



Sensitivity of ski resorts in the western US to climate change

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Abstract. Winter recreation's vulnerability to climate change, especially to warming, is widely recognized but few studies report quantitatively on the observed effects of climate change on ski resorts, in part because consistent and available data directly from ski resorts is scarce. Instead, we use proxy data from nearby SNOTEL (snow telemetry) and snow course sites to examine sensitivity of snow depth (HS) and snow water equivalent (SWE) to temperature and precipitation at 41 select ski resorts in Washington, Idaho, Oregon, and California, during the ski season. Multiple regression on climate variables then permits statistical projections of future snow depth from projected changes in temperature and precipitation. We also use projected future SWE from a hydrology model with climate input from CMIP5 models with the RCP4.5 and RCP8.5 scenarios to evaluate future changes in snow depth at the selected ski resorts. While many resorts indeed face substantial declines in ski-season snow depth, many of those in Idaho and a few at high elevation are likely to be minimally affected. Mitigating factors include (a) projected increases in winter precipitation over the Rockies that partly offset the effects of warming; (b) low temperature sensitivity there and over high altitudes; (c) lower observed declines and temperature sensitivity for snow in winter compared with spring; and (d) many ski resorts are located in areas of high snowfall and/or span a considerable range of altitudes.

1 Introduction

Winter recreation, in particular skiing and snowboarding, are popular activities at resorts across the Pacific Northwest and California. The health of the winter recreation economy is directly related to the quality and quantity of precipitation falling as snow and the length of the snow season (Burakowski and Magnusson, 2012). While the industry is accustomed to intra-seasonal and interannual variations, the changing climate has introduced new challenges.

Declines in Northern Hemisphere snow cover since the 1960s (Robinson 1991, Brown and Robinson 2011) are also observed in nearly all regions including in the western US (Mote et al 2005, 2018) especially in spring, and are caused primarily by rising temperatures (*ibid.*, also Hamlet et al 2005, Mote 2006, Pierce et al 2008, Brown and Mote 2009, Brown and Robinson 2011, Rupp et al. 2013). Low-elevation snowpack in the Cascade mountains, including at some ski resorts, is especially “at-risk” (Nolin and Daly 2006) owing to the frequency of snowfall at temperatures near 0°C. A warming of 1°C decreases 1 April SWE in the Cascades by about 22% and has the biggest impact at elevations between 1000m and 1500m (Casola et al. 2009; Mote et al. 2008). Patterns of climate variability like ENSO affect the interannual variability of snowpack (Cayan



1996), and removing the variability associated with Pacific climate patterns leaves a clearer downward trend (Mote 2006, Stoelinga et al. 2010, Siler et al. 2018).

Continued reductions in snowpack in the western US are virtually certain (Fyfe et al. 2017, Huning and AghaKouchak 2018, Rhoades et al. 2018, Ikeda et al. 2021) owing to the influence of warming on snow accumulation and melt. Regionally-averaged decreases in snow water equivalent (SWE) depend on emissions scenario, time horizon, model resolution, and other factors, but Rhoades et al (2018) summarize several high-resolution studies with western US average SWE declining by 19% to 38% for winter (DJF) late-century RCP8.5 climate despite a 15% increase in winter precipitation, and the mountain ranges in the Pacific time zone experiencing larger losses (45-50%) than those to the east (20-33%).

An inexorably warming climate clearly threatens snow quantities and by extension the winter sports industry. Numerous studies have documented decreases in various snow quantities - maximum SWE, snow cover duration, and HS, to name a few - in different parts of the world (see Vaughan et al. 2013; also Beniston et al. 2018 and Vorkauf et al 2021 for more recent studies in Europe). In a comprehensive review, Steiger et al. (2019) summarize the global literature describing the effects of climate warming on ski resorts, including snow quantity and conditions, statistics of skier visits, visitor and operator perceptions, and adaptation actions including snowmaking. Of these topics, we focus on snow quantity both in our paper and in the summary of previous studies in this paragraph. Similar such studies date to the 1980s in Canada (Harrison et al, 1986) using a threshold snow depth (HS) of 5cm; they projected reductions by 2050 of HS of 40-100% for various ski resorts. The first European study of conventional ski resorts examined 230 ski resorts in Switzerland and projected changes in number of skiable days for +2°C and +4°C warming scenarios (Abegg 1996). Reductions were projected to be more pronounced in the eastern Alps (Abegg et al. 2007). In the northeastern US, one study described observed reductions in snow accumulation and in the duration of snow cover (Burakowski et al., 2008).

The next generation of studies, according to Steiger et al. (2019), began explicitly including snowmaking in their calculations of ski resort sensitivity, representing with growing sophistication the physical and operational realities of snowmaking, and found much more modest reductions in season length. Scott et al. (2014) applied a snowmaking model to 19 locations of past Olympic winter games and concluded that a combination of reduced HS and increased probability of minimum temperature >0°C would reduce the number of locations to 10-11 by the 2050s and 6-10 by the 2080s, depending on emissions scenario. Knowles et al. (2020) noted the prevalence of observed declines in ski season duration across ski resorts in the northern hemisphere, but also with large disparities owing to snow sensitivity to climate change and the use of snowmaking.

Very few studies have looked at the future impacts, let alone currently observed impacts, of climate change on western US ski resorts. In Utah, winter temperatures increased at statistically significant rates at all 14 ski resorts in the state over the 1980-2018 period, by amounts ranging from 2.6°C to 6.7°C for minimum temperatures which increased faster than maximum temperatures (and many times faster than the global land average); early-season conditions worsened considerably with the number of days with minimum temperatures <-5°C decreasing significantly (~10 days) at all but two ski resorts



65 (Wilkins et al., 2021). Wobus et al. (2017) estimated
 future climate change impacts on winter sports at
 247 winter recreation locations in the continental US
 using a snow model, representation of snowmaking,
 and five climate scenarios from CMIP5 models,
 finding reductions in season lengths of over 50% by
 70 2050 and in particular a large reduction in being
 open by the Christmas holiday even with snowmak-
 ing.

A poor snow season can devastate ski resorts eco-
 nomically, especially during early winter, and poor
 75 early-season conditions can have a lasting effect on
 the success of a season (e.g., Dawson and Scott,
 2013; Falk and Hagsten 2016). For the northeastern
 US at least, the period from 23 December to 3 Jan-
 uary accounts for up to 20% of the seasonal total skier

80 visits (Dawson et al. 2013). Changes to the snow season start date, early season conditions, length, amount of snowfall, qual-
 ity of snow, and mid-season melt events can all have negative economic impacts on resorts. In January 2005, for example, an
 atmospheric river event in which several days of rain, wind, and warm weather (accompanied by high dew points promoting
 rapid melt) stripped the Cascade mountains of snowpack, curtailing the ski season at some resorts; among the worst affected
 was Mt Baker (skimountaineer.com). Just 6 years earlier, in 1998-99, Mt. Baker had set a world record for 12-month snow-
 85 fall; so copious was the snowfall that the resort struggled to keep the roads, parking lots, and even ski lifts clear of the snow
 (Seattle Times 2024). In 2014-15, record winter warmth sharply limited snow accumulation below about 1600m in the Cas-
 cades and somewhat higher in the Sierras (Mote et al 2016); in 2013-14 some resorts did not open at all (New York Times
 2023). The 2023-24 season had a dismal start (New York Times, 2023) but recovered when snow finally began accumulating
 in January (Fig. 1), after the period of highest daily skier visits. In short, ski resort revenue is affected directly by skier be-
 90 havior and only indirectly by a complex set of snow conditions.

The winter sporting industry (including downhill skiing and snowmobiling) contributes over \$12.2 billion to the U.S. econ-
 omy per year, and 38 states have economically valuable winter recreation industries (Burakowski and Magnusson 2012). In
 Idaho, Oregon, and Washington, winter tourism supported approximately 5,000-6,000 jobs in 2009-10 while in California it
 supported 24,000 jobs and \$1.4billion in economic value, the second highest after Colorado (*ibid.*). The average difference in
 95 skier visits for low-snowfall years vs high-snowfall years in the decade between November 1999 and April 2010 was 5% for
 California, resulting in a loss of nearly \$100m in resort revenue; 17% for Idaho, 28% for Washington, and 31% for Oregon,
 the largest percentage difference in their study.

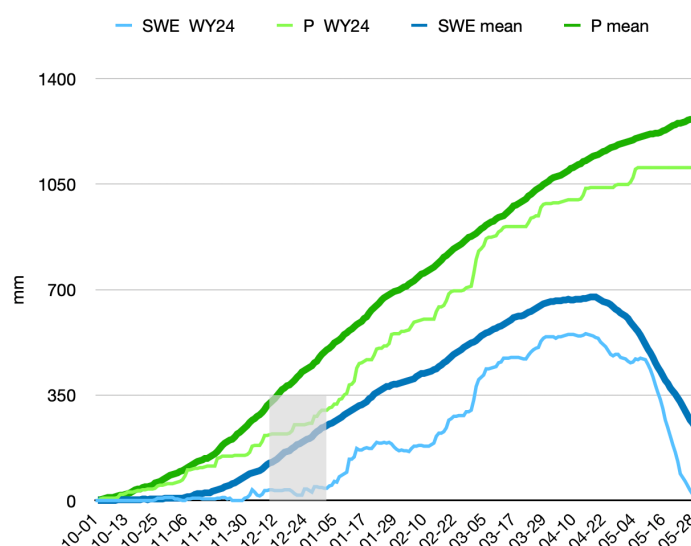


Figure 1: Long-term average (thick curves) and 2023-24 values (thin curves) of cumulative precipitation (green) and snow water equivalent (blue) at Big Red Mountain, OR (elevation 1850m). The winter holiday period is highlighted by the grey box.



The question we pose here, which has not been adequately addressed in the literature especially using observations, is: just how unfavorable is climate change for the winter sports industry in the western US? To address the question, we use a combination of past variability in snow water equivalent (SWE) and snow depth (HS) recorded at or near selected ski resorts, statistical relationships with seasonal climate, and predictions of future snow depth using two independent approaches. We focus on the states of Washington, Idaho, Oregon, and California, which include a broad range of climate and snow conditions and ski resort types. While other research has focused on the documented declines in SWE, (1) much of the focus has been on the sensitivity to temperature changes and (2) much of the focus has been on 1 April owing to data availability in the early decades, but as noted above, the demand for winter sports places more attention on early-season conditions (particularly December and January) and the quantity of relevance to winter sports is HS instead of SWE; while HS and SWE are related, their relationship changes over the season.

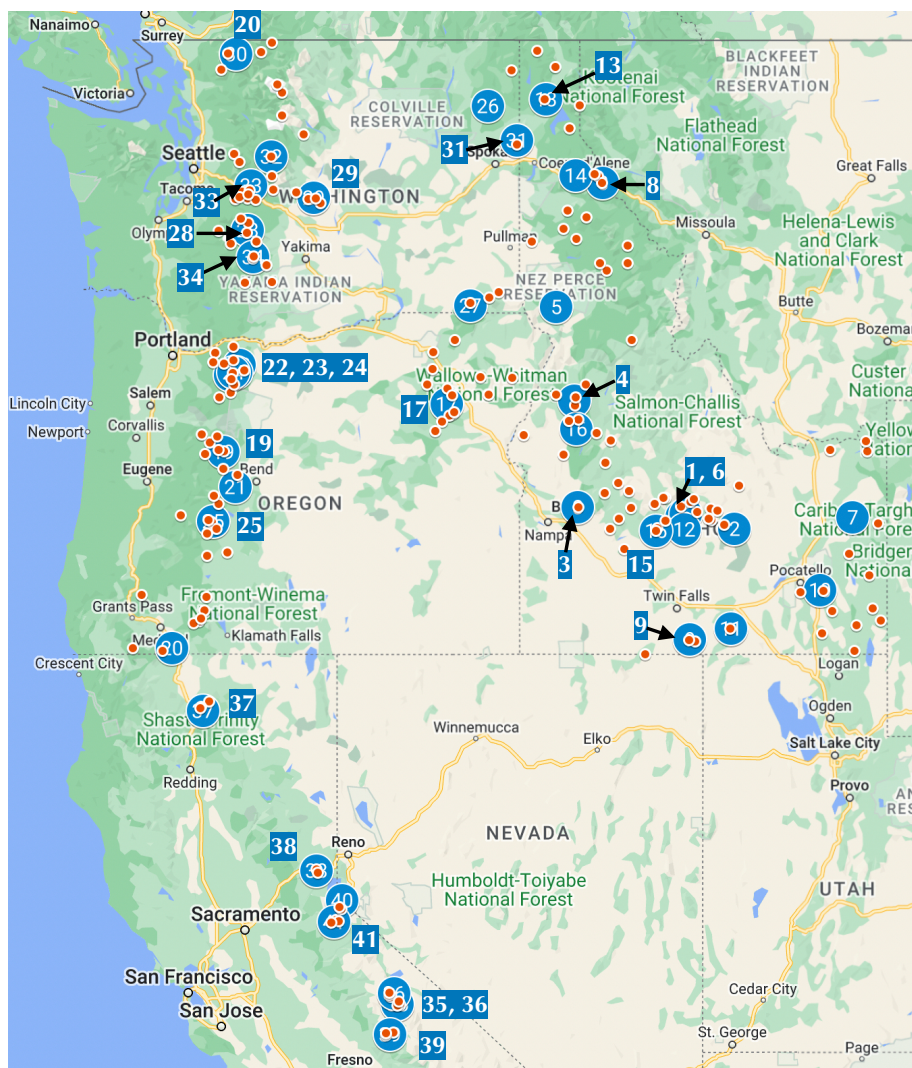


Figure 2: Ski resorts (blue circles) and SNOTEL or, for California, snow course sites (red dots). Where a ski resort number is obscured, an alternate label is provided in a blue square. Map data ©2025 Google, INEGI.

2 Data and Methods

Ski resorts typically take daily measurements of snow depth at one or more locations throughout the ski season, and post them along with daily weather observations, lift conditions, and other information on their web sites, but do not maintain



130 publicly accessible long-term records. We contacted a number of individual ski resorts but none agreed to share their private data. As a proxy, we use publicly available data from nearby sites.

We selected 41 ski resorts (Fig. 2 and Appendix A) in Washington (9), Oregon (9), Idaho (16), and California (7), that offered downhill skiing and/or snowboarding, and obtained their geographic locations from Google maps and their elevations from the Pacific Northwest Ski Areas Association (<https://pnsaa.org>) and the Ski Central website (<https://www.skicentral.com>). For California, we had to exclude two ski resorts (Big Bear and Baldy) in the San Gabriel/San Bernardino mountains that had no publicly available snow data available for the period of record. There are so many resorts in the Lake Tahoe area (11-15 depending on definitions) that we used only three of those: one north of the Tahoe basin, one in the basin, and one south of the basin. In our results, we do not explicitly indicate which resort is which. As Steiger et al. (2019) noted, translating changes in HS into ski resort viability requires assumptions about how HS translates into skier visits which includes local physical and behavioral factors, details of the altitudinal distribution of snow in the resort, availability of snowmaking at a given resort, etc., which are beyond the scope of this study. Our purpose here is to estimate the range of sensitivities to observed and projected climate change, incorporating the range of projected temperature and precipitation. A degree of anonymity concerning where the snow conditions are most sensitive reduces the likelihood that results will be taken out of context and imply that those resorts are most likely to face economic hardship.

145 For observed snow water equivalent and snow depth, we used the Natural Resources Conservation Service SNOTEL network (NRCS 2024) and the California Department of Water Resources California Data Exchange Center (CDEC 2024) since NRCS data do not cover most of California's mountains. We considered any SNOTEL sites or snow courses within 50km of a ski area, and if none were available within 10 km we used the nearest two. Between ski resorts and snow measurement locations, the average horizontal distance is 14km and the average vertical distance 194m. SNOTEL data include daily SWE values rounded to the nearest 0.1 inch (0.254 cm) and daily snow depth rounded to the nearest inch (2.54 cm) (Wilkins et al., 2021); SWE is available for the entire record at each site, since the early 1980's in some cases (Serreze et al., 1999), and snow depth data begins mostly from around the year 2000 and as early as 1996. We analyzed observations from the first of the month for January through April but given the importance of the winter holiday (as noted in the previous section), we show results from 1 January and 1 February. Many more California snow courses have data for 1 February (17) than for 1 January (9).

For observed climate (temperature and precipitation) data, we use two sources: for computing interannual variability we use NOAA's climate division data (<https://www.ncei.noaa.gov/access/monitoring/reference-maps/rockies-and-westward>), which aggregates observations in climatically similar regions, roughly ten each for the states in our study area. We also use PRISM gridded climatological data (Daly et al. 2008) for assigning a mean seasonal temperature and precipitation to each ski resort. We define the season-to-date for a given date as the months beginning in November; in the case of 1 February, for example, the season-to-date climate data are monthly means for November, December, and January. Because the correlation length scale of monthly to seasonal climate data is much larger than the typical distances in our study, the potential added value of



using climate data for 170 locations from, say, PRISM, was insufficient to justify the effort. Instead, we combine the best attributes of both datasets: we use the month-to-month variability over the period of analysis from climate division data and adjust the monthly climate division precipitation by taking the ratio of the long-term mean precipitation at each location from PRISM to the long-term mean climate division precipitation.

For scenarios of future climate and SWE, we used the Climate Toolbox (climatetoolbox.org; Abatzoglou, 2013) climate mapper tool to extract baseline (1971-2000) and 30-year future period (2040-69) statistically downscaled outputs for temperature and precipitation from ten Coupled Model Intercomparison Project Phase 5 (CMIP5) models (Taylor et al. 2012) individually and from a 10-model average, at each ski resort location, for representative concentration pathways RCP4.5 and RCP8.5. We focus on changes in mid-century (2040-69) as more relevant for capital planning and for those considering whether to introduce the next generation to winter sports than end-of-century, and because uncertainty about emissions scenarios and climate sensitivity grows substantially toward the end of the century. We also obtained projections of SWE from simulations with the Variable Infiltration Capacity (VIC) macroscale semi-distributed hydrologic model (Liang et al, 1994; Hamman et al 2018) driven by the same downscaled CMIP5 data (Gergel et al. 2017). Although the VIC outputs do not include snow depth, we calculated snow density (SWE/snow depth) for the observed data at each SNOTEL site and used the 1-10 January average snow density to convert VIC SWE to snow depth.

We performed regression analysis of observed SWE and HS on season-to-date temperature (T) and precipitation (P), similar to Mote (2006) and Luce et al. (2014), but with important modifications. We constructed a single large table of SNOTEL data with date (1 January, ...1 April), station identifier (station_ID), with which ski resort the SNOTEL is associated, SWE, HS, climate division, season-to-date temperature and precipitation, and elevation. We ran linear regressions using different combinations of variables including interactions and used the one with highest variance explained: $SWE \text{ (or HS)} = f(T, P, station_ID \times date \times T, station_ID \times date \times P)$. This approach permits subsetting the regression coefficients by date, SWE or HS, and station_ID. We then constructed present and future HS using the regression coefficients: $\Delta HS = a_T \Delta T + a_P \Delta P$ where ΔT and ΔP are projected future changes in season-to-date temperature and precipitation from climate models. A quadratic equation was fitted to the regression coefficient a_T vs. long-term mean season-to-date temperature in order to adjust the values of a_T to account for any difference in mean temperature between the SNOTEL site, where it is computed, and the ski resort, using PRISM temperature data. We performed the same regression analysis on VIC SWE at each of the ski resort locations yielding complementary regression coefficients a_{TV} and a_{PV} . All analyses were done using R Statistical Software (v4.2.2, R Core Team 2016).

We thus have two complementary and independent ways of estimating the effects of future climate change on snow depth at ski resorts: model output of SWE from VIC converted to snow depth, and snow depth estimated using the regression equation. While both products come from the same set of 10 climate models downscaled using MACA in the Climate Toolbox, the VIC inputs are daily Tmax, Tmin, and P, whereas the regression approach aggregates season-to-date mean T and P from model output. Results for these approaches are shown below in section 3.2 and 3.3.

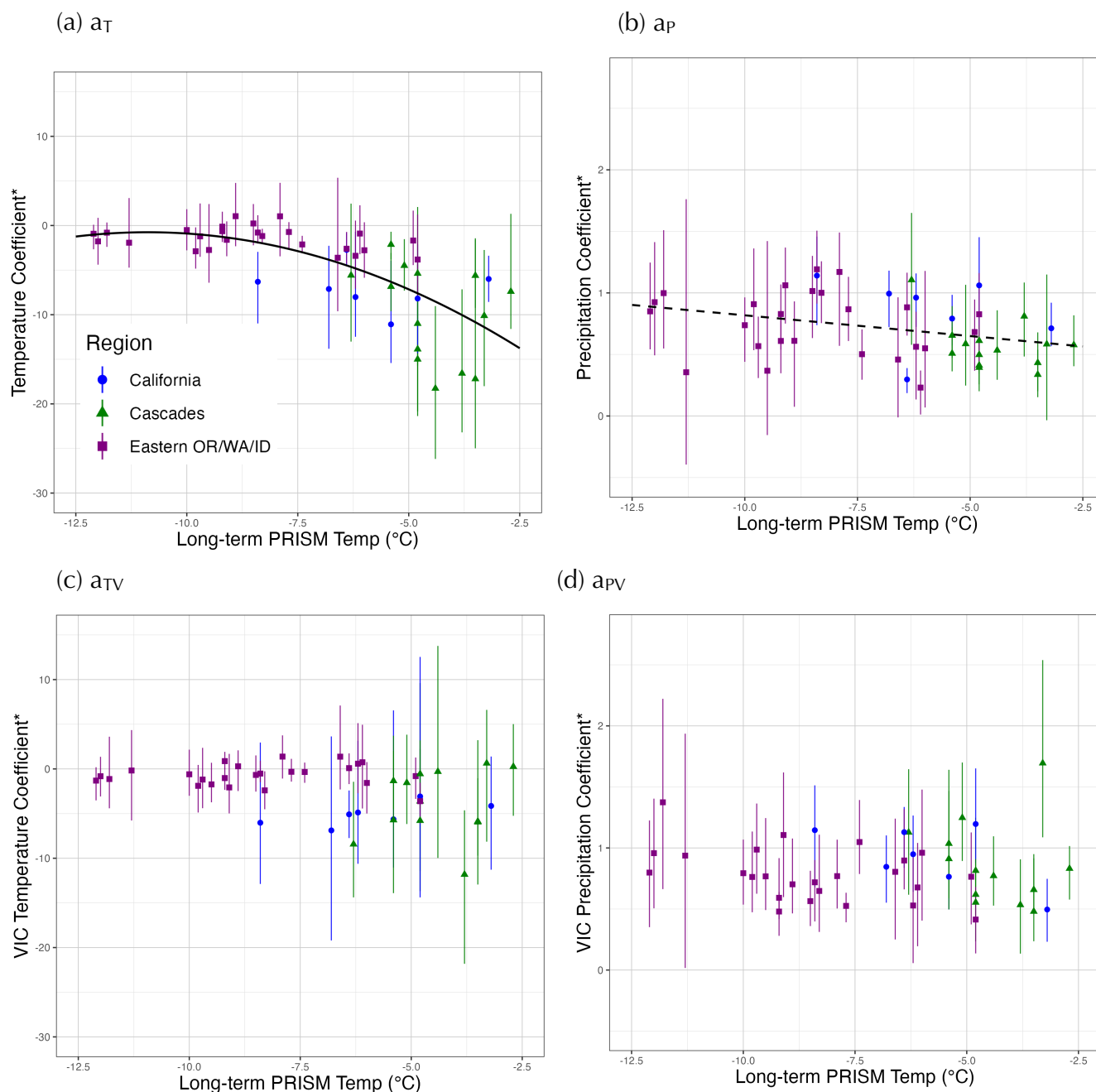


Figure 3. Regression coefficients a_T (panel a, c; units $\text{cm}/^\circ\text{C}$) and a_P (panel b, d; units cm/cm) of 1 February SWE from SNOTEL (a, b) and VIC (c, d) on November through January climate division temperature and precipitation, plotted against site temperature from PRISM. Quadratic and linear fits are included in (a) and (b). Each symbol is a ski resort location in one of the three regions as indicated by the colored symbols.



3. Results

We first describe the statistical analyses of SNOTEL data and then use those and the Climate Toolbox data to present two estimates of future snow depth during the winter sports season.

3.1 Climate variability and snow depth

Figure 1 illustrates how snow accumulates through a season, in that case for a high-elevation site with high precipitation and a medium to high ratio of SWE to cumulative P. Figure 3a shows the relationship between the SWE- temperature regression coefficient a_T for 1 February and the climatological mean November-January site temperature. (The relationship for 1 January, not shown, is very similar, but fewer California sites report 1 January SWE.) Across all regions, the coldest locations, with average winter temperatures less than about -7°C , have low sensitivity to temperature. The regression coefficient a_T is generally between 0 and $-2.5 \text{ cm}/^\circ\text{C}$ at these locations, and for a handful of sites a_T is slightly positive. By contrast, above -7°C each degree of increase in temperature leads to a strong increase in sensitivity of SWE to temperature. The relationship is similar for the three regions, although warm ($> -5^\circ\text{C}$) sites in the Cascades have much stronger temperature sensitivity than those in California. The warmest few in eastern OR/WA/ID appear less sensitive and none of the sites there have an average winter temperature above -4°C . It may be that the typically higher wet bulb temperatures in the Cascades and the mountains of California provide more latent heat available to melt than in the drier climates to the east (e.g. Wang et al 2019).

The equivalent diagram for precipitation plotted against local temperature (Fig. 3b) shows a very weak tendency toward lower sensitivities for the warmest locations. Differences among regional climates may help explain the differing relationships that the temperature and precipitation sensitivities have with mean temperature. In the drier eastern portion of our analysis area, SNOTEL sites generally have very weak sensitivity to temperature and most are very sensitive to precipitation ($a_P > 0.8$) because they are moisture-limited. For the warmest locations, which are almost all in the Pacific states, temperature clearly predominates; for moderately cold locations precipitation plays a greater role (see also Mote 2006, their Fig 6a).

The relationships between a_T and T are similar in other months (Fig. S1), with the warmest sites (which are mostly in the Cascades) having highest sensitivity to temperature. January and February are fairly similar, and March begins to show the transition to April which has the highest temperature sensitivity including in the previously less sensitive California and even the eastern locations. Relationships between a_P and T suggest that February is a bit of an anomaly (Fig. S1); for the other three months, there is a general downward tendency of a_P toward warmer locations across the regions.

Month	a_T	a_P	a_{TV}	a_{PV}
Jan	-43.92	0.727	-31.73	0.967
Feb	-48.99	0.712	-22.82	0.831
Mar	-57.20	0.706	-16.09	0.882
Apr	-101.36	0.702	-67.71	0.836

Table 1. Regression coefficients for SWE from SNOTEL and VIC for each month.

Across all stations and season-to-dates, the variance explained (not shown)

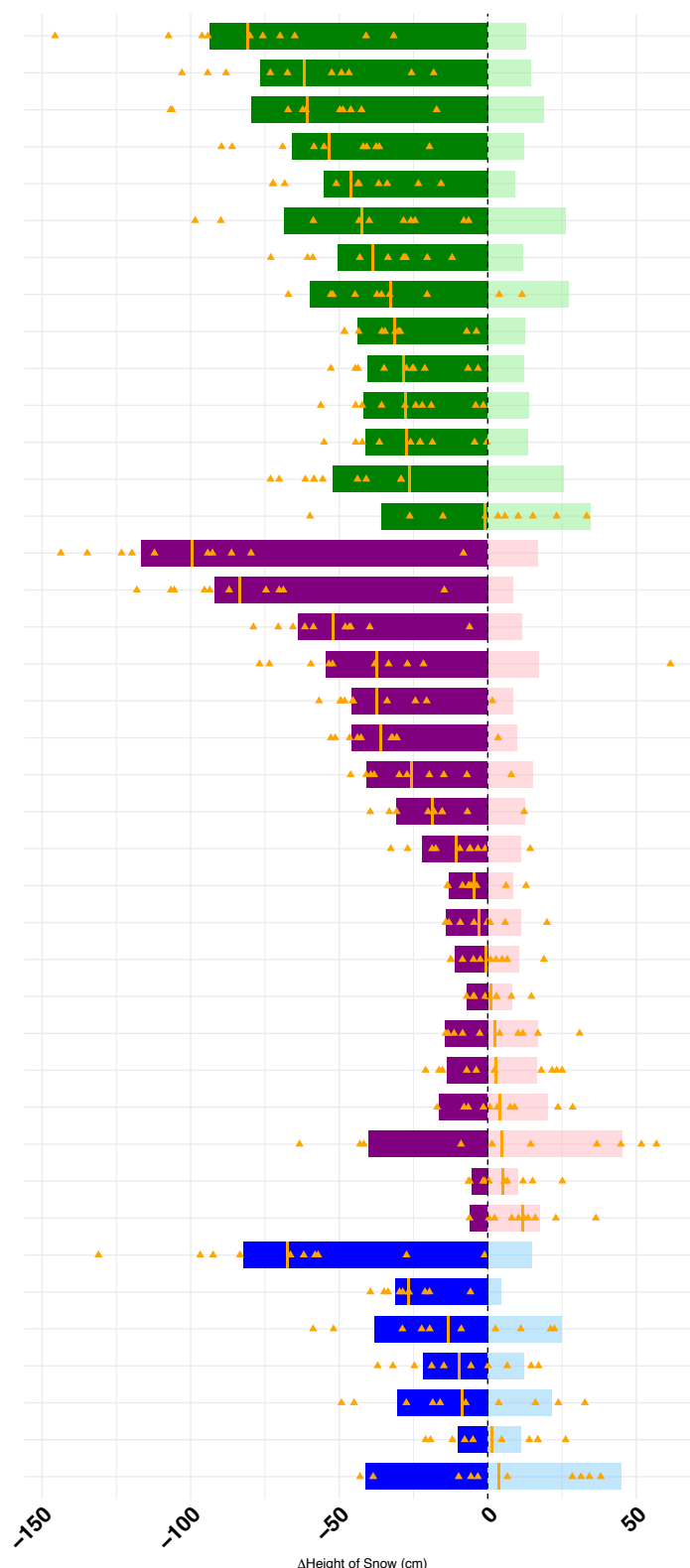


ranges from 0.1 to 0.85 with an average of 0.5. The average is close to 0.5 for all four months, though the month with highest variance explained is April (at four sites) and lowest are February and March. As noted above, the simple seasonal regression approach obscures the variety of physical processes aggregated up from the instantaneous to the seasonal timescale but permits simple statistical predictions.

Next we evaluate the same sensitivities to climate in the VIC calculations (Fig. 3c, 3d). As with a_T , the corresponding VIC coefficient a_{TV} is small and negative for most of the cold locations (PRISM temperature $< -5^\circ\text{C}$; Fig. 3c) which are also dry locations (PRISM November-December precipitation < 40 cm; Fig. S2). For milder locations ($> -5^\circ\text{C}$), especially those in the Cascades but some of which are also fairly dry, a_{TV} becomes increasingly negative, though not as much as for SNOTEL sites. In all months (Fig. S2), some of the colder sites have positive a_{TV} though not exactly the same sites as for SNOTEL.

The distribution of values of the VIC coefficient a_{PV} (Fig. 3d) is similar to that for the observed a_P in that coefficients trend somewhat lower toward warmer locations. This relationship persists in the other months (Fig. S2) and is stronger in January and April. Both the observed and VIC regression coefficients for precipitation demonstrate a somewhat puzzling attribute: values greater than 1. In theory, the accumulated

Figure 4. Projected change in 1 February snow depth (cm) for 2040-69, RCP4.5, using the regression method and 10 individual climate scenarios. Each row represents one ski resort with colors delineating regions as shown in the legend and the ski resorts ordered by projected change. For each bar, the components $a_T\Delta T$ and $a_P\Delta P$ are plotted separately for the average climate scenario with the deeper colors pointing left denoting the $a_T\Delta T$ component and the lighter components denoting $a_P\Delta P$ pointing right. The vertical orange line indicates the sum, and the orange triangles represent the ten climate model scenarios.



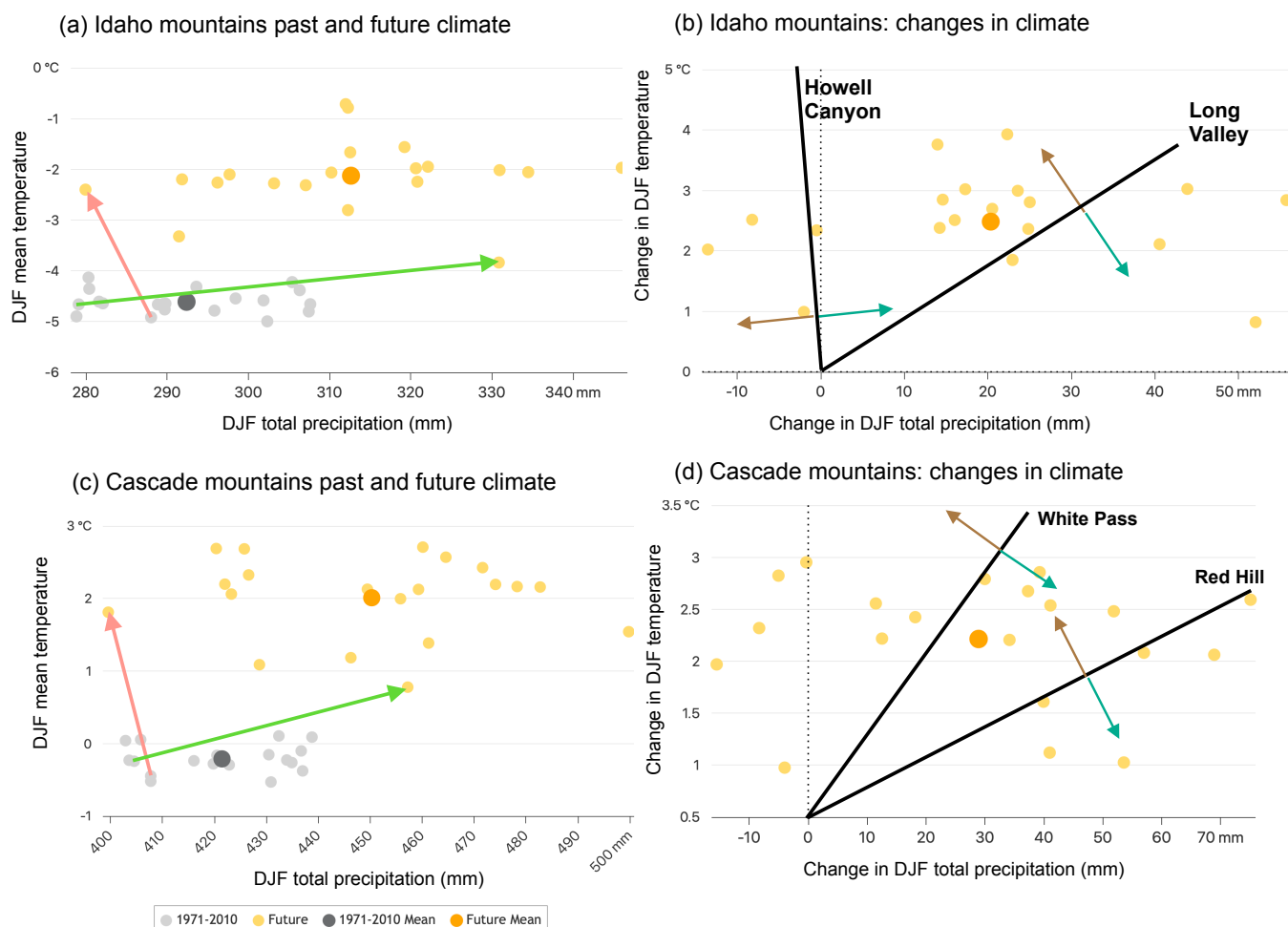
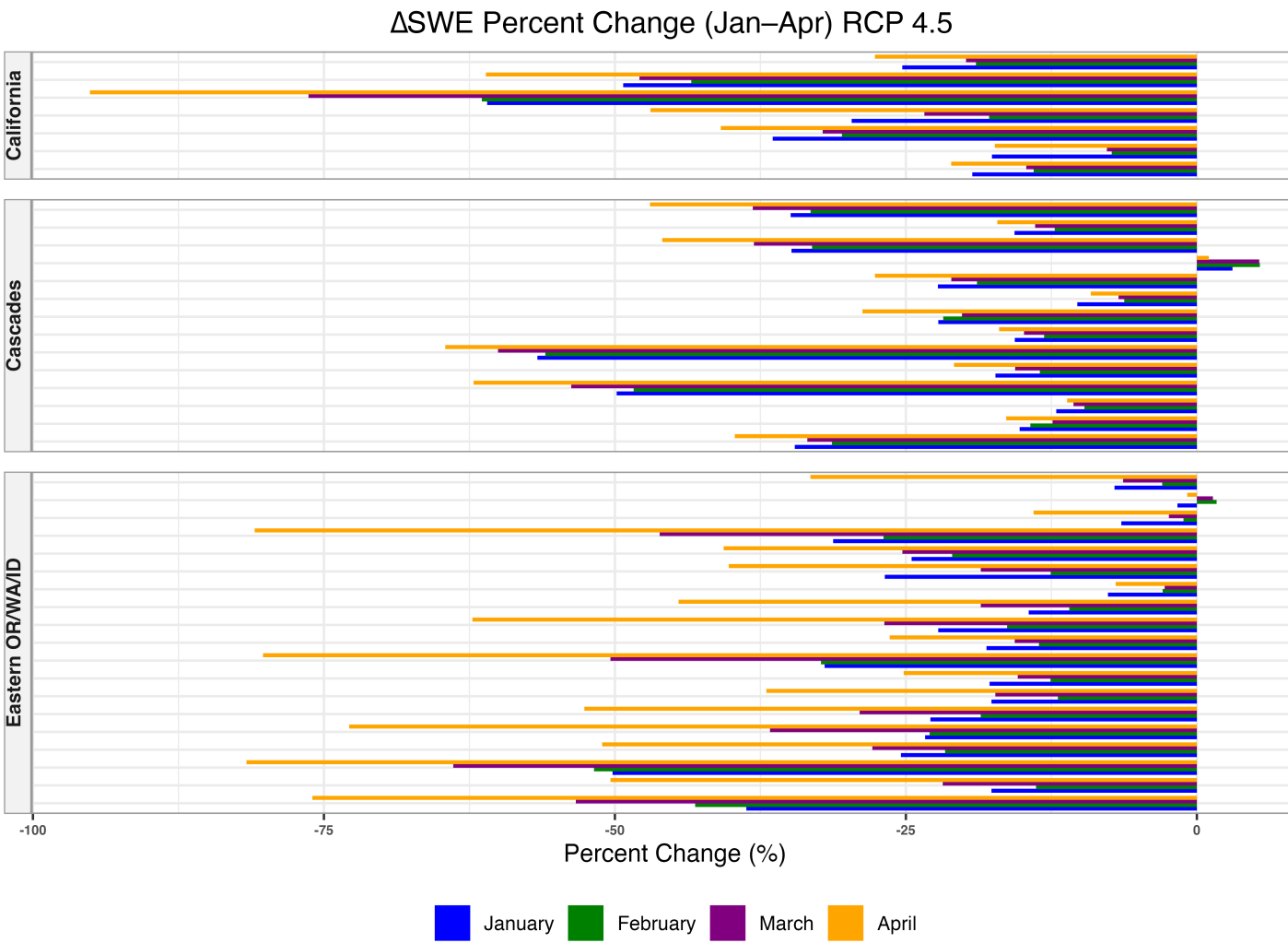


Figure 5. Climate averages for DJF from 10 climate models and 2 downscaling approaches, for 1971-2010 (grey) and 2040-69 (orange). Top row, for the mountains of central Idaho, the past and future climate (a) and the difference (b); bottom row, similarly, the Cascades of Oregon and Washington, past and future (c) and difference (d). Larger darker circles represent the all-model averages and the black sloping lines in (b) and (d) indicate the range of slopes of $-a_P/a_T$, in °C/cm. Red and green arrows in (a) and (c) represent the extremes of climate changes, for the IPSL-CM5B-LR and GFDL-ESM2M simulations respectively. Figure created with the Climate Toolbox, climatetoolbox.org.

site precipitation on a date at a given location should represent an upper limit for the SWE (see, e.g., Fig. 1), with a_P approximating the ratio of accumulated SWE to total P. In fact, various approximating assumptions we have made could contribute to $a_P > 1$. First, we have neglected October accumulation, since it is a transitional month in many locations, but at the colder locations it could represent an accumulation of SWE. Second, for expediency we are regressing against the climate division precipitation and temperature rather than the site-specific precipitation and temperature. Given the lower-altitude distribution of long-term stations that contribute to computing the climate division temperature and precipitation, this assumption probably leads to too-high values of temperature and too-low values of precipitation. (This difference does not affect the horizontal position of points displayed in Fig. 3 since those are determined from site PRISM values.) Our adjustment to the precipi-



285 **Figure 6. Projected change in SWE at the 41 ski resorts for 2040-69, RCP4.5, for each month as indicated in the legend, using VIC output.**

tation time series (see Section 2) considerably reduced the instances of $a_p > 1$ and, importantly, changed the appearance of Fig. 3b and 3d. Third, even with this adjustment, there are bound to be variations between the exact precipitation experienced at a location and the gridded PRISM value at its native resolution.

290 On average, the regression coefficients for SNOTEL indicate higher sensitivity to temperature and lower sensitivity to precipitation than those for VIC SWE (Table 1). For both, the sensitivity to temperature is highest for April, and in the observations, grows monotonically in time. The sensitivity to precipitation remains very similar from month to month, except that in VIC January is considerably higher than the other months.

3.2 Future - from regressions

295 As noted in section 2, one purpose of develop-
 ing the regression relationships is to use them in
 conjunction with projected climate changes
 from 10 climate models to predict changes in
 SWE and HS. Figure 4 shows the results of this
 300 approach. The large majority, but not all, of the
 ski resorts are projected to see decreases in 1
 January and 1 February snow depth. All but one
 of the ski resorts in the Cascades are projected
 to experience decreases in snow depth for nearly
 305 all climate scenarios. For some ski resorts in
 colder areas of eastern Oregon/eastern Washing-
 ton/Idaho and several in California, the project-
 ed increase in precipitation in most scenarios
 offsets the effects of warming. Individual cli-
 mate scenarios can vary widely from the mean:
 310 for many locations, especially in California,
 even the sign of change varies depending on the
 climate scenario.

Consistent with several other studies (e.g., Mote
 et al. 2018), the projected changes shift toward
 315 greater decreases in snow depth for 1 March and
 1 April (not shown, but see Fig. S1) than for 1
 January and 1 February.

Figure 5 illustrates how different sites map onto
 320 the climate-change space ΔT vs ΔP . Each small
 colored dot in Fig. 5a, b shows the simulated
 past (gray) or future (orange) climate from a
 different GCM. Two extreme changes are illus-
 trated, small warming and large increase in pre-
 325 cipitation (green arrow) from the GFDL-ESM2M
 model and large warming with a decrease in precipita-

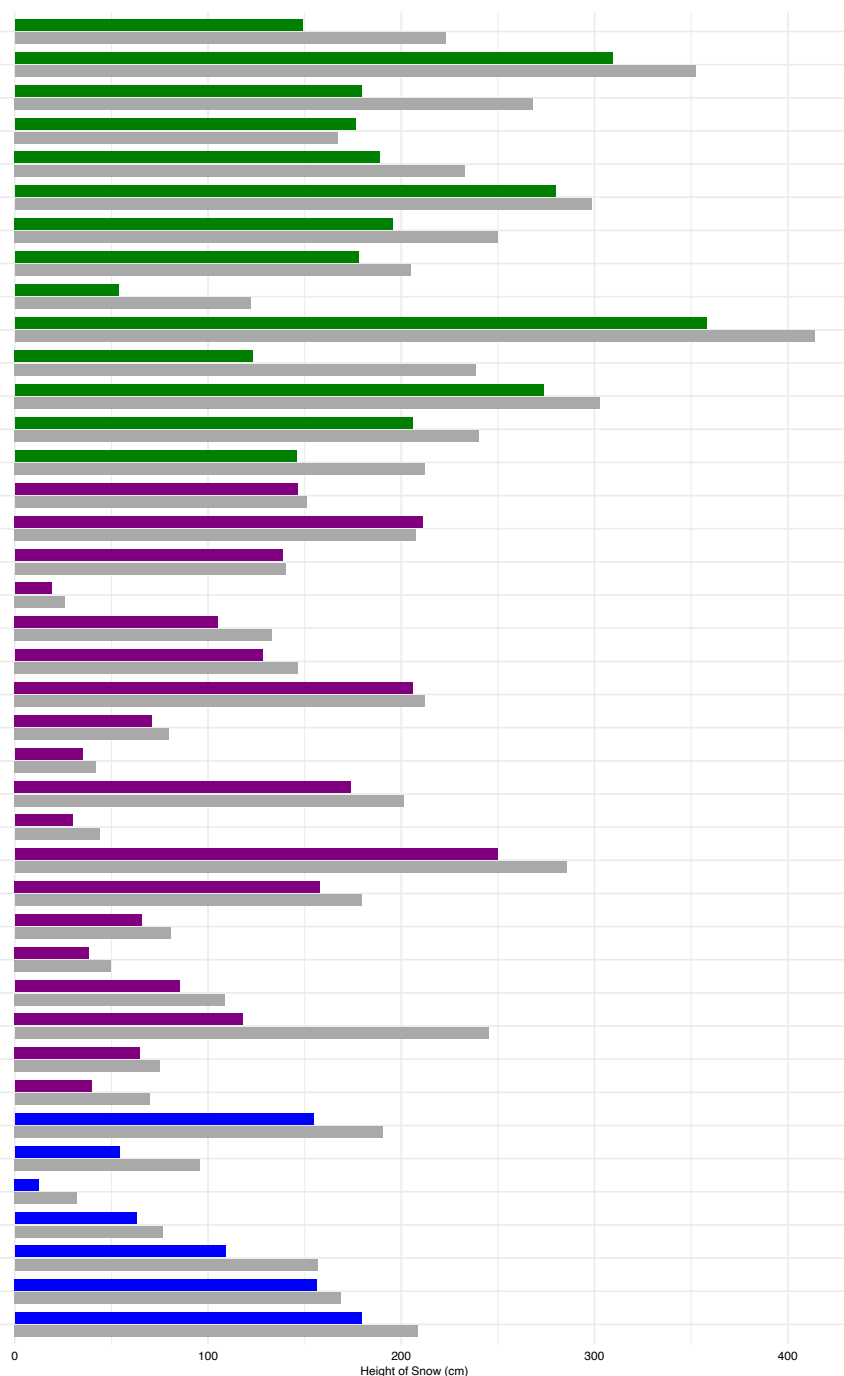


Figure 7. Simulated past and projected change in snow depth at the 41 ski resorts for 2040-69, RCP4.5, for February, using VIC output, with colors denoting region.



tion (red arrow) from the IPSL-CM5B-LR model. Panel (a) is for the mountains of northern Idaho and panel (b) is for the Cascades. Note that for Idaho, all climate models simulate a reference period climate between -4° and -5°C and a large majority of models project mid-century temperatures around -2°C , whereas for the Cascades, the reference period climate is close to 0°C and the projected mid-century temperatures are around $+2^{\circ}\text{C}$. The profoundly different reference-period climates help explain the difference in sensitivities shown in Figure 3 and also reflect very different proportions of the mountain ranges that have local temperatures well below freezing. Note that these average climates are computed from the statistically down-scaled MACA values which represent the fine-scale terrain. For precipitation, the Cascades receive on average about 45% more precipitation (much more on the windward side) than the mountains of Idaho, and in both cases the average climate scenario indicates a change of +7% but with some models projecting drier winters.

Given the simple linear model $\Delta\text{HS} = a_T\Delta T + a_P\Delta P$, isopleths of linear changes in HS in climate-change space ΔT vs ΔP in Fig. 5c would have slope $-a_P/a_T$ for each ski resort. These are illustrated for February sensitivities in panels b and c for the Cascades and Idaho. This ratio ranges from steep values for small a_T — weakly or not temperature-sensitive — to shallow values as low as 0.1 for Idaho and 0.05 for the Cascades, illustrated with black lines in Figs 5b and 5c. Climate projections to the right of one of the black lines, as indicated by green arrows in panel c, would produce increases in HS in this linear model whereas projections to the left (brown arrows) would see decreases. Even for the most temperature-sensitive location in Idaho, almost half of the climate projections produce increases in HS. Conversely, for the locations with a weakly positive temperature effect, every climate scenario but one (identified red arrow in Fig. 5a) produces an increase.

3.3 Future - from VIC

The linear regression approach in the previous section has advantages of simplicity and of disaggregating the effects of changes in temperature (whose sign is certain) and precipitation (whose sign varies depending on climate model), but it lacks

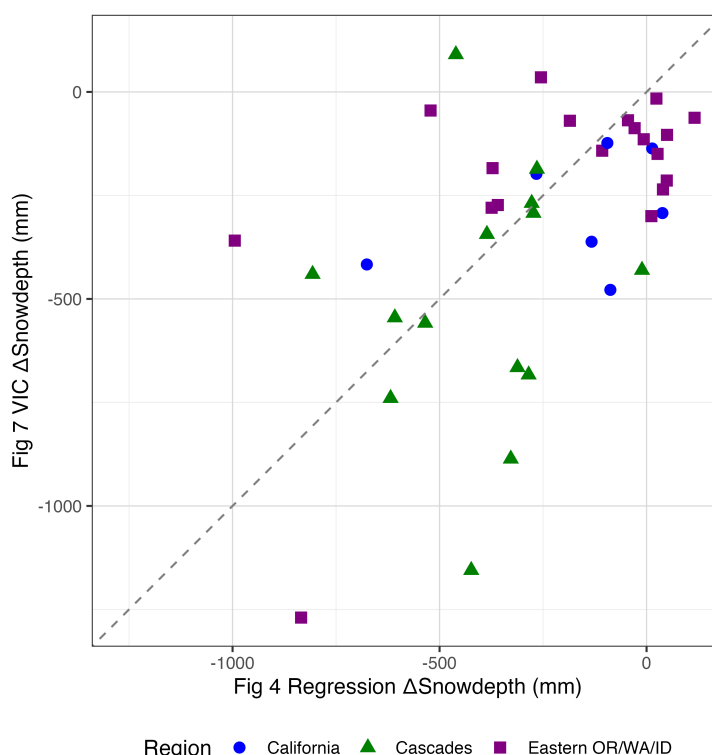


Figure 8. Comparison of the VIC (y axis) and statistical (x axis) methods of estimating change in snow depth at the 41 ski resorts for 2040-69, RCP4.5, from Figs. 4 and 7.



360 an explicit representation of physical processes. Our second method for projecting future change uses the VIC projections of SWE at each ski resort location and converts to snow depth using historical relationships. The VIC simulations use daily weather data as inputs and consequently capture nonlinear interactions and detailed time evolution missing from the regression approach.

365 Focusing first on the seasonality of changes in SWE (Fig. 6), at all resorts larger (in many cases much larger) decreases are projected for April, in several places exceeding 70%. But losses are generally projected to be more modest in January and February, typically 10-40%. Two of the 41 resorts, one each in eastern Oregon and eastern Washington, may experience slight increases in SWE and a couple in Idaho are projected to see only single-digit percent decreases in SWE during January and February.

370 Converting VIC SWE to HS (Fig. 7) and including the historical snow depth (gray bars), it is striking what a wide range of conditions under which the resorts operate, ranging by an order of magnitude. On average, the baseline snow depths are greatest in the Cascades, and even the resort with the lowest baseline snow depth in the Cascades is above the average for the other two regions. In this context, the percentage change may be more impactful to operations and skiability than the absolute change.

375 Some ski resorts, notably in the Cascades, are projected to lose considerable snow depth but from such a large base that the effects may be minimal. Others, including one in the Cascades and a couple in California, start from a small base and are projected to lose half or more of their snow - and this is for the average climate scenario, with a more modest RCP4.5 emissions scenario. As is evident from Fig. 5, the projected climate changes vary widely and some climate scenarios could lead to much larger losses.

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4. Discussion

The two complementary approaches, though not entirely independent, offer a valuable perspective not available through either approach alone. The regression approach links seasonally averaged climate to observed snow depth and SWE, with minor adjustments to account for differences in temperature sensitivity between each ski resort and the SNOTEL site(s) used for that resort. The VIC approach computes daily hydrologic balance from daily interpolated weather data. The future climate scenarios, though fundamentally the same, enter the calculations somewhat differently. Applying the regression approach to the VIC data (Table 1) reveals that VIC is somewhat less sensitive to temperature and more sensitive to precipitation on average. Comparing the two approaches directly (Fig. 8) is instructive: although there is broad agreement that a large majority of resorts would see decreases of at least 25 cm snow depth, and that a small minority of resorts might even experience increases, the two methods entirely disagree about which ski resorts might experience increases and also disagree about which resorts would see the largest decreases. As was evident in Figs. 4 and 7, many more of the resorts are projected to see increases (mainly in Eastern OR/WA/ID) in the regression approach, but as we can see by comparing Figs. 3 and 5, these

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395 locations are likely to shift into climate zones where they are more sensitive to temperature and so the ameliorating effects of precipitation increases are likely weaker than this approach would indicate. For similar reasons as well as the nonlinearity of a_T (Fig. 3), several of the ski resorts in the Cascades and one in Eastern OR/WA/ID (lower right quadrant) are projected to see considerably larger decreases with the VIC estimate than with the regression estimate.

400 Although a warming climate clearly poses an existential risk to winter sports, our analysis shows that this broad-brush picture misses some important exceptions. In the western US, the wide variety of climates under which ski resorts operate means that they have very different exposures to climate change. There are several reasons why the vulnerability to climate change is so varied.

First, more than half of the ski resorts in our study, notably excluding most of those in the Cascades, are in sufficiently cold locations that 2-3°C of warming poses little risk to wintertime snow depth in the mean — although two or three snow droughts in a row could be quite impactful (e.g. Marshall et al. 2019). At these ski resorts, historical observations show a 405 weak relationship between one season's temperature and snow depth. It is worth noting that, as Mote et al (2018) showed, the temperature sensitivity increases from winter to spring (see also our Table 1) owing in part to the snow-albedo effect. Some previous studies of climate-driven declines in SWE (e.g. Stoelinga et al 2010) presented results for 1 April only, and the effects of warming on ski-season snow quantity are less acute than on April and May snow. The focus on spring—originally because 1 April was the most common observation date in the early records —paints an overly dire picture of the ski-relevant trends. 410

Second, most of the climate scenarios in our study indicate increases in winter precipitation at our study sites, although in California more scenarios show decreases. At some locations the projected increases in precipitation are enough to offset the small decreases caused by warming (Fig. 4). However, it is worth noting that, as illustrated by the uncertainty in the sign of 415 change, precipitation projections have less confidence associated with them than projections in temperature. This is one important difference between our study and others (e.g. Casola et al 2009, Huning and AghaKouchak 2018) which examined only the sensitivity to temperature without factoring in the possible ameliorating effects of increases in precipitation, which turn out (at least for CMIP5 models) to be substantial.

420 Third, we present results for the *base* elevation of ski resorts, but for some resorts the terrain covers 1000m or more of vertical range. Upper reaches of such resorts may on average be 5°C or more colder than the base, putting them in the zone where winter snowpack is insensitive to temperature fluctuations (Fig. 3a); high-resolution climate simulations actually project increases in SWE at high elevations (McCrary and Mearns, 2019). Such resorts may even be able to operate almost normally even with no snow at the base elevation. At Heavenly, for example, a gondola transports skiers from the base to nearly 2800m altitude (and, if necessary, back again) over a travel distance of 4km ([skiheavenly.com](https://www.skiheavenly.com)), permitting access to substantial 425 skiable terrain at altitudes that are relatively insensitive to warming.



Fourth, artificial snowmaking provides a pathway to resilience for many ski resorts (Dawson & Scott 2013), partially decoupling ski resort revenue and the skier experience from climate conditions. However, snowmaking represents a significant capital investment, and successful operation requires sufficient water, consumes considerable electricity, and requires low enough wet bulb temperatures. Even in locations where those conditions are normally met today, they may be met less often in the future, so the effectiveness of this adaptation option may diminish (e.g., Scott et al 2019).

A couple of other factors are worth discussing. From a business perspective, particularly for independently owned resorts, the pattern of year-to-year variability might be as important as the long-term trend: two bad years in a row might be devastating. Second, the high-end scenario of atmospheric CO₂ concentrations (RCP8.5) is now (and, some would argue, always has been) viewed as highly unlikely, especially with the decline in global coal consumption in the past decade or so (Hausfather and Peters 2020). For this reason we have not included it in our discussions, but from a planning standpoint it might be worth considering this unlikely worst-case scenario of emissions.

5. Conclusions

To estimate future changes in HS across a range of 41 selected ski resorts in the western US, we use data from nearby SNOTEL and snow course sites to examine sensitivity of HS and SWE to temperature and precipitation. Using these regression coefficients along with CMIP5 models and concentration pathways RCP4.5 and RCP8.5 downscaled to the region, along with projected future SWE from a hydrology model, we find a wide range of responses of HS across the results. While many resorts indeed face substantial declines in ski-season snow depth, many of those in Idaho and a few at high elevation are likely to be minimally affected for mid-century and RCP4.5, though all are projected to experience significant declines in RCP8.5.

Our regression method reveals the nonlinearity of a_T (Fig. 3), a fact that may lead to underestimates in the reductions in HS in some locations. As the West continues to warm, regions with average winter temperatures less than -5°C that are currently insensitive to temperature fluctuations will shift into increasingly temperature-sensitive conditions. In ΔT - ΔP space of Fig. 5, this could be represented by showing the black lines curving to the right: weakly for the already-sensitive lower line, and more strongly for the vertical line. The VIC simulations include such effects, though. Another important caveat is that both our statistical and VIC projections come from statistical downscaling that poorly accounts for the effect that orography has on the changes in winter precipitation (e.g. Currier et al. 2025). Several studies using dynamical downscaling show only relatively small increases, if any, in winter precipitation over certain mountain ranges, like the Cascades, and some show substantial differences between lee side and windward side changes (Rupp et al. 2017, Koszuta et al. 2024, Rahimi et al. 2024). Also, the statistical downscaling may underestimate the enhanced winter warming in the mountains found in some dynamical models (e.g., Rupp et al. 2017).



Our study relies on the CMIP5 generation of climate modeling results. The advantage of our simple linear regression approach is that we can easily map new climate scenarios, such as those from CMIP6, onto the sensitivities as illustrated in Fig. 5. Comparisons (e.g. Lukas and Vano 2024) of the climatic inputs (seasonal temperature and precipitation) between CMIP5 and the next-generation CMIP6 (Eyring et al 2016) indicate some important differences over the western US that would modify our projections. Annual-mean and winter mean changes in temperature between CMIP5 and CMIP6 averaged over the western US are about 0.5°C higher even when ‘hot models’ (those with a transient climate response exceeding the IPCC range) are excluded. Projected temperature changes are similar in western Washington and Oregon, slightly lower in the mountains of California, and >1°C higher in the eastern part of our domain (Martel et al. 2022). For winter (DJF) precipitation, multimodel averages from CMIP6 indicate a considerably larger increase (~10% vs <5%) over Idaho and eastern Oregon and smaller increases elsewhere. Taken together, these results suggest that CMIP6 climates will be quite a bit less favorable for ski resorts in the Cascades and perhaps a bigger disparity among responses at ski resorts in the eastern part of the domain.

The extreme (and unlikely) emissions scenario RCP8.5, especially at the end of the century, produces large declines at every ski resort (not shown). We chose to focus on the moderate-emissions scenario RCP4.5 and mid-century to provide results that may be more relevant to a current assessment of viability of winter sports at these locations over the conceivable life cycle of capital investments. This study fills a niche between the ample studies documenting declines in snow in the western US and the more comprehensive assessments, generally in Europe and the eastern US, on the effects of climate change on economic realities for ski resorts taking into account skier behavior, snowmaking, and more. Those studies have generally found, as did ours, that the sensitivity of ski resorts to climate change ranges from fairly insensitive to quite sensitive; however, we also explored a wider range of climate scenarios than most studies and found that increases in precipitation are projected to ameliorate some of the effects of warming at some resorts. Snowmaking, which is not yet widespread in the western US, may ameliorate some of those effects.

A generation ago, one of us (PWM) gave several presentations about the future of snow in the West with the title “should I teach my kids to ski?” The answer, we find, is yes; today’s young people will still have opportunities to enjoy winter sports, but many will have to travel farther to do so, preferably via climate-friendly modes of transportation.



Appendix A. Ski resorts and SNOTEL locations

Table A1. Ski resorts and corresponding SNOTEL site(s) used

	Ski Resort	State	SNOTEL	SNOTEL Latitude	SNOTEL Longitude
485	Mt. Baker Ski Area	WA	Wells Creek	48.8661	-121.78976
	49 North Mountain Resort	WA	Bunchgrass Mdw	48.68688	-117.17633
			Quartz Peak	47.87927	-117.08938
	Mt Spokane Ski Area	WA	Quartz Peak	47.87927	-117.08938
	Stevens Pass Ski Resort	WA	Stevens Pass	47.74607	-121.09288
490	The Summit At Snoqualmie	WA	Olallie Meadows	47.37406	-121.44213
	Mission Ridge Ski Resort	WA	Upper Wheeler	47.28734	-120.37015
	Crystal Mountain	WA	Morse Lake	46.90585	-121.4827
	White Pass Ski Resort	WA	White Pass E.S.	46.64142	-121.38153
	Bluewood Ski Resort	WA	Touchet	46.11868	-117.8505
495	Anthony Lakes Mountain Resort	OR	Wolf Creek	45.06703	-118.15192
			Eilertson Meadows	44.86887	-118.11387
	Cooper Spur Mountain Resort & Ski Area	OR	Red Hill	45.4643	-121.70428
	Mt. Hood Meadows	OR	Mt Hood Test Site	45.32097	-121.7158
	Mt. Hood Ski Bowl	OR	Mt Hood Test Site	45.32097	-121.7158
500	Timberline Lodge & Ski Area	OR	Mt Hood Test Site	45.32097	-121.7158
	Hoodoo Ski Area	OR	Hogg Pass	44.42042	-121.85655
	Mt. Bachelor Ski Area	OR	Three Creeks Meadow	44.14425	-121.64095
			Mckenzie	44.2103	-121.87292
	Willamette Pass Resort	OR	Cascade Summit	43.59042	-122.0601
505	Mt. Ashland Ski Area	OR	Big Red Mountain	42.05257	-122.85487
			Fish Lk.	42.3801	-122.34943
	Schweitzer Mountain Resort	ID	Schweitzer Basin	48.37428	-116.63917
	Silver Mountain	ID	Sunset	47.55545	-115.82422
			Humboldt Gulch	47.53178	-115.77643
	Lookout Pass	ID	Lookout	47.45749	-115.70457
510	Brundage Mountain	ID	Brundage Reservoir	45.04315	-116.13253
	Tamarak Resort	ID	Long Valley	44.78835	-116.08878
			Puhi Flat	44.77091	-116.24805
	Bald Mountain - Sun Valley	ID	Chocolate Gulch	43.7685	-114.41812
			Hyndman	43.71077	-114.15894
515	Dollar Mountain - Sun Valley	ID	Chocolate Gulch	43.7685	-114.41812
			Hyndman	43.71077	-114.15894



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Ski Resort	State	SNOTEL	SNOTEL Latitude	SNOTEL Longitude
Bogus Basin	ID	Bogus Basin	43.76377	-116.09685
Blizzard Mountain Ski Hill	ID	Smiley Mountain	43.72718	-113.83402
		Garfield R.S.	43.6104	-113.9308
Rotarun	ID	Hyndman	43.71077	-114.15894
		Dollarhide Summit	43.6025	-114.67417
Kelly Canyon	ID	Pine Creek Pass	43.56998	-111.21157
		Sheep Mtn.	43.2103	-111.68792
Soldier Mountain	ID	Soldier R.S.	43.48407	-114.82692
Pebble Creek	ID	Wildhorse Divide	42.75743	-112.47783
		Sedgwick Peak	42.52497	-111.95635
Pomerelle	ID	Howell Canyon	42.32029	-113.61587
Magic Mountain Resort	ID	Magic Mountain	42.18072	-114.28662
Mount Shasta Ski Park	CA	Sand Flat (SFT)	41.353	-122.247
Boreal Mountain	CA	Castle Creek 5 (CC5)	39.34947	-120.35392
Heavenly Mountain Resort	CA	Upper Truckee (UTR)	38.873	-119.983
Kirkwood Mountain Resort	CA	Caples Lake (CAP)	38.71079	-120.04158
June Mountain	CA	Agnew Pass (AGP)	37.72663	-119.14173
Mammoth Mountain	CA	Mammoth Pass (MAM)	37.61	-119.033
China Peak	CA	Huntington Lake (HTT)	37.228	-119.222



535 *Data availability*

Publicly available SNOTEL data were downloaded from the California Data Exchange Center <https://cdec.water.ca.gov/> and the Natural Resources Conservation Service Water and Climate Center <https://wcc.sc.egov.usda.gov/reportGenerator/>.

540 *Author contribution.* EK conceived the study, obtained the data, performed all analyses, and made most or all of figures 2, 3, 4, 6, and 7, as well as supplementary figures. DR advised on statistical analysis and edited text. PM wrote the text, created Figures 1 and 5, and augmented Figures 2 and 3.

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