequency of consecutive early SWE snow drought, defined as multiple years with DMS before the historic 25th percentile. In cases where three consecutive years had SWE_{max} below the first quartile, two years would be tallied. Sensitivity analyses with 4-year durations were conducted, though we urge caution in interpreting GCM results pertaining to the ability of GCMs to capture lower-frequency climate variability (Abatzoglou & Rupp, 2017).

We used a bootstrap approach to test statistical significance of changes in variability. For each GCM and grid cell, we resampled 30 years with replacement 100 times from the historical model years 1970-1999 and calculated variability metrics for each sample. Differences were deemed significant where the variability calculated for model years 2050–2079 fell outside of the historical 5th–95th percentiles. As GCM variability has been cited as a key source of uncertainty for early-century to midcentury regional climate projections (e.g., Chegwidden et al., 2019; Chen et al., 2011; Hawkins & Sutton, 2011), we consider changes to be robust when significant changes in the same direction are observed in at least five of 10 GCMs. Results are also presented as supporting information in an interactive tool at https://snowvariability.nkn.uidaho.edu/.

3. Results and Discussion

3.1. SWE_{max} Variability

Historical SWE_{max} IQR is largest in high elevation, cold regions of the Sierra Nevada and Cascades, and lower across the colder interior mountains. Lower elevations throughout the study area exhibit lower IQR due to lower upper quartile values of SWE_{max} (Figure 1a). Changes in SWE_{max} IQR from historical to future periods show distinct spatial patterns (Figure 1b). In lower elevations of maritime mountains, SWE_{max} IQR decreases due to greater declines in the upper versus bottom quartile of SWE_{max} distributions, suggesting that there will be fewer years with what would historically be considered an above average snowpack. In higher elevations of the Sierra Nevada, Cascades, Northern Rockies, and Idaho Batholith SWE_{max} IQR increases. In the southern Rockies, both quartiles decreased (Figure S7), such that SWE_{max} IQR was relatively unchanged. Across the entire domain, the largest decreases in SWE_{max} IQR occur at sites where historical average winter (November–March) temperatures are greater than 0 °C (Figure S7) and SWE_{max} is highly sensitive to warming. At colder sites (historical winter temperature < -3 °C), changes in SWE_{max} IQR are not well explained by temperature. Historical winter precipitation and changes in both winter precipitation and temperature IQR were generally not strongly linked to changes in SWE_{max} IQR (Figures S8–S11).

At least 5 out of 10 GCMs simulate significant decreases in SWE_{max} IQR for 21.8% of grid cells, while 1.0 % of grid cells meet this criterion for increases (Figures S13 and S14). Sites with significant decreases in SWE_{max}

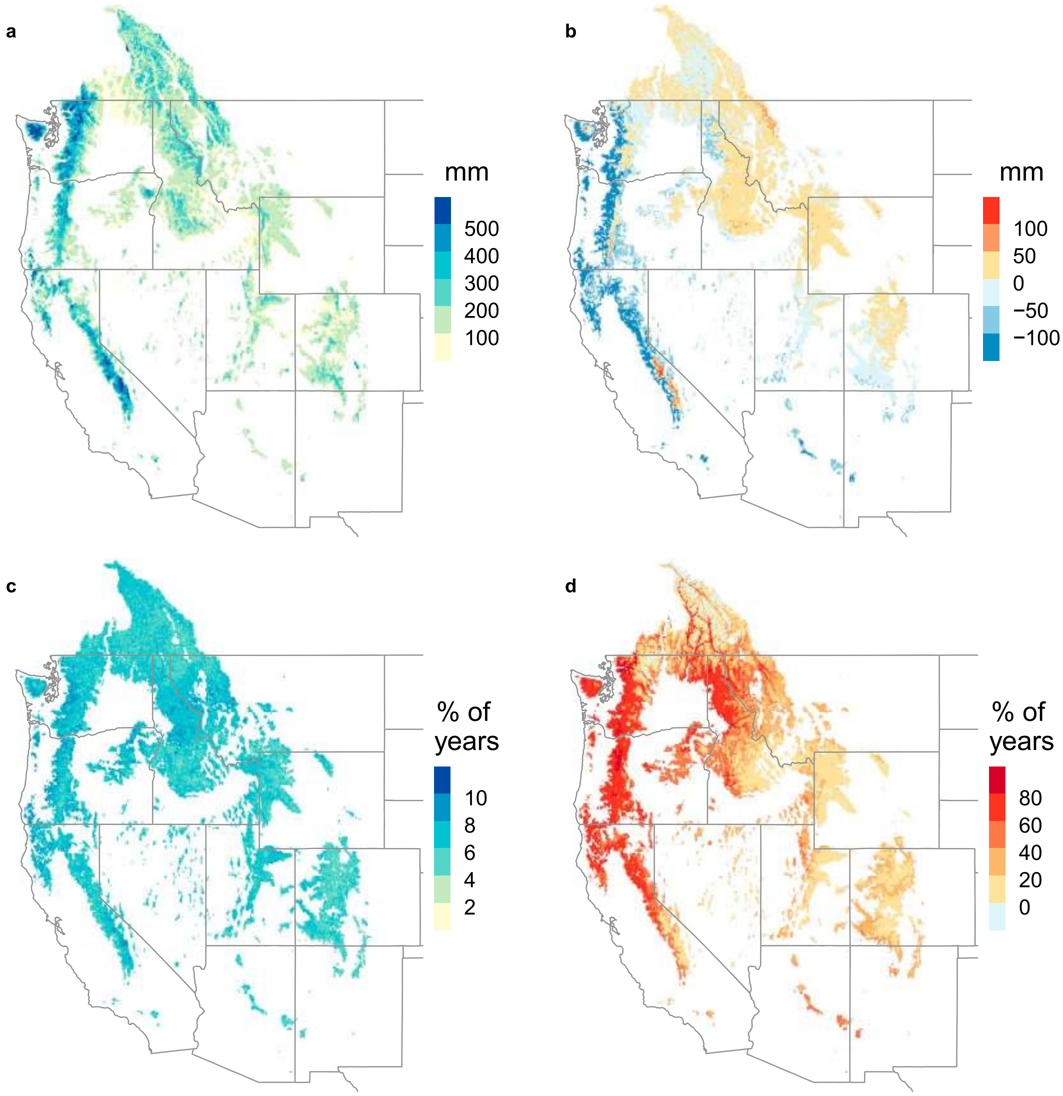

Figure 1. (a) Historical and (b) change in SWE_{max} IQR. (c) Historical and (d) change in percent of water years classified as 2-year consecutive low SWE_{max} snow droughts. SWE_{max} = annual maximum snow water equivalent; IQR = interquartile range.

IQR are predominantly in warmer regions that are likely to experience a transition toward a greater fraction of precipitation falling as rain, rather than snow (Klos et al., 2014). 76.7% (4.4%) of pixels show a robust increase (decrease) in consecutive snow droughts.

Historically, the frequency of consecutive low SWE years showed minimal spatial variability with an average of 6.6% of water years identified as part of a 2-year or longer snow drought (Figure 1c). In 2050–2079, an average of 42.2% of water years classify as consecutive snow droughts. These changes are greatest in maritime regions and across the large area that comprises the lower elevations of the northern Rockies (Figure 1d). Spatial patterns of change in consecutive low SWE years are broadly similar to percentage changes in mean SWE_{max} (Figure S5). The average frequency of a 4-year consecutive low snow drought increased from 0.26% of water years to 25.0%.

To illustrate the spatially complex nature of changes in variability, SWE_{max} IQR is depicted for three grid cells along a transect in the Sierra Nevada for a single GCM (Figure 2; other GCMs in Figures S16 and S17). Distributions of annual SWE_{max} for the historical and mid-21st century cases reveal distinctly different patterns of change across the transect. At the low- and midelevation pixels, which were historically near the winter 0 °C isotherm, zero or near-zero SWE_{max} values become increasingly common in the future, and both

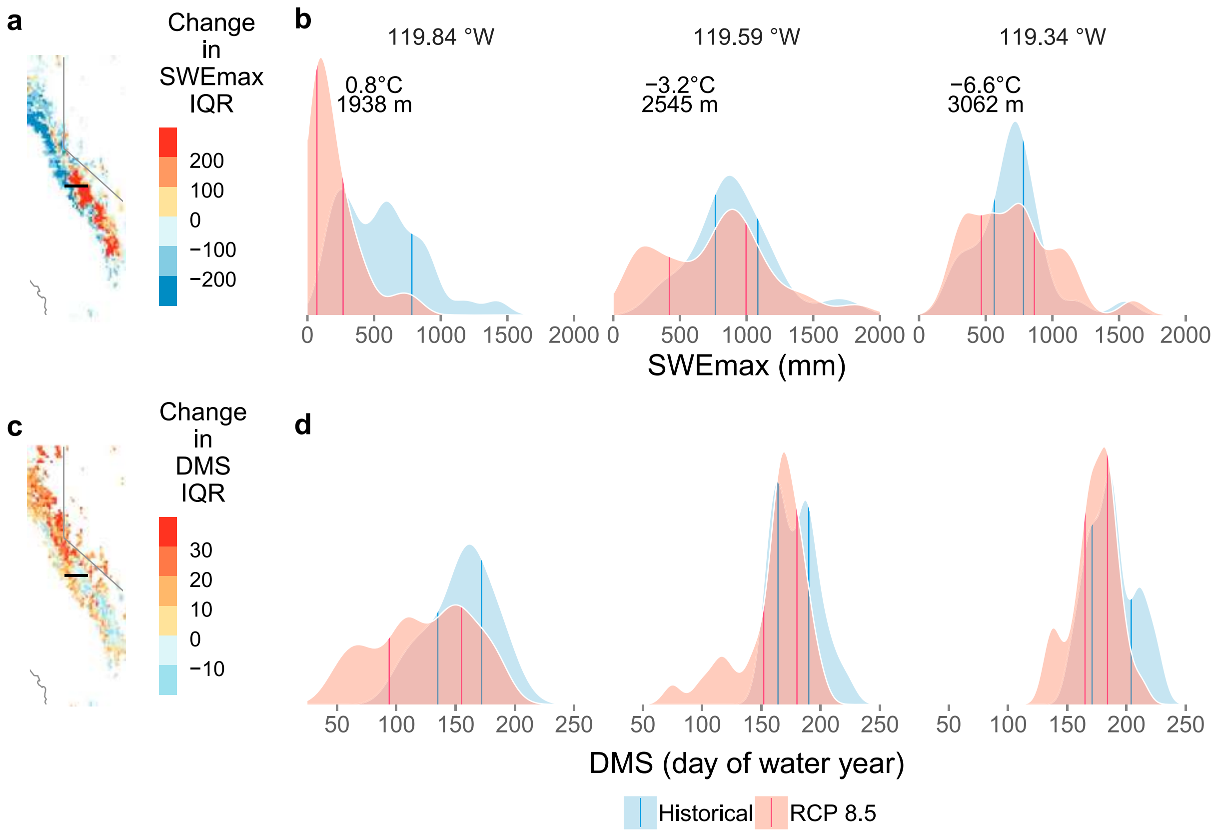

Figure 2. (a, c) Maps of changes in SWE_{max} and DMS IQR for CNRM-CM5 with transects marked at 38.0°N (Figure S15 for area map). (b, d) Distributions of (b) SWE_{max} and (d) DMS in CNRM-CM5 for three points on the transect marked in (a) and (c). Vertical lines indicate first and third quartiles in the historical and mid-21st century cases. Historical average winter temperature and elevation are noted. SWE_{max} = annual maximum snow water equivalent; IQR = interquartile range; DMS = date of SWE_{max}.

the upper and lower quartile values decrease (Figure 2b). At the low elevation pixel, the upper quartile decreases much more than the lower quartile, decreasing the SWE_{max} IQR by over 60%. At the midelevation pixel, the lower quartile decreases more than the upper, doubling SWE_{max} IQR. Finally, at the highest elevation pixel, the upper quartile increases, likely due to increasing winter precipitation (Rupp et al., 2017), and the lower quartile decreases, likely due to warmer years with low SWE_{max}, producing a 130% increase in SWE_{max} IQR.

These findings suggest that SWE_{max} IQR decreases and consecutive low SWE years increase in areas that are near the historical 0 °C isotherm, where warming causes a shift from snow to rain (Klos et al., 2014), primarily due to the loss of years with exceptionally deep snowpack. This is in agreement with Lute et al. (2015), who found a maritime-continental gradient of changes in SWE_{max} standard deviation, with increases in colder continental inland ranges and decreases in warmer maritime regions. The continental-scale patterns of historical SWE_{max} IQR and large decreases in SWE_{max} IQR in maritime regions are likely due to the contribution of snowfall intensity and extreme events to interannual variability (Lute & Abatzoglou, 2014). In maritime regions, larger SWE_{max} years depend on a few large events (Guan et al., 2010), which are susceptible to warming and precipitation phase shifts from snow to rain (Lute et al., 2015) and increased winter ablation (Kapnick & Hall, 2012). The warming-induced loss of a few large snowfall events in years that would otherwise have large SWE_{max} values would reduce SWE_{max}, producing a large decline in IQR.

3.2. DMS variability

Historically, DMS IQR was largest at lower elevations in the Sierra Nevada and Cascades and lower in the colder Rocky Mountains (Figure 3a). This pattern illustrates that peak snowpack timing was historically most variable in warmer regions with high interannual precipitation variability and relatively intermittent

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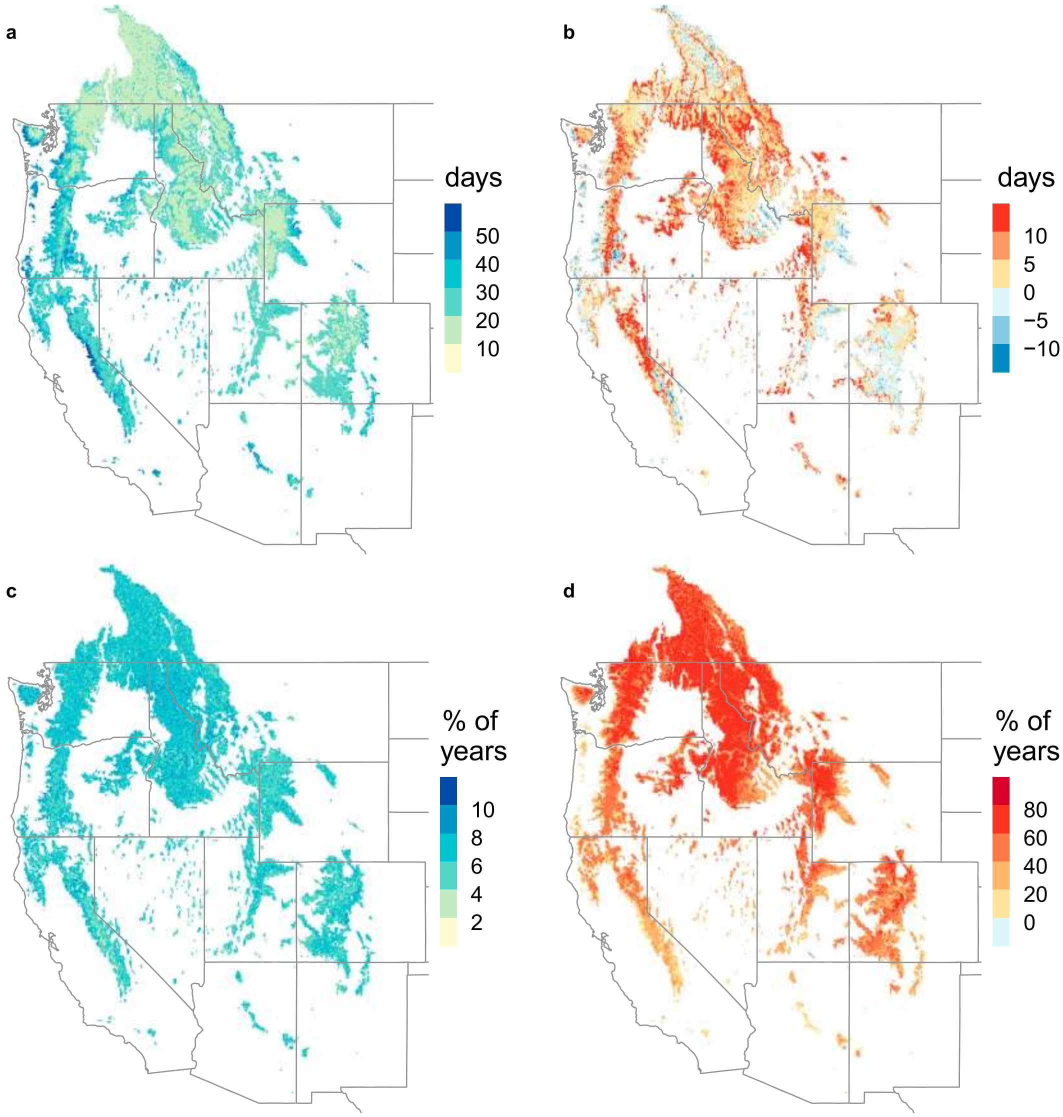

Figure 3. (a) Historical and (b) change in DMS IQR. (c) Historical and (d) change in frequency of consecutive early SWE years. DMS = date of SWE_{max}; SWE = snow water equivalent; IQR = interquartile range.

snowpack. Conversely, changes in DMS IQR display complex spatial patterns (Figure 3b) that are not well explained by historical climate or changes in climatic variability (Figures S8–S11). DMS IQR generally decreases in the highest elevation, coldest regions and increases in warmer areas, though there are some exceptions to this pattern, such as the foothills of the Oregon Cascades. More areas exhibit significant increases in DMS IQR that are robust across GCMs (24.8% of pixels) than decreases (0.6%; Figure S13).

The complex spatial patterns of change in DMS variability is illustrated through inspection of grid cells along a transect (Figure 2d). In the lowest elevation Sierra Nevada pixel, DMS was historically quite variable, but the earliest quartile advances more than the latest, so DMS IQR increases from 34 to 57 days in the future case. In the midelevation pixel, the first and third quartiles change by the same amount, and variability is unchanged. At the highest elevation, the latest quartile of years changes much more than the earliest quartile, and DMS IQR decreases from 31 to 19 days.

The increase in DMS IQR in warmer regions is likely indicative of sites in the snow-to-rain transition zone that historically had relatively low DMS IQR. As temperatures warm and snowpack declines, DMS becomes increasingly dependent on the synchrony of precipitation events and subfreezing temperatures, and thus more variable. For example, in the Sierra Nevada and Cascades, a few large storms deliver a large fraction

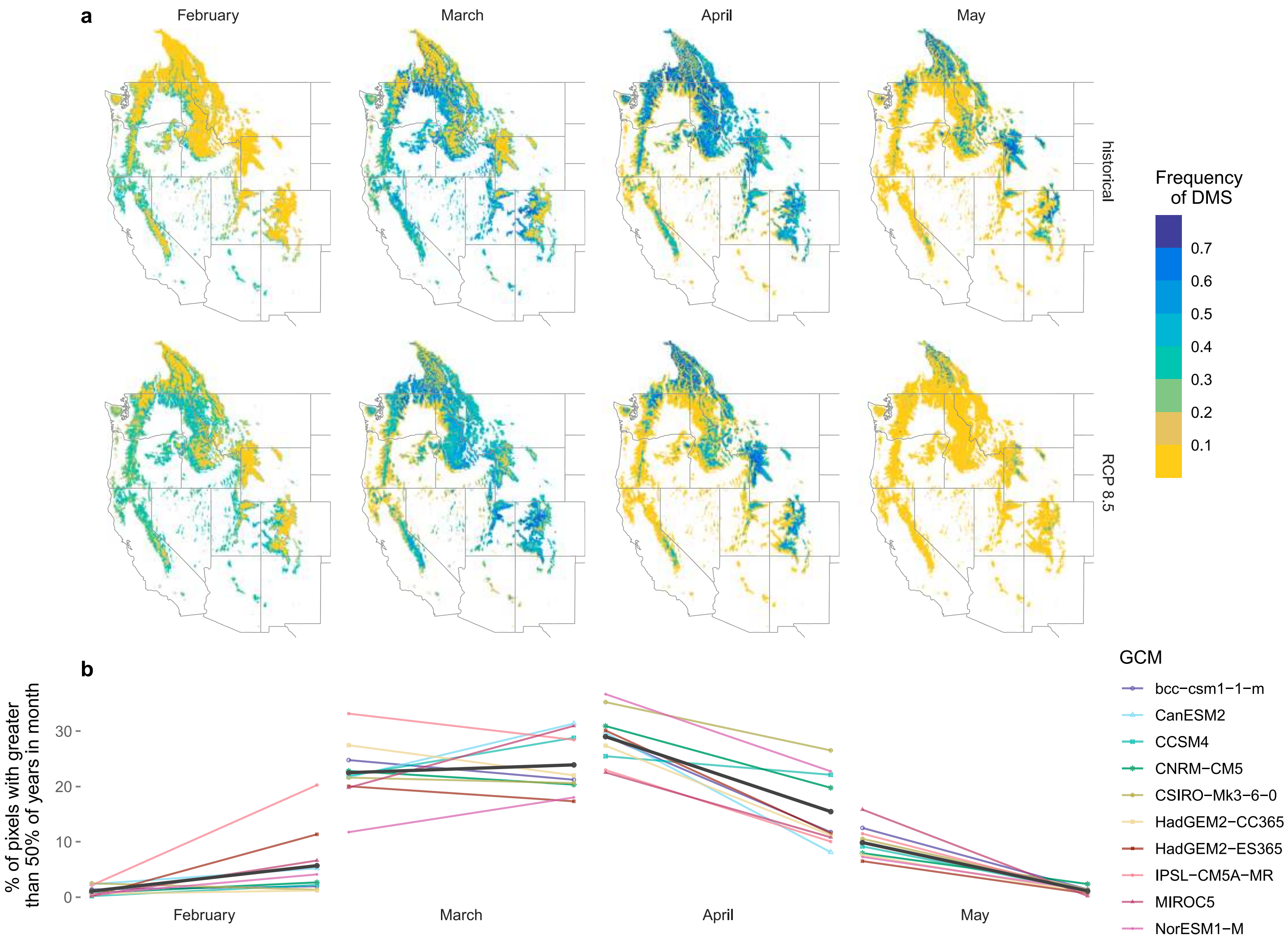

Figure 4. (a) Historical and mid-21st century frequency of date of peak SWE occurring in each month. (b) Change in percent of pixels from historical (left) to mid-21st century (right) for which DMS occurs in a given month the majority of the time, with 10-GCM mean in black. SWE = snow water equivalent; global; GCM = global climate model; DMS = date of SWE_{max}.

of the annual snowfall (Lute & Abatzoglou, 2014), which may be of heightened importance in a warmer climate with fewer days conducive to snowfall (e.g., Lute et al., 2015). Late DMS years can be heavily affected when one early winter storm produces rain, rather than snow. To the extent that DMS is related to runoff timing, increasing variability suggests increased runoff timing variability, though these impacts will be mediated by post-DMS ablation rates and runoff generation processes, which may in turn be affected by climate change (e.g., Barnhart et al., 2016; Musselman et al., 2017).

Historically, an average of 6.4% of water years were consecutive early SWE years; this number increases to 56.7% in the mid-21st century case. GCM agreement was high, with 96.9% of grid cells meeting our criteria for robust increase in consecutive early SWE years. As with SWE_{max}, the historical frequency of consecutive early DMS years does not show obvious spatial patterns (Figure 3c). Consecutive early SWE years increase across the domain, with a pattern of change that is similar to change in mean DMS (Figure S4), with greatest changes in the northern Rockies and Cascades, but without the maritime-to-continental climate gradient evident for changes in SWE_{max}. For 4-year durations, the average frequency of consecutive early DMS years increases from 0.27% to 38.0%.

A frequency analysis of the historical and potential future timing of DMS summarizes this variability (Figure 4). We define "reliable DMS" as cases where a grid cell has at least 50% of DMS values in a given month. April was the predominant month in which SWE_{max} occurred historically (29.0% of grid cells had reliable April DMS). March DMS was more common at lower elevations, and May was relatively common at higher elevations, particularly in the continental interior. In 2050–2079, April is no longer the most common month in which peak SWE occurs, with only 15.5% of grid cells having reliable April DMS. Pixels with reliable DMS in May decrease from 9.9 to 1.2% of grid cells. Instead, peak SWE values in March and February become increasingly common. These findings are broadly consistent with existing literature showing that DMS has shifted earlier and is projected to continue to do so in future climates (Kapnick & Hall, 2010; Montoya et al., 2014), though here we add more spatially explicit and detailed projections. Moreover, these changes reflect increasing variability of DMS, as the total percentage of pixels that had no months with reliable DMS increased from 37.1 to 51.1%.

Model agreement on significant changes in SWE_{max} and DMS IQR varies regionally. On average, model agreement on changes in SWE_{max} and DMS IQR is lower than model agreement on changes in means (Figure S13). Warming is a robust feature of modeled future climates, while changes in precipitation and temperature variability exhibit greater uncertainty and model disagreement (Rupp et al., 2016, 2017). Snowpack variability may be affected by warming, changes in precipitation magnitude, and spatiotemporal variability of temperature and precipitation, as well as other contributors to the snowcover energy balance, such as shortwave radiation (Musselman et al., 2017; Painter et al., 2017) and atmospheric humidity (Harpold & Brooks, 2018). Different snow models may affect results but have previously been identified as a relatively small source of uncertainty (Chen et al., 2011). Further work may be needed to assess the robustness of these results given the multiple sources of uncertainty, including climate forcing due to intermodel, interscenario, and internal variability (Hawkins & Sutton, 2011), choice of downscaling approach and reference observational data (Alder & Hostetler, 2018), and choice of hydrologic model. To the extent that GCMs agree on changes in snowpack variability, we propose that these changes are likely incurred due to warming, but future work should quantitatively assess physical mechanisms for changes in snowpack variability.

4. Implications and Conclusions

Interannual variability of SWE_{max} in the western United States is projected to change, with large decreases in IQR for regions transitioning from snow- to rain-dominated climates, particularly in maritime regions, and smaller changes in cooler continental climates. In contrast, DMS may become more variable across much of the western United States. Spatial patterns of the magnitude and direction of these trends are critical for understanding their impacts. Here, we discuss several potential implications of these findings.

For water resources operations, regions with increases in interannual variability of runoff volume and timing that have large engineered or natural storage may be more resilient to changes than those with less storage, particularly when storage exceeds the average annual discharge (Gaupp et al., 2015; Langbein, 1959). The impacts of snowpack magnitude and timing variability on water resources also depend on the combined effects of snow and rain on runoff, particularly as previously snowmelt-dominated systems experience increasing contributions from rainfall (e.g., Knowles et al., 2006; Kormos et al., 2016). Changing snowpack variability will likely be very different from changing precipitation variability, which is generally projected to increase (e.g., Konapala et al., 2017; Pendergrass et al., 2017; Swain et al., 2018), and the combinations of these changes will determine changes in water resources. The increased frequency of consecutive low SWE years will also affect water resources, requiring improved early drought detection methods (AghaKouchak et al., 2015) and optimization of reservoir operation rule curves to account for antecedent storage (Anderson et al., 2008; Ralph et al., 2014; Willis et al., 2011) as the natural snowpack storage reservoir is depleted.

Recreational activities, such as ski resort operations, which depend on a minimum amount and relatively early snowpack accumulation as well as reliability of snow conditions coinciding with peak visitation periods (Scott et al., 2008), will likely be affected by altered interannual variability. Our results suggest that low snowpack years will be more common, with reduced interannual variability and that the frequency of consecutive low SWE_{max} years will increase for ski resorts at lower elevations where precipitation will increasingly fall as rain rather than snow. Similar findings apply for ecosystem functions that are influenced by interannual snowpack variability. For example, deep snowpack facilitates subalpine seedling establishment (Andrus et al., 2018). Reduced variability of SWE_{max} and the loss of high SWE_{max} years could limit seedling establishment and alter successional dynamics. High snowpack years also limit early season fire activity in many mountainous regions of the West (Abatzoglou & Kolden, 2013; Westerling, 2016); loss of these years could enable more consistent early onset of fire activity in flammability-limited regions, barring increased spring and early-summer rainfall.

While studies of the importance of average snowpack conditions for water resources and ecosystems abound, the impacts of changing variability on these systems are less well established. Our results suggest that snowpack variability will be substantially altered in the future climates considered here, with robust increases in the frequency of recurrent snow drought and reduced interannual variability of annual SWE_{max}. To the extent that changes in snowpack variability affect water resources and ecosystem function, climate change impact studies and adaptation planning efforts should account for future changes in snowpack variability.

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