The Uneven Response of Different Snow Measures to Human-Induced Climate Warming

DAVID W. PIERCE
Division of Climate, Atmospheric Sciences, and Physical Oceanography, Scripps Institution of Oceanography, La Jolla, California

DANIEL R. CAYAN
Division of Climate, Atmospheric Sciences, and Physical Oceanography, Scripps Institution of Oceanography, and U.S. Geological Survey, La Jolla, California

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ABSTRACT

The effect of human-induced climate warming on different snow measures in the western United States is compared by calculating the time required to achieve a statistically significant linear trend in the different measures, using time series derived from regionally downscaled global climate models. The measures examined include the water content of the spring snowpack, total cold-season snowfall, fraction of winter precipitation that falls as snow, length of the snow season, and fraction of cold-season precipitation retained in the spring snowpack, as well as temperature and precipitation. Various stakeholders may be interested in different sets of these variables. It is found that temperature and the fraction of winter precipitation that falls as snow exhibit significant trends first, followed in 5–10 years by the fraction of cold-season precipitation retained in the spring snowpack, and later still by the water content of the spring snowpack. Change in total cold-season snowfall is least detectable of all the measures, since it is strongly linked to precipitation, which has large natural variability and only a weak anthropogenic trend in the western United States. Averaging over increasingly wider areas monotonically increases the signal-to-noise ratio of the 1950–2025 linear trend from 0.15 to 0.37, depending on the snow measure.

1. Introduction

Climate change will affect most of the world’s snowpack, imposing important impacts on people’s livelihood and living conditions considering that more than one-sixth of Earth’s population relies on melting snow for part of their water supply (Barnett et al. 2005). Snow responds to both temperature and precipitation, as well as other factors such as dust deposition on the surface and net absorbed solar radiation. Temperature has risen across the globe because of human activity (i.e., Solomon et al. 2007), a trend that is likely to accelerate in coming decades and which tends to reduce snowpack. Precipitation changes are more regional and uncertain, with increases likely in higher latitudes but declines in already-dry midlatitudes (Solomon et al. 2007), so precipitation changes can have conflicting effects on snowpack (Brown and Mote 2009). Future changes in snowpack are also likely to be elevation dependent, since high elevations tend to be colder, and therefore require more warming to reach the melting point.

Although these factors come into play in all snowy regions of the world, in this work we analyze in detail one region where the population relies on snowpack as a natural reservoir to capture and store precipitation from intense winter storms, the western United States (e.g., Palmer 1988; Mote et al. 2005). Numerous works have examined changes in snow over the western United States from observations and projected human-induced climate change (e.g., Groisman and Easterling 1994; Cayan 1996; Hayhoe et al. 2004; Mote et al. 2005; Hamlet et al. 2005; Regonda et al. 2005; Mote 2006; Knowles et al. 2006; Maurer et al. 2007; Das et al. 2009). Formal detection and attribution studies have shown that anthropogenic climate change has already increased winter
Decision makers have different regional interests as well, with some concerned with a local watershed and others with region-wide impacts. This can give rise to questions such as why a local basin does not show a climate trend even though one is seen in the western United States as a whole, or whether lack of a climate trend in a local basin refutes the identification of a region-wide trend. We lay the foundation for addressing these kinds of questions by systematically exploring the effect that regional averaging has on the significance of trends in different snow variables. Natural short-term climate and weather variability affects different snow variables to a greater or lesser degree; averaging across successively larger regions reduces this variability, resulting in clearer trends. Our second goal is to quantify how regional averaging affects the anthropogenic signal in various snow variables. Finally, since anthropogenic climate change is likely to continue for the foreseeable future, our third goal is to examine how those changes progress to the end of the century.

We evaluate linear trends in time series beginning in 1950, using standard significance tests. This evaluation differs from formal optimal fingerprint detection and attribution techniques, which use long preindustrial climate model simulations to evaluate the likelihood of finding observed trends by chance and optimize the fingerprint of anthropogenic forcing to provide the largest signal-to-noise ratio (SNR) (e.g., Solomon et al. 2007). Our reason for examining simple trends is pragmatic. There are little or no snow observations in preindustrial conditions, and water managers, planners, and stakeholders are more likely to assess whether a significant trend can be seen in observations. Decadal climate trends can also be associated with natural variability, for example the Pacific decadal oscillation (PDO) or Atlantic multidecadal oscillation (AMO). We take this into account by using multiple climate model simulations; since a check verified that (as expected) the models are not synchronized in their natural climate variability, they simulate a random spread of phases of the PDO, AMO, and other climate oscillations in any particular year. In the multimodel-ensemble average the different phases tend to cancel, allowing us to estimate both the mean response in the absence of natural climate variability and the spread that is caused by natural variability.

2. Data and methods

We use daily temperature, precipitation, and wind speed from multiple global climate models as described below, bias corrected and downscaled to a 1/8° × 1/8° latitude–longitude grid over the western United States. We use the downscaled fields to force the variable infiltration capacity (VIC) hydrological model, which calculates the snow variables. These steps will now be described in more detail.

a. CMIP5 global climate models

We use 13 global climate models from the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project, version 5 (CMIP5; Taylor et al. 2012). The models are listed in Table 1. For every model, daily minimum and maximum near-surface air temperature, precipitation, and wind speed were obtained from the CMIP5 archive (pcmdi.llnl.gov). The periods covered are 1950–2005 (the historical era) and 2010–99 (the future era). Two greenhouse gas and aerosol emissions scenarios are used in the future era: representative concentration pathways (RCP) number 4.5 and 8.5 (van Vuuren et al. 2011). The RCP numbers indicate the approximate anthropogenic forcing by the end of the century (W m\(^{-2}\)). These RCPs correspond to medium and high greenhouse gas emission scenarios, respectively. The 13 models used were all the CMIP5 models that had the required daily data accessible for the historical and two RCP runs at the time the study was undertaken, although the number is continually growing.

b. Bias correction with constructed analog downscaling

The western United States is an area of pronounced topographic variation so downsampling the relatively coarse global model fields to a finer spatial grid is required. We use a variant of the bias correction with constructed analog (BCCA) statistical-downscaling technique (Hidalgo et al.
BCCA coarsens daily observations on the 1/8° latitude–longitude grid over the western United States. Briefly, BCCA coarsens daily observations on the 1/8° grid to the GCM’s grid and finds the 30 observed days that best match the GCM daily field being downscaled. The optimal weights needed for the 30 observed days to best reproduce the GCM day are computed from the coarsened fields and are then applied to the observations on the finescale. The process takes topographic effects implicitly into account. For example, a heavy precipitation event on the coarse scale is downscaled to days that show, on the finescale, orographic enhancement of precipitation on the windward side of mountain ranges and rain shadows on the leeward side. Like all statistical-downscaling methods, BCCA is subject to the drawback that it assumes that historical relationships between large-scale and local features are maintained into the future. Maurer and Hidalgo (2008) evaluated an earlier version of the BCCA technique’s skill in downscaling temperature and precipitation and found that correlations between finescale observations and downscaled reanalysis data generally exceed 0.8 for monthly mean temperature and precipitation, but degrade on a daily time scale, especially for extremes.

Our procedure differs from that described in Hidalgo et al. (2008) in two ways. First, we apply a bias correction step to the final, downscaled field. [The method used in Hidalgo et al. (2008) only applies the bias correction to the coarse GCM field before downscaling.] Second, our analysis suggests that BCCA downscaling can at times produce fields that underrepresent the original global model trend, perhaps because late in the century conditions can be quite different from the historical period. To address this, we separately downscale ~30-yr segments of the data (1950–75, 1976–2005, 2010–39, 2040–69, and 2070–99). BCCA downscaling works on anomalies, and in our technique the anomalies are computed with respect to the climatology of each 30-yr segment [as opposed to the climatology of the historical period, as in Hidalgo et al. (2008)]. We then downscale the GCM-predicted change in model climatology between the historical period (1976–2005) and the segment being downscaled and add that to the downscaled anomalies and observed finescale climatology. By construction, this yields trends that closely match the original GCM. For example, pooled across the models, the RMS difference between the GCM and downscaled temperature trends over the period 2010–99 is less than 1%.

We used gridded observations of daily temperature, precipitation, and wind speed over the period 1970–2010 to construct the library of patterns for the BCCA downscaling (Maurer et al. 2002; downloaded from http://www.engr.scu.edu/~emaurer/data.shtml). The wind speed field in Maurer et al. 2002 is based on the National Centers for Environmental Prediction (NCEP) reanalysis rather than on station observations, and so it captures only broad-scale features over the western United States. However we believe that downscaling the actual daily GCM wind speeds, even at only broadly resolved scales, is an improvement over using fixed daily climatology for the winds, as has typically been done in previous studies.

### Table 1. Model acronyms, expansions, and realization used for the historical, RCP 4.5, and RCP 8.5 runs (a single “r1i1p1” means that realization was used for all runs).

<table>
<thead>
<tr>
<th>Model</th>
<th>Expansion</th>
<th>Realization used</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC-CSM1.1</td>
<td>Beijing Climate Center, Climate System Model, version 1.1</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Second generation Canadian Earth System Model</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Météorologiques Coupled Global Climate Model, version 5 (France)</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CSIRO-Mk3.6.0</td>
<td>Commonwealth Scientific and Industrial Research Organisation</td>
<td>r9i1p1/r9i1p1/r1i1p1</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>Geophysical Fluid Dynamics Laboratory Climate Model, version 3</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>Geophysical Fluid Dynamics Laboratory Earth System Model with GOLD ocean component</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>Geophysical Fluid Dynamics Laboratory Earth System Model with MOM4 ocean component</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>INM-CM4</td>
<td>Institute of Numerical Mathematics Coupled Model, version 4 (Russia)</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Hadley Centre Global Environmental Model, version 2 (Earth System)</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>L’Institut Pierre-Simon Laplace Coupled Model, version 5, coupled with NEMO, low resolution</td>
<td>r1i1p1/r2i1p1/r2i1p1</td>
</tr>
<tr>
<td>MIROC 5</td>
<td>Model for Interdisciplinary Research on Climate, version 5</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>Model for Interdisciplinary Research on Climate, Earth System Model</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>Meteorological Research Institute Coupled Atmosphere–Ocean General Circulation Model, version 3</td>
<td>r1i1p1</td>
</tr>
</tbody>
</table>
c. VIC hydrological model

Once the downscaled meteorological fields are available, we need to compute the snow cover in a way that is consistent across models and takes into account both the topography and the surface energy budget. We use the VIC hydrological model for this purpose (Liang et al. 1994; Cherkauer et al. 2003; Hamlet and Lettenmaier 2005). VIC simulates snow cover and hydrological processes given the meteorological forcing fields, topography, and descriptions of soil and vegetation. VIC includes an energy balance snow accumulation and ablation model for simulating the interaction of snow with vegetation, and estimates the necessary humidity, shortwave and longwave radiative forcing from the supplied daily minimum and maximum temperatures, precipitation, topography, and time of year using empirical formulae as described in Maurer et al. (2002). In the configuration used here, five elevation bands are used to take into account subgrid-scale variations in topography. We ran the model using a daily time step, and a one-hour time step for the snow model.

Mote et al. (2005) examined the ability of VIC to model snow conditions in the western United States, and concluded that VIC reproduces observed snow water equivalent (SWE) at snow course locations quite well when driven with observed meteorological fields. Correlations between observed and modeled SWE values averaged 0.74. However, their Fig. 1 shows that VIC does not reproduce the observed increase in SWE in the southern Sierra Nevada; they attributed discrepancies chiefly to problems interpolating station meteorological observations to snow course locations. Similar conclusions on the overall quality of VIC snow simulations and importance of accurate applied meteorological fields to the final result are given in Hamlet et al. (2005).

d. Snow-dominated locations and regional averages

We include only locations that are dominated by snow, identified as grid cells that average at least 1 cm of SWE on 1 April over the climatological period (1976–2005). We also require that at least 25% of the cold-season (October–March) precipitation remains in the snowpack on 1 April. Finally, the VIC model does not include glacier dynamics, which would otherwise transport snow that continually accumulates in a few high, cold locations to surrounding grid cells where it can melt. We therefore excluded 4 grid cells that continually accreted snow over the historical period from the analysis.

To reduce noise, we regionally average the snow data into the eight mountain ranges shown in Fig. 1. In mountainous regions, different locations can have very different climatological snow accumulation. We treat snow variables in different locations equally by normalizing the data in each grid cell by the mean value in that grid cell over the climatological period (1976–2005). The normalized values are then averaged to form the regional average. We also show the multiregion average, which is computed as the area-weighted average of the eight regions.

The regions cover a wide range of mean cold-season (October–March) temperature and precipitation (Fig. 2, left), spanning 7°C and a factor of 3 in precipitation. When applying these results to other regions, the climatological mean and future changes in temperature and precipitation are the dominant factors determining the behavior of snow, although other factors such as latitude, wind speed, and humidity have an effect as well.

Figure 2 (right panel) shows the multimodel ensemble-mean temperature and precipitation change by 2070–99 with respect to the climatological period (1976–2005). Temperatures warm by 2°C–3°C for RCP 4.5 and 4°C–5°C for RCP 8.5. Cold-season precipitation is projected to increase over this area by about 5% for RCP 4.5 and 12% for RCP 8.5. Note that warm-season precipitation in this region is generally projected to decline, especially in spring (e.g., Pierce et al. 2013), partially offsetting the cold-season increases shown here.
e. Variables analyzed

In this work, we analyze the following snow-related variables.

SWE: The amount of water contained in the snowpack on 1 April.

SWE/P: The fraction of precipitation \( P \) from 1 October to 31 March that remains in the snowpack on 1 April.

Snowfall: The total amount of snow that falls from 1 October to 31 March, measured as the amount of water contained in the falling snow. This has been referred to as snowfall water equivalent (SFE) (Knowles et al. 2006).

SFE/P: The fraction of total water in the precipitation from 1 October to 31 March that has fallen as snow (cf. Knowles et al. 2006).

The above variables are normalized to climatology over the period 1976–2005, and so are expressed as percentages; values can thus be directly compared.

First and last days of snow cover: Taken as the first and last days of the water year (1 October–30 September) that at least 10% of the climatological 1 April SWE is present on the ground; measured in days.

Mean temperature \( T \) (°C) and total precipitation relative to climatology (%) during the cold season (October–March).

f. Trend calculation

All trends are calculated using ordinary least squares linear fits. Statistical significance of trends is computed as described in Santer et al. (2000), where the standard error in the trend estimate is adjusted based on the lag-1 autocorrelation in the residuals of the fitted time series. The SNR is taken as the trend divided by twice the autocorrelation-adjusted standard error in the estimated trend.

3. Results

a. Future changes in snow-related variables

Figure 3 summarizes projected changes in several of the snow variables averaged across the region, relative to the 1976–2005 climatology, using RCP 4.5 forcing for the 13 CMIP5 models and their multimodel-ensemble average (MMEA) (Fig. 4 shows similar results for RCP 8.5 forcing). Decreases in snowpack are projected to be substantial in the western United States by the end of this century. Both SWE and SWE/P decline by 40%–70%, depending on the emissions scenario. Snowfall and SFE/P declines are smaller, about 25%–40% by 2100. Precipitation has a weak tendency to increase over the cold season, which contributes an increasing tendency to snowfall and SWE. Accordingly, SWE/P, the fraction of winter precipitation that is retained in the snowpack on 1 April, declines more than SWE. Changes in the snow season are asymmetric, with more retreat in the last day of snow cover than advancement in the first day of snow cover, particularly in the RCP 8.5 emissions scenario.

Note that somewhat different values would be obtained were the variables measured over the full water year rather than during the cold season (i.e., snowfall can occur after 31 March). Also, variables such as precipitation show less noise when averaged over the entire
However, the noise reduction is modest, as much of the region receives the majority of precipitation in the cold season.

b. Multimodel ensemble–average trends

The MMEA value is useful because it tends to show better agreement with historical observations than the individual models, even in measures of variability and in a regional context such as the western United States (Pierce et al. 2009). Additionally, averaging across independent realizations of natural internal climate variability reduces their effects, better revealing any underlying response to the anthropogenic forcing.

All of the snow variables in both emission scenarios show a decline of snow over the twenty-first century. The MMEA linear trends in three key snow variables, SWE, SWE/P, and SFE/P, along with their 95% confidence intervals, are shown in Fig. 5 (RCP 4.5) and Fig. 6 (RCP 8.5). We consider trends to be significant when the 95% confidence interval no longer includes zero. Here, SWE has the widest uncertainty range (green-stippled area), but normalizing by precipitation (SWE/P; pink-shaded area) reduces the uncertainty and reveals a stronger trend. Snowfall (not shown) has roughly the same uncertainty as SWE/P, depending on the region, but only about half the trend of SWE or SWE/P. The variable SFE/P yields about the same trend as snowfall, but with less uncertainty; individual regions have statistically significant trends in the MMEA starting in about 2010. In comparison, the all-region average has significant trends starting in about 2000, indicating that the noise is reduced somewhat by averaging across regions. In most regions and the all-region
average, the SFE/P trend becomes significant first, then SWE/P, followed by SWE, and finally by snowfall (not shown). Differences between the RCP 4.5 and 8.5 emissions scenarios only become evident after about 2070, with declines in the snow variables flattening toward the end of the century in RCP 4.5 but continuing to decrease in RCP 8.5. In sum, Fig. 5 and Fig. 6 show that the noise-reducing MMEA allows significant trends in key snow variables to be seen relatively early in the twenty-first century, although below we show that individual models generally do not display significant trends so soon.

c. Fraction of individual models with significant trends

Although the multimodel ensemble–average trend is useful for uncovering the physical response of the noisy climate system to anthropogenic forcing, by construction the MMEA has different noise characteristics than the observations. As a result, the significance of an observed trend cannot be compared with the significance of the MMEA trend—by reducing noise from short-term natural climate and weather fluctuations, the MMEA trend will have more significance at any time. An observed trend should be compared with the distribution of trends across the individual model runs. What do the models indicate is the likelihood of obtaining a significant trend in any particular snow variable as a function of time?

The variables SWE, SWE/P, snowfall, and SFE/P all show negative trends in the models. The fraction of models exhibiting a significant trend \( (p < 0.05) \) is shown in Fig. 7 for RCP 4.5 and Fig. 8 for RCP 8.5. Plotted values have been smoothed with a 5-yr-centered moving average to reduce noise. Cold-season (October–March) air temperature generally shows the strongest signal. All simulations show warming, with 80% of the models producing a significant trend by about 2020 (depending on the region), regardless of the RCP.
The year when 80% of the models show a significant trend is summarized as a function of the region’s mean cold-season temperature in Fig. 9. Significant trends in SFE/P are shown by 80% of the models by about 2030. Significant trends in SWE/P are found a few years later (2035), followed by trends in the last day of the snow season (2040). None of those snow measures shows a strong relationship between cold season–mean temperature and the year 80% of the models find a significant trend. Significant trends in SWE generally are reached considerably later (2030–80), with a lapse of many decades in cold locations such as the Colorado Rockies and the Wasatch, but with little delay after SWE/P in the warm Oregon Cascades. Significant trends in snowfall are found later still, with 80% of the models showing a significant trend only by year 2045 or after (depending on the region) with RCP 4.5. In the two coldest locations, the Wasatch and Colorado Rockies, less than 80% of the models have a significant decline in snowfall even by the end of the century.
although this threshold is reached in the RCP 8.5 scenario. In the Sierra Nevada, the time when 80% of the models show a significant snowfall trend is no sooner than about 2060, in accord with observations (Christy 2012).

Similar to results shown in Fig. 3, the significance of changes in the first and last days of the snow season are asymmetric. Most models produce a faster (~10 years earlier) spring advance than autumn delay in the start of the snow season. The exception is the Washington Cascades, where changes in the first and last days of the snow season show significant trends at about the same time. There is no obvious reason why the first day of snow should show earlier trends in colder regions in RCP 4.5 (Fig. 9), but we note that the relationship is not replicated in RCP 8.5.

Precipitation trends are the weakest of all the variables. Even by 2100, and when averaging over the entire region to reduce noise, only 75% of the models show a statistically significant precipitation trend over the western United States. Along the west coast (Washington and Oregon Cascades, and Sierra Nevada) no more than 20% of the models show a statistically significant trend by 2100 in RCP 4.5. In general, the western United States straddles the zero line of changes in annual precipitation expected because of anthropogenic warming, with drying...
in the subtropical subsidence regions (such as the southwestern United States) and wetter conditions to the north (such as the Pacific Northwest; Solomon et al. 2007), although cold-season precipitation generally increases (Fig. 2).

d. Probability of experiencing a given change

The distribution of projected changes across models can provide one estimate of the probability of experiencing changes of a given magnitude. It should be noted that, although the CMIP5 models have important differences, they were not designed to systematically sample uncertainty across model formulations and may lack key mechanisms that affect snow falling and melting. Different models share physical parameterizations or code and so may not produce truly independent future climate projections (Pennell and Reichler 2011). Accordingly, the probabilities developed here should be viewed as an
estimate based on a sample of the most recent climate models currently available.

The model-estimated likelihood of changes in SWE, SWE/P, and snowfall expected by 2040–69 is given in Fig. 10 (Fig. 11 for years 2070–99). For example, the models indicate there is a 50% chance SWE in the Sierra Nevada will decline by at least one-third by 2040–69. There is an 80% chance SWE will decline by at least 20%, but only a 20% chance SWE will decline by 40% or more. Fractional changes in SWE/P are never less than changes in SWE at a given probability and generally are more, although the differences are not great. However, the models indicate that changes in snowfall of a similar magnitude are much less likely; for example, in the Sierra Nevada the models indicate less than a 20% chance that there will be a 20% or more decline in snowfall by 2040–69.

By the latter part of the century (2070–99; Fig. 11) the effect of the stronger warming in the RCP 8.5 scenario simulations than in the RCP 4.5 scenario is more evident. For example, in the Sierra Nevada the models suggest a 50% chance of a decline in SWE/P of 40% or more under the RCP 4.5 emissions scenario, but a 50% chance of a decline of 70% or more under RCP 8.5. Averaged

![Graphs showing model estimates of SWE, SWE/P, snowfall, and air temperature changes across different regions and time periods.](image)

**Fig. 8.** As in Fig. 7, but for the RCP 8.5 emissions scenario.
across the regions, the decline in any snow variable expected for a given probability level nearly doubles under RCP 8.5 in comparison with that under RCP 4.5.

e. Factors contributing to changes in SWE

Reductions in SWE arise from at least two sources: more snowmelt and the transition of precipitation from snow to rain (e.g., Hamlet and Lettenmaier 2005; Mote et al. 2005; Knowles et al. 2006). Increasing cold-season precipitation opposes these tendencies in the western United States (Fig. 3), as well as in the higher latitudes of the Northern Hemisphere generally (Brown and Mote 2009). Kapnick and Hall (2012) show how these factors have played out over the snow season in recent decades in the western United States.

Figure 12 summarizes how the changing disposition of precipitation is likely to affect future SWE. Let SAS$_{clim}$ be the snow accumulation season over the climatological period, which we take as 1 October to the day of peak SWE calculated separately for each grid cell, averaged over the period 1976–2005. Figure 12 shows that modest increases in precipitation over the SAS$_{clim}$ are overwhelmed by greater melting and more precipitation falling as rain instead of snow over the SAS$_{clim}$, leading to declines in SWE of 20%–50% by the end of this century.

The relative importance of the factors that determine changes in peak SWE can be quantified by noting that

$$SWE = g \cdot P - m,$$

where $g$ is the fraction of precipitation that falls as snow, $P$ is the total precipitation, and $m$ is the total snowmelt over the SAS$_{clim}$. Linearizing under the assumption of small changes,

$$\Delta SWE = \Delta gP + \gamma \Delta P - \Delta m + \varepsilon.$$

The first term on the right-hand side shows the contribution from the transition from snow to rain, the second term shows the contribution from more precipitation, the third term shows the contribution from more...
snowmelt over the $S_{\text{SASclim}}$, and the last term is the error in the linear approximation arising from higher-order terms. These values were extracted from the VIC simulations; results are given in Table 2 for the MMEA. All changes are for the end of this century relative to the climatological period. Since SWE decreases, the sign convention is taken such that the factors contributing to the change in SWE sum to $-100\%$. The largest contributor to decreasing SWE is the conversion of precipitation from snow to rain, which on average does 1.3 times as much to decrease SWE as does the increased snowmelt. This varies by region, however, with warmer locations more influenced by the conversion of snow to rain and colder regions more influenced by increased melting over what had been the snow accumulation season in the climatological period. There is also a tendency toward increased cold-season precipitation over the twenty-first century, which acts to increase SWE, but this effect is overwhelmed by the warming changes of snow to rain and increased snowmelt.

### f. Effect of regional averaging

Regional averaging tends to increase the significance of trends in the snow variables, since short-term natural climate and weather variability is not perfectly correlated across different regions. However, the amount that regional averaging increases the significance of any trends depends on the magnitude of the trend, how well correlated projected anthropogenic change is across the regions, and how well correlated short-term noise is in the variable of interest.

The correlation of variables in different regions is shown in Fig. 13. The temporal correlation between two regions’ time series has been computed for each variable, model, and pair of regions, and the results binned by correlation value. The period covered is 1950–2025 (sans the 2006–09 gap in model data), because Fig. 7 shows that by later in the century most models show significant trends even without regional averaging, while before 2000 few models do. It is in the intermediate period between that regional averaging is of most interest. Cold season–mean (October–March) air temperature is the most well correlated variable across the western United States, with 70% of the regional pairs showing a correlation greater than 0.8. Precipitation is the least well correlated, and shows a stronger tendency than any other variable for negative correlations between the regions [both El Niño–Southern Oscillation and the PDO produce dipoles in the precipitation response across the western United States—for example Mo and Higgins (1998) and Cayan (1996)].

To explore the effects of regional averaging on the significance of trends, we performed a Monte Carlo experiment where $n$ regions were randomly chosen to be averaged together ($n = 1, 2, 4, \text{ or } 8$), and the SNR of the trend from 1950 to 2025 calculated. The SNR for each model was calculated separately, and results from all models pooled to obtain the distributions shown in Fig. 14.

Regional averaging makes little difference in the resultant trends in air temperature, snowfall, or precipitation. Air temperature already has nearly the highest SNR values and the best correlation across regions, so regional averaging has little effect. Precipitation has so little a trend to begin with (Fig. 3) that even regional averaging does not uncover a significant trend by 2025 (or later); and as discussed below, snowfall is strongly linked to precipitation. However, for SFE/P and the last day of snow cover, averaging across regions reduces the noise in the trends, increasing the mean SNR by 0.37 when going from no regional averaging ($n = 1$) to averaging across all regions ($n = 8$). Trends in SWE/P and the first day of snow cover are sharpened less by regional averaging, with SNR increases of about 0.25.

### g. Components of the SNR

Although the statistical significance of a trend reflects the SNR, the amplitudes of the signal and noise are themselves of interest. The multimodel ensemble–averaged values of the climate change signal and noise by 2025 are shown in Fig. 15. The signal (solid bars) is computed as the change implied by the linear least squares trend between 1950 and 2025, while the noise (hollow bars) is taken as twice the standard error in the trend estimate. These values have the same units as the underlying variable and are grouped by color in Fig. 15 according to the units. SNR is shown as the red dots and is directly comparable across variables.

The largest SNR is found for SFE/P, but its signal is only about half as large as that of SWE/P or SWE. Instrument measurement errors, not relevant to this model-based exploration, might have more of an effect on this variable than others with a stronger signal if such an evaluation is applied to observational records. The largest signal for variables measured in percent is in SWE/P, which has both more signal and less noise than SWE. The relative rankings of SNR across the variables change little with time out to 2100, although values scale up, increasing by a factor of 2.0 by 2050 and 3.2 by 2080, relative to the values for 2025 shown in Fig. 15.

### 4. Discussion

Model simulations indicate that climate change will be seen first in temperature and SFE/P, then in SWE/P and the retreat of spring snowpack (last day of the snow
season), followed by SWE, the first day of the snow season, snowfall, and finally precipitation. The relative ranking of precipitation could be different in other regions that show a more consistent precipitation change.

Do observations agree with this ranking, which is based on global climate models? To address this question, we assessed historical variability over the period 1915–2003 using the VIC hydrological model forced by daily-gridded meteorological fields derived from station observations (Hamlet and Lettenmaier 2005). The effect of cold season-averaged temperature and precipitation fluctuations on each variable was determined by ordinary least squares linear regression. This only approximates the sensitivity to future changes; nonlinear effects on snow variables can become important when extrapolating outside the range of historical variability, so we refer to this estimate as a proxy for SNR rather than as SNR itself.

Results are shown in Table 3, ordered by SNR proxy for a warming of 1.75°C and a change in precipitation of 1%, values taken from Fig. 3 as indicative of changes by the middle of this century. The ranking of SNR from this pseudo-observation series is similar to that from the general circulation models. Temperature and SFE/P have the highest SNR and snowfall and precipitation the least. The main difference between the historically
observed and model future projection rankings is in the last day of the snow season, which is ranked higher in the global model projections than those based on linear regressions over history. This may be because, while most of the other snow variables are more integrated measures over the entire cold season, the last day of the snow season is heavily influenced by spring temperatures. Historic cold-season temperatures are not well correlated to spring temperatures, but anthropogenic changes in temperature are well correlated between the cold season and spring, imparting a stronger relationship than found with natural variability alone.

Table 3 shows that over 90% of the historical variance in snowfall is explained by precipitation, by far the highest fraction of any snow variable save precipitation itself, while its dependence on temperature is the least of any snow variable except precipitation again. Overall, when considering areas that are snow dominated over the climatological period (1976–2005), as in this study, snowfall is more of an indication of precipitation than temperature.

5. Conclusions

In this work we have used 13 of the latest general circulation models from the CMIP5 archive, forced with two representative greenhouse gas concentration pathways (RCPs) and statistically downscaled to the western...
FIG. 12. Model-mean estimate of the future disposition of total cold-season precipitation (mm), summed from 1 Oct to the day of maximum SWE (typically near 1 Apr). Gray represents precipitation falling as rain. Pink denotes precipitation falling as snow, but melting before the day of maximum SWE. Blue represents precipitation falling as snow and remaining in the snowpack on the day of maximum SWE. Numbers indicate the change in water equivalent by the end of the century (mm; %), with respect to the climatological period 1976–2005.
United States, to investigate the relative timing when different snow variables show a significant trend. Previous studies have used the earlier CMIP3 models to examine fewer variables on a hemisphere-wide basis (Brown and Mote 2009) and used a formal, optimal fingerprint detection and attribution methodology over the western United States to show that the hydrology of the region is already changing because of anthropogenic effects (e.g., Barnett et al. 2008; Pierce et al. 2008; Hidalgo et al. 2009). However, water resource managers and other stakeholders concerned with snow may be interested in additional variables, such as the snow season length for the recreation industry or the fraction of precipitation that falls as snow for flood control purposes. Furthermore, many users do not have the resources to consider a noise-optimized multivariate fingerprint, and so rely on simple trends. The present study shows that classical significance testing of linear trends reveals important differences in the strength and time required for a significant trend to emerge in different snow variables.

Besides temperature itself, the fraction of precipitation that falls as snow (SFE/P) and the fraction of snowfall retained in the snowpack as of 1 April (SWE/P) show the earliest significant trends. Averaged over the snow-dominated regions of the western United States, 80% of the model simulations show a significant trend in these indicators by 2030. The multimodel-ensemble average can show significant trends decades before a given individual model, which speaks to the power of natural variation in obscuring the trend (cf. Deser et al. 2012). Normalizing by precipitation reduces the effects of year-to-year changes in overall precipitation, reducing the effects of short-term climate and weather variability (Pierce et al. 2008). Significant changes in SWE typically lag by 5–20 years behind SWE/P and SFE/P, depending on location.

As the climate warms, the transition of precipitation from snow to rain accomplishes almost 30% more of a reduction in SWE than does greater snowmelt over what had historically been the snow accumulation season. In the western United States, increasing precipitation also plays a role in changing SWE by providing a tendency to increase SWE. This is partly because precipitation increases in the cold season but declines in the spring, tending to increase snow quantities measured over the cold season even when the annual change in precipitation is small.

Table 2. Estimates of the linear contribution to end-of-century changes in peak SWE from different mechanisms. Values are for the RCP 4.5 emissions scenario and the multimodel-ensemble average. Please note, the third and fourth columns from the left refer to ΔSWE by the end of this century with respect to the climatological period. The fifth–seventh columns from the left refer to ΔSWE taken over the historical snow accumulations season (from 1 Oct to the historical day of max SWE). The last column provides the error in the linear estimate. Because SWE decreases, the sign convention is taken such that the contributions from different sources sum to 100% (i.e., the sum of fifth–eighth columns is = 100%). Also shown (boldface) is the mean across all regions.

<table>
<thead>
<tr>
<th>Region</th>
<th>Day with max SWE (1976–2005)</th>
<th>ΔSWE (mm)</th>
<th>ΔSWE (%)</th>
<th>Contribution (%) to ΔSWE</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Incr. P</td>
<td>Incr. melting</td>
</tr>
<tr>
<td>WA Cascades</td>
<td>94</td>
<td>−379</td>
<td>−34.9</td>
<td>15.4</td>
<td>−29.3</td>
</tr>
<tr>
<td>Blue Mountains</td>
<td>82</td>
<td>−154</td>
<td>−33.8</td>
<td>18.6</td>
<td>−59.4</td>
</tr>
<tr>
<td>N. Rockies</td>
<td>86</td>
<td>−162</td>
<td>−35.0</td>
<td>18.6</td>
<td>−54.4</td>
</tr>
<tr>
<td>OR Cascades</td>
<td>90</td>
<td>−334</td>
<td>−51.6</td>
<td>2.3</td>
<td>−29.8</td>
</tr>
<tr>
<td>Great Basin</td>
<td>70</td>
<td>−88</td>
<td>−39.6</td>
<td>26.4</td>
<td>−65.3</td>
</tr>
<tr>
<td>Wasatch</td>
<td>93</td>
<td>−87</td>
<td>−21.6</td>
<td>47.1</td>
<td>−83.4</td>
</tr>
<tr>
<td>Sierra Nevada</td>
<td>89</td>
<td>−169</td>
<td>−30.3</td>
<td>11.4</td>
<td>−37.2</td>
</tr>
<tr>
<td>Colo. Rockies</td>
<td>103</td>
<td>−79</td>
<td>−21.3</td>
<td>59.8</td>
<td>−93.2</td>
</tr>
<tr>
<td>Mean</td>
<td>88</td>
<td>−182</td>
<td>−33.5</td>
<td>24.9</td>
<td>−56.5</td>
</tr>
</tbody>
</table>
Significant trends emerge earlier, and reductions in the snow variables are stronger, in the RCP 8.5 emissions scenario relative to RCP 4.5. And although there is considerable variability in projected changes between model simulations, the trend toward reduced snow is present in all cases. Averaging over multiple regions gives a stronger signal than found in any one region.

**Fig. 14.** Effect of averaging together $n$ regions ($x$ axis) before computing the SNR of the trend from 1950 to 2025. Symbols show the mean value (central heavy line), interquartile range (box), and 10th–90th percentiles (whiskers) of the SNR distribution. The SNR distribution is taken across all models, with the regions to be averaged together selected randomly using 250 trials for each combination of variable, model, and $n$. In the top-left corner of each plot, $\Delta$ represents the change in mean SNR from $n = 1$ to $n = 8$. Results are for RCP 4.5.

**Fig. 15.** Comparison of the climate change signal in 2025 (the change estimated by the least squares linear trend in the indicated variable from 1950 to 2025; solid bars), noise (twice the autocorrelation-adjusted standard error in the uncertainty in the trend; hollow bars), and SNR (red dots), averaged across snow locations in the western United States for the RCP 4.5 scenario. Colors indicate the units of the variable being considered: black ($\%$), blue ($^\circ C$), and green (days). The SNR (red dots; rightmost $y$ axis) is dimensionless, and so can be directly compared across all variables.
Table 3. Observation-based proxy for SNR computed from historical observations (1915–2003), ordered from highest to lowest magnitude. Columns from left to right provide the variable, linear sensitivity to changes in cold-season precipitation (October–March) with the percent of variance explained (% var.) in parentheses, linear sensitivity to changes in cold-season temperature with the percent of variance explained in parentheses, linear change $\Delta$ in the variable from a warming of 1.75°C and increase of precipitation of 1%, standard deviation $\sigma$ of the detrended time series over the historical period, and the SNR proxy (the linear change; fourth column from the left divided by the fifth column from the left). The unit of days is used in the table (i.e., d).

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\partial \phi \partial P$ (% var.)</th>
<th>$\partial \phi \partial T$ (% var.)</th>
<th>$\Delta$</th>
<th>$\sigma$</th>
<th>$\Delta \sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>0.0°C $%^{-1}$ (0.3%)</td>
<td>1.0°C $%^{-1}$ (100%)</td>
<td>1.75°C</td>
<td>0.97°C</td>
<td>1.8</td>
</tr>
<tr>
<td>SFE/P</td>
<td>0.04% $%^{-1}$ (2.6%)</td>
<td>−3.47% $%^{-1}$ (51.7%)</td>
<td>−6.03%</td>
<td>4.9%</td>
<td>1.23</td>
</tr>
<tr>
<td>SWE/P</td>
<td>0.50% $%^{-1}$ (20.9%)</td>
<td>−10.6% $%^{-1}$ (41.8%)</td>
<td>−18.05%</td>
<td>16.8%</td>
<td>1.07</td>
</tr>
<tr>
<td>SWE</td>
<td>1.43% $%^{-1}$ (69.9%)</td>
<td>−9.41% $%^{-1}$ (17.5%)</td>
<td>−15.04%</td>
<td>25.8%</td>
<td>0.58</td>
</tr>
<tr>
<td>First day</td>
<td>−0.22 d $%^{-1}$ (22.5%)</td>
<td>1.72 d $%^{-1}$ (7.7%)</td>
<td>2.79 d</td>
<td>7.04 d</td>
<td>0.40</td>
</tr>
<tr>
<td>Last day</td>
<td>0.53 d $%^{-1}$ (49.2%)</td>
<td>−2.60 d $%^{-1}$ (7.4%)</td>
<td>−4.01 d</td>
<td>11.3 d</td>
<td>0.35</td>
</tr>
<tr>
<td>Snowfall</td>
<td>1.04% $%^{-1}$ (91.1%)</td>
<td>−3.36% $%^{-1}$ (6.9%)</td>
<td>−1.28%</td>
<td>16.3%</td>
<td>0.08</td>
</tr>
<tr>
<td>$P$</td>
<td>1.0% $%^{-1}$ (100%)</td>
<td>0.0% $%^{-1}$ (0.3%)</td>
<td>1.0%</td>
<td>14.7%</td>
<td>0.07</td>
</tr>
</tbody>
</table>

In general, significant declining trends in SWE and snowfall emerge earlier and more strongly in regions with a warmer cold-season climate, for example, the Oregon Cascades, Sierra Nevada, and Washington Cascades, and emerge later in cooler climates, for example, in the Colorado Rockies and Wasatch. All of these regions are likely to still have a snowpack at the end of the twenty-first century, but it is likely to diminish substantially over present day levels.

Changes in snowfall are statistically discerned last of all the snow variables. In many locations, 80% of the models show a significant trend in snowfall only after 2050, and in the coldest locations this threshold is not reached by the end of this century. Trends in snowfall are about half the magnitude of those found in SWE or SWE/P. In the Sierra Nevada, 80% percent of the CMIP5 models only achieve a statistically significant trend after 2060, consistent with observations that show no significant trend in snowfall over the instrumental period (Christy 2012).

These results indicate that finding a statistically significant trend in a particular snow variable in any given region can lag considerably behind the finding of a robust signature of anthropogenic change in the overall hydrological cycle of the entire region in a detection and attribution analysis. This can be understood as a combination of the regional averaging and noise-optimized fingerprint used in the detection and attribution analysis, and the uneven rate of future decline and signal to noise ratio amongst different snow measures. The difference illustrated here between finding changes in the region-wide optimized fingerprint and finding statistically significant trends in a single snow-related variable in a particular region will help stakeholders better understand the evolving state of snow in the western United States.

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REFERENCES


