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Higher snowfall intensity is associated with reduced impacts of warming upon winter snow ablation

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Key Points:

- Winter snowfall intensity is associated with reduced accumulation season ablation, particularly at warmer winter temperatures.
- Projected changes in snowfall intensity may exacerbate ablation in maritime western U.S. mountains and buffer losses in interior ranges.
- As temperatures warm, a larger area will experience conditions in which snowpack ablation is sensitive to snowfall intensity.

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Abstract

Warming temperatures are altering winter snowpack accumulation and ablation. Physically-based snowpack simulations have indicated that increasing precipitation intensity may buffer the impacts of warming on annual maximum snow water equivalents. Here, we assess this relationship using an observational dataset from the western U.S. and show that greater snowfall intensity is associated with reduced accumulation season ablation, particularly in warmer conditions. We also use outputs from a hydrological model to evaluate the effect of snowfall intensity on ablation in future climate scenarios. Snowfall intensity is projected to increase in the continental interior, which could reduce the average effects of warming on accumulation season ablation by as much as 6.3%, and decrease in maritime climates, increasing the effects of warming on ablation by up to 6.0%. These results indicate the importance of accurately modeling changing snowfall intensity and considering snowfall intensity in climate change impact assessments of snow-dependent ecosystems and water resources.

Plain Language Summary

The warming temperatures associated with climate change are impacting mountain snowpack, with major consequences for water resources. We assess the potential for snowfall intensity to mediate the effects of warming on mid-winter snowmelt, finding that higher snowfall intensity is associated with reduced melt during the snow accumulation season. Our findings suggest that in the western United States, increased snowfall intensity in the continental interior will likely reduce the effects of warming on winter snowmelt, while decreased snowfall intensity in maritime regions will increase the effects of warming on winter melt. These findings underscore the importance of accurately capturing changes in precipitation intensity in climate change projections.

1 Introduction

Two major features associated with anthropogenic climate change in the western United States (U.S.) are decreasing snowpack (Barnett et al., 2008) and increasing precipitation intensity (Giorgi et al., 2011; Min et al., 2011; Seneviratne et al., 2012). In the western U.S., warming temperatures have already resulted in large-scale declines in spring snowpack (Hamlet et al., 2005; Knowles et al., 2006; Mote et al., 2018; Pierce et al., 2008) due to both a transition from snow to rain (Klos et al., 2014) and increased ablation of winter snow. Decreases in spring snowpack are projected to continue into the 21st century (Fyfe et al., 2017; Gergel et al., 2017; Marshall et al., 2019; Rhoades et al., 2018), and runoff timing in snowmelt-dominated watersheds will continue to advance (Stewart et al., 2004). The impacts of decreases in spring snowpack and advances in melt timing include reduced water supply and increased conflict between users (Berghuijs et al., 2014; Dettinger et al., 2015), and altered soil moisture (Harpold

& Molotch, 2015; Maurer & Bowling, 2014), forest greenness (Trujillo et al., 2012), and carbon sequestration (Arnold et al., 2014) dynamics.

The increasing precipitation intensity associated with anthropogenic climate change is characterized by more frequent dry days (Polade et al., 2014), more precipitation occurring on wet days (Giorgi et al., 2011, 2014; Orlowsky & Seneviratne, 2012), and increased relative contribution of atmospheric river events to annual precipitation in the maritime western U.S. (Gershunov et al., 2019). Both observations (Alexander et al., 2006; Frich et al., 2002; Karl & Knight, 1998; Kiktev et al., 2003; Papalexiou & Montanari, 2019) and projections (Meehl et al., 2005; Min et al., 2011; Tebaldi et al., 2006) indicate increases in precipitation intensity, including in the western U.S. (Kim, 2005; Ma et al., 2020). Although most research conducted on precipitation intensity has focused on rainfall, snowfall intensity will respond differently. Both theory and climate models suggest that the most extreme snowfall events will decrease much less than mean snowfall, and in some locations may even increase (Danco et al., 2016; Lute et al., 2015; O’Gorman, 2014, 2015).

Although changes in snow accumulation are predominantly caused by a warming-induced shift from snow to rain, changes in snowpack ablation are the result of changes in the snowpack energy balance and are subject to the alteration of processes that affect net radiation and turbulent fluxes, including snow albedo (Painter et al., 2017; Skiles et al., 2018), temperature, humidity (Harpold & Brooks, 2018), and wind (Mott et al., 2018; Pohl et al., 2006). Changes in the simulated snowcover energy balance under more extreme precipitation regimes were found to reduce ablation during the snow accumulation season, thereby partially mitigating the effects of warming on annual maximum snow water equivalent (SWE) (Kumar et al., 2012). Three general reasons have previously been posited for this dynamic: first, deeper snowpacks require larger energy inputs to satisfy the cold content and initiate melt. Second, larger snowfall events contribute more negative advective energy to the snowpack than smaller events, increasing cold content. Third, in relatively intense, intermittent snowfall regimes, available energy is not optimally used for snowmelt due to the higher probability of complete melt-out early in the accumulation season. While the sensitivity of SWE ablation to snowfall intensity has been established in simulation experiments, it has not been tested with observational data, nor has the spatial distribution of these effects been assessed.

In this study, we test the empirical evidence for the effect of snowfall intensity on ablation during the snow accumulation season using observational data across the mountainous regions of the western U.S. In order to assess the importance of this effect in future climate conditions, we evaluate whether the effect is evident in spatially distributed snowpack simulations and quantify the impacts of projected changes in snowfall intensity on accumulation season ablation.

Building on previous physically-based modeling simulations of snowfall intensity impacts (Kumar et al., 2012), we use evidence from both observed and simulated data to enhance scientific understanding and confidence in our findings.

2 Methods

2.1 Historical data

Daily SWE data were obtained from the National Resources and Conservation Service (NRCS) Snow Telemetry (SNOTEL) Network and the California Department of Water Resources (DWR) snow pillow network. Quality assurance and control is conducted by the NRCS; in addition, we removed water years in which more than 10% of the data were missing and conducted additional quality control on the California snow pillow data (Text S1). We also removed observations with less than seven days between first SWE and the date of peak SWE, or with less than 100 mm peak SWE. This resulted in the use of data from 818 stations and 20298 station-years of data, with an average of 25 years of data per station (Table S1). For each site and water year, data were extracted from the first date of snow accumulation until the date of peak SWE, and snowmelt and intensity metrics were calculated on this subset.

Previous work on precipitation intensity has identified many ways to represent both intensity and extremes (Alexander et al., 2006; Frich et al., 2002); we used the simple daily intensity index, in which total precipitation is divided by the number of days on which precipitation occurred. We applied the simple daily intensity index only to SWE accumulation, rather than total precipitation ($SDII_{SWE}$). $SDII_{SWE}$ was calculated as:

$$SDII_{SWE\ i} = \frac{\sum_{w=1}^W snowfall_{wi}}{W} \quad (1)$$

where $SDII_{SWE\ i}$ is the snowfall intensity for the i^{th} water year at a site, $snowfall_{wi}$ is the liquid snow water equivalent accumulation on days where accumulation is greater than 1 mm, and W is the number of days on which snowfall occurs, from the first snowfall greater than 1 mm in a water year (1 Oct) until the date of peak SWE. Accumulation season ablation, the response variable, was calculated as peak SWE divided by the sum of snowfall liquid water equivalent that accumulated before the date of peak SWE.

SNOTEL temperature data were not used because of known inhomogeneities in the temperature record (Oyler, Dobrowski, et al., 2015). As an alternative, we used homogenized, infilled daily temperature data from TopoWx at SNOTEL stations (Oyler, Ballantyne, et al., 2015; Oyler et al.,

2016); these values are a precursor to the gridded TopoWx product. For California DWR snow pillows, we used the gridded TopoWx data from collocated grid cells. Daily $T_{\min}$ and $T_{\max}$ TopoWx values were obtained for each site over the period of record and averaged over November-March, hereafter referred to as “winter T_{avg} .” Temperatures averaged over a static calendar window may differ from temperatures during any given accumulation season, but serve as a stronger basis for site specific conditions during a given winter.

2.2 Future scenarios data

To determine the effects of snowfall intensity on accumulation season ablation under future climate scenarios, we used publicly available snowpack projections under future climate scenarios. Ten global climate models (GCMs) used in the CMIP5 (Taylor et al., 2011) were run for historical and representative concentration pathway (RCP) 8.5 conditions. These model outputs were statistically downscaled to $1/16^{\text{th}}$ degree grid cells (Abatzoglou & Brown, 2012; Livneh et al., 2013); we obtained daily average temperature from these scenarios from 1951-2099. The Variable Infiltration Capacity (VIC) model was run with these downscaled results (Liang et al., 1994). These data contain several possible sources of uncertainty, including GCM variability, choice of downscaling method and reference dataset, lapse rates (Minder et al., 2010), and choice of hydrologic model, but represent historical snowpack variability well at SNOTEL sites (Gergel et al., 2017) and have been used extensively in hydrological research (e.g., Li et al., 2017; Marshall et al., 2019). Variability between GCMs is likely the largest source of uncertainty (Chegwidden et al., 2019).

We obtained daily SWE data for each grid cell containing a SNOTEL site from the VIC outputs. As with the SNOTEL data, T_{avg} was averaged over November-March, and SDII_{SWE} and accumulation season ablation were calculated for each water year. One important difference is that due to SNOTEL data resolution, the effective threshold for SDII_{SWE} calculations was 2.54 mm for SNOTEL, while a 1 mm threshold was used for VIC. When SDII_{SWE} was calculated with a 2.54 mm threshold with the VIC data, SDII_{SWE} values were highly correlated (correlation coefficient = 0.91) with those calculated with the 1 mm threshold, suggesting that this decision had minimal impact on our results.

2.3 Statistical models

We used a generalized additive mixed modeling approach to test the relationship between SDII_{SWE} and winter season ablation, and its sensitivity to winter T_{avg} (Wood, 2017). This method was selected to account for spatial and temporal correlation structures within the data. The model for water year j at station i was constructed as:

$$g(A_{i,j}) = \alpha + \beta_j + f_1(wy_j, N_i, E_i) + f_2(elev_j, region_j) + f_3(SDII_{i,j}, T_{avg\ i,j}) + \varepsilon_{i,j},$$

$$\beta_j \sim N(0, \psi_\theta), \varepsilon \sim N(0, \Delta\sigma^2) \quad (2)$$

where g indicates a beta family of model with a logit link, A is accumulation season ablation, α is an intercept, β_j is a site-specific random effect, and f_1 , f_2 , and f_3 are tensor product smooths with cubic regression bases. In addition to winter T_{avg} and $SDII_{SWE}$, the model includes northing (N) and easting (E) using the Albers projection, elevation (elev), and snow region (as defined in Serreze, 1999). Each observation was weighted by annual maximum SWE in order to reduce the influence of very low snow years. A test of the model without the weights included suggested that weighting the model did not alter our overall conclusions. The model was developed iteratively to ensure that relevant model assumptions were met (Figures S1-S3).

Tensor product smooths are a basis function appropriate for multivariate smooths with different units; similar approaches have been applied previously (Augustin et al., 2009, 2013; Montoya et al., 2014). The beta distribution is conceptually appropriate for this dataset but requires values to be inside the interval (0, 1). We reset zero values to be equal to half the smallest non-zero value; tests of this approach with zero values set to one-tenth the smallest non-zero value indicated that this threshold did not impact our conclusions. The site random effect was included to account for site-specific effects, such as topographic or vegetation effects, and f_1 and f_2 were included in order to account for spatiotemporally varying factors that were not otherwise included in the model, while f_3 tests the climatic variables of interest. The effect of SDII_{SWE} on accumulation season ablation was determined via comparison of R^2 , Akaike's Information Criterion (AIC), and deviance explained with a model in which the SDII_{SWE} term was removed.

To test for possible confounding effects of omitted physically meaningful variables, we also tested models that included number of snowfall days, quantity of precipitation that fell in rain-on-snow events, specific humidity from the date of first snowfall to peak SWE, and average downward shortwave radiation over the same period. Specific humidity (q) and shortwave radiation were obtained from the gridMET dataset (Abatzoglou, 2013), using grid cells collocated with SNOTEL stations. These variables were added as independent cubic splines.

2.4 Estimated effect size of changes in SDII_{SWE}

To assess the impacts of snowfall intensity on accumulation season ablation under future climates, Equation 2 was fitted with the VIC data for each of the 10 GCMs, randomly sampling one in every four water years for computational efficiency. We also estimated the impact of projected trends in SDII_{SWE} on changes in ablation. For each site and GCM, we calculated the 30-year average value of SDII_{SWE} in historical (1970-1999) and late-21st century (2070-2099) climates, and difference between these two climatologies. We subtracted this difference from the late 21st century data in order to build a future time series with the difference in SDII_{SWE} removed. Then, accumulation season ablation was modeled using the model fitted in Equation 2 with both the observed and detrended SDII_{SWE} time series. Accumulation season ablation calculated with the detrended SDII_{SWE} was subtracted from that calculated with SDII_{SWE} from the original VIC time series for the years 2070-2099 in order to estimate the effects of projected changes in SDII_{SWE} on accumulation season ablation in the late 21st century. These values were averaged over GCMs and water years.

3 Results

3.1 Historical snowfall intensity impacts on accumulation season ablation

Figure 1 shows the spatial distribution of the snowpack variables used in our statistical model. Mean accumulation season ablation is generally lowest in the continental western U.S. and higher in the lower elevations of the Cascades as well as mountains of the southwest. $SDII_{SWE}$ is generally greater in maritime regions and lower in continental regions, likely due to the large contributions made by atmospheric rivers to overall winter snow accumulation in maritime regions (Lute & Abatzoglou, 2014).

Results of statistical modeling with in situ data show that greater $SDII_{SWE}$ is associated with reduced accumulation season ablation, particularly in regions where winter T_{avg} exceeds 0 °C (Figure 2). For example, at the site with the median random effect for the average water year, when winter T_{avg} is 3 °C and $SDII_{SWE}$ is 20 mm/day, the model predicts that 22.5% ($\pm 2.3\%$ s.e.) of accumulated SWE would ablate before the date of peak SWE. If $SDII_{SWE}$ is reduced to 8 mm/day, the model estimates accumulation season ablation of 33.6% ($\pm 3.0\%$); this suggests an average difference of 11.1%. In contrast, when winter T_{avg} is -3 °C, the same calculation suggests only a 3.4% difference in ablation. Comparisons with a null model support the hypothesis that including $SDII_{SWE}$ in a model of accumulation season ablation improves the model, though these differences are relatively small (Table S2). The model indicates some non-monotonic effect of $SDII_{SWE}$ at high snowfall intensities and warm temperatures; however, in these cases, the date of peak SWE is relatively stochastic and dependent on individual storms, which yields highly variable values of accumulation season ablation.

Models including other potential important variables (q , shortwave radiation, and number of snowfall days) indicated that inclusion of these variables slightly affected the quantitative estimates of the $SDII_{SWE}$ effect, but did not affect our overall conclusions (Figure S4; Table S1; Text S3); therefore results are presented with these variables omitted. When q was included, AIC was lower for the model excluding $SDII_{SWE}$, suggesting possible overfitting when $SDII_{SWE}$ was included. However, q and winter T_{avg} were very highly correlated (Pearson's $r = 0.75$), complicating the interpretation of results with both these terms included. These should be considered as a possible source of uncertainty when interpreting the effect size of our results.

The relatively small differences in fit statistics between the models including and excluding $SDII_{SWE}$ may be because snowfall intensity has the largest effects at temperature ranges that comprise a relatively small portion of the data. A model limited to observations for which winter

T_{avg} was greater than 0 °C showed stronger evidence for the full model than the case with all observations included (Table S2; Figure S5). In contrast with model results from the full dataset, there is some evidence for non-monotonic effects of SDII_{SWE} in the model with warmer conditions, though these effects occurred only in regions with very warm winter temperatures, low SDII_{SWE} , and very low peak SWE. These findings indicate that snowfall intensity is particularly important in warm conditions, between winter T_{avg} values of ~0 to +5 °C. Of the area of the western U.S. where historical mean peak SWE was at least 100 mm, 11.3% on average was historically in this winter temperature range, but 44.3% is projected to fall in this winter temperature range in the RCP 8.5 scenario by 2070-99 (Figure S6).

3.2 Snowfall intensity impacts based on simulated snowpacks

When our statistical framework was applied to modeled VIC outputs, results indicate that SDII_{SWE} is associated with reduced accumulation season ablation in all GCMs, primarily at warmer temperatures (Figure S8). Some GCM results have the same general shape as results based on measured in situ data; others suggest a non-monotonic effect of winter T_{avg} on accumulation season ablation at very warm winter T_{avg} . As with in situ data, the data in the regions contributing to non-monotonic tendencies have relatively warm winter T_{avg} (~2 to +5 °C); peak SWE at these locations is generally 4-9% of the average peak SWE of the full dataset.

Comparisons with null models also support the hypothesis that SDII_{SWE} affects accumulation season ablation for all 10 GCMs (Table S2). The results suggest a larger difference between the full and null models than did the findings with in situ data. This may be due to the fact that the VIC data include more warm data points in future climates, conditions for which SDII_{SWE} is more likely to affect accumulation season ablation.

3.3 Snowfall intensity importance in future climates

Projected changes in SDII_{SWE} exhibit distinct geographic patterns that are fairly consistent between GCMs (Figure 3; Figure S9). SDII_{SWE} is generally projected to decrease in the maritime western and southwestern mountains, where it was historically largest, and increase in the cooler interior mountain west. An important exception is the higher elevation southern Sierra Nevada, where SDII_{SWE} is projected to increase. The spatial patterns observed here are in agreement with previous findings regarding the magnitude of extreme snowfall events (Lute et al., 2015; Serreze et al., 2001), and findings that individual snowfall events are particularly important in California (Lundquist et al., 2015). The projected decreases in SDII_{SWE} in maritime regions are likely due to warming temperatures and a transition from snow to rain; as large precipitation events increasingly occur as rain, rather than snow (Gonzales et al., 2019; Minder, 2010), SDII_{SWE}

decreases. In contrast, at cooler continental sites and the highest elevation southern Sierra Nevada sites, the change in $SDII_{SWE}$ may more closely reflect changes in overall precipitation intensity, as the sites are colder and therefore less subject to transitions from snow to rain. Winter T_{avg} is projected to increase consistently, with the greatest increases in the continental interior (Figure S10). Accumulation season ablation is predominantly projected to increase, with a few sites showing decreases; these sites historically had relatively high ablation, so may have less potential for increases in ablation (Figure S11).

Figure 4 shows the average difference in estimated accumulation season ablation from 2070-2099 projected with our statistical model, using downscaled GCM outputs as compared to the same outputs with the trend in $SDII_{SWE}$ removed. Average differences in ablation with and without a trend in $SDII_{SWE}$ range from -6.3 to +6.0%. Positive values indicate that ablation was greater when the trend in $SDII_{SWE}$ predicted by the GCMs was included; negative values indicate that ablation was reduced when the trend in $SDII_{SWE}$ was included. That is, the positive values in the lower elevation Sierra Nevada and Cascades indicate that projected increases in accumulation season ablation are likely to be exacerbated by the generally decreasing trends in $SDII_{SWE}$, whereas the negative values in the Rocky Mountains and high elevation Sierra Nevada indicate that projected increases in ablation will likely be reduced by the generally increasing trends in $SDII_{SWE}$.

4 Discussion and Conclusions

Using both empirical and simulated snowpack data in historical and future climates, we found that greater average snowfall intensity is associated with reduced winter snow ablation at relatively warm winter temperatures. These effects were broadly similar between the empirical and modeled datasets, despite potential differences between the two, such as the spatial resolution of the model, lack of drifting snow, and incomplete physical representation of thermal gradients in the modeled snowpack, and potential errors in the estimated snow albedo in the modeled dataset (Essery et al., 2013).

Empirical studies based on observational data, such as this one, are subject to several limitations. Most importantly in this case, it is impossible to control for all potential omitted variables. While tests with shortwave radiation and number of snowfall days lend additional confidence to our results, tests with q included indicated potential overfitting when $SDII_{SWE}$ was included, though these results are difficult to interpret given the high correlation between q and T_{avg} . Triangulated evidence between empirical and physically-based modeling approaches may reduce these limitations, as these two approaches have differing limitations. Indeed, this study tests empirical support for the conclusions of a physically-based modeling study (Kumar et al., 2012). Further

mechanistic investigations using physically-based models could be used to further evaluate these findings by using spatially distributed approaches and testing for potential conflation with q or other variables.

Kumar et al. (2012) suggested several mechanisms by which snowfall intensity may affect accumulation season ablation. We also propose two additional mechanisms. First, snowfall intensity may alter canopy interception. If snowfall occurs in relatively few, intense storms, then the forest canopy may more often reach its maximum snow interception capacity and unload more frequently. Higher snowfall intensity would therefore be associated with reduced interception losses. This effect should be present in the VIC model, which includes forest canopy interception, but to a much lesser degree in SNOTEL data because SNOTEL sites are usually located in small forest gaps. Second, snow albedo dynamics may change with altered snowfall intensity. On average, there should be longer intervals between storm events with higher snowfall intensity; this would be associated with greater albedo decay and thus greater potential for accumulation season ablation. This mechanism would act in the opposite direction of the effects observed in this study, and should be present in both the observed SNOTEL and simulated VIC model data (Andreadis et al., 2009). This effect may be complicated by the fact that small snowfall events may not completely mask the albedo of the underlying surface (Baker et al., 1991).

The increasing importance of snowfall intensity in warmer climates suggests a need for high confidence estimates of changes in snowfall intensity and represents one example of a mechanism that produces non-stationarity between seasonally averaged climatological variables and snowpack accumulation and subsequent runoff. Moreover, snow accumulation and melt models that account for the full snowcover energy balance should reflect the effects of snowfall intensity, while simpler temperature index models may not.

Given spatially varying projections of changes in snowfall intensity in the western U.S., altered snowfall intensity may reduce the effects of warming on winter snow ablation in the colder continental ranges by up to 6.3%, and exacerbate the effect of warming in relatively warm maritime ranges by as much as 6.0%. Particularly in regions where large sectors of the economy depend on a limited supply of water, and/or where aquatic species are on the margins of viability, these differences in accumulation season ablation may be critical. These findings demonstrate the power of integrating multiple lines of evidence to enhance confidence in scientific results in a sector with important implications for snow-dependent social and ecological systems. In conjunction with other climate-induced alterations to the snow energy balance, changing snowfall intensity is an important factor to consider in projections of climate-induced changes in snowpack and water resources, as well as associated adaptation planning.

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Figure captions

Figure 1. Distribution of (a) accumulation season ablation as a percent of total SWE accumulation between the first date of snowfall and date of peak SWE and (b) snowfall accumulation intensity over the historical period from 1996-2015 shown for both in situ and VIC data. Only snow pillow sites with 20 years of data over the 1996-2015 period are included in the figure.

Figure 2. The fraction of total snowfall that ablates before the date of peak SWE modeled as a function of mean November-March temperature (T_{avg}) and snowfall intensity ($SDII_{SWE}$) using in situ observations. For variables not plotted, fitted values are estimated at the median values, and the site with the median random effect was used. Changing the factor variables alters absolute values but does not change the contour shapes (Figure S7).

Figure 3. Change in average (a) accumulation season ablation, (b) winter T_{avg} , and (c) $SDII_{SWE}$ from 1970-1999 to 2070-2099, averaged across GCMs (individual GCMs for each variable in Figures S8-10). Only sites for which at least 3 GCMs had at least 10 out of 30 water years with

greater than 100 mm peak SWE in the late 21st century scenario are mapped to avoid sites with very few water years in the future scenario. Points are filled if at least 50% of GCMs agreed on a statistically significant change (two-sided t-test $p < 0.05$).

Figure 4. Effect of changes in $SDII_{SWE}$ on future ablation rates, calculated as difference in accumulation season ablation predicted with GCM-projected $SDII_{SWE}$ versus difference-adjusted $SDII_{SWE}$. Results are averaged over 10 GCMs and water years 2070-2099 (results for individual GCMs are in Figure S12). Histogram shows the distribution of mapped values.

a

a

b

c

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