Current Climate Change Reports (2019) 5:322–333
https://doi.org/10.1007/s40641-019-00143-w

CLIMATE CHANGE AND SNOW/SEA ICE (PJ KUSHNER, SECTION EDITOR)

Snow and Climate: Feedbacks, Drivers, and Indices of Change

Chad W. Thackeray[1] · Chris Derksen[2] · Christopher G. Fletcher[3] · Alex Hall[1]

Published online: 31 August 2019

Abstract

Purpose of Review Highlight significant developments that have recently been made to enhance our understanding of how snow responds to climate forcing and the role that snow plays in the climate system.

Recent Findings Widespread snow loss has occurred in recent decades, with the largest decreases in spring. These changes are primarily driven by temperature and precipitation, but changes in vegetation, light-absorbing impurities, and sea ice also contribute to variability. Changes in snow cover can also affect climate through the snow albedo feedback (SAF). Recently, considerable progress has been made in better understanding the processes contributing to SAF. We also highlight advances in knowledge of how snow variability is linked to large-scale atmospheric changes. Lastly, large-scale snow losses are expected to continue under climate change in all but the coldest climates. These projected changes to snow raise considerable concerns over future freshwater availability in snow-dominated watersheds.

Summary The results discussed here demonstrate the widespread implications that changes to snow have on the climate system and anthropogenic activity at large.

Keywords Snow · Climate variability · Climate change · Feedbacks · Earth system models

Introduction

Terrestrial snow cover is a crucial component of the earth system, having major impacts on the surface energy budget, water resources, and the ground thermal regime. At its peak each winter, snow covers approximately 47 million km^2, about 40% of the Northern Hemisphere (NH) land [1], and over three times the maximum extent of Arctic sea ice. Snow can also be present for nearly 9 months of the year at high latitudes [2•]. Snow cover's naturally high reflectivity has a large-scale cooling influence on climate [3], which, when altered, can be an important driver of extratropical climate change [4, 5]. The low thermal conductivity of snow also helps to insulate ground temperatures with implications for permafrost conditions [6] and soil moisture [7]. Additionally, snow is a vital source of freshwater to nearly one-fifth of the world's population [8, 9]. It acts as a natural reservoir, storing water until the warmer seasons when demand is high for agricultural and other uses [10•]. Changes to the timing of spring snowmelt are linked to both subsequent summer heat extremes [11] and wildfire activity [12]. Beyond this, anomalous snow cover can also indirectly influence large-scale atmospheric circulation on weekly seasonal timescales [13, 14]. These processes are associated with direct human impacts, such as the link between anomalously high Eurasian snow and extreme haze conditions over the East China Plains [15], and higher dust concentrations in East Asia [16]. Lastly, snow supports winter tourism, a major revenue stream in many countries with abundant snow-covered regions [17, 18].

For these reasons, it is essential to monitor changes in snow associated with warming temperatures and precipitation changes, and attempt to better understand the mechanisms at play. Here, we critically assess recent literature to address the following questions: what is the current understanding of how snow (extent and mass) is changing and how it will evolve under further anthropogenic warming? What are the driving

This article is part of the Topical Collection on *Climate Change and Snow/Sea Ice*

Chad W. Thackeray
cwthackeray@ucla.edu

1 Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, Los Angeles, CA, USA

2 Climate Research Division, Environment and Climate Change Canada, Toronto, Canada

3 Department of Geography & Environmental Management, University of Waterloo, Waterloo, Canada

mechanisms behind these changes? What have we learned in recent years about the role of snow in the climate system and the mechanisms behind snow-atmosphere interactions? How well do climate models capture these processes and the observed changes in snow? What is the outlook for this topic going forward? Since seasonal snow primarily resides in the NH, that is our focus here. We seek to understand the radiative and hydrological impacts of changes in snow cover extent (SCE), which is the area covered by snow, and snow water equivalent (SWE), which represents the amount of freshwater stored in the snowpack.

How Is Snow Changing?

One of the first attempts to connect observed snow cover variability with climate change was documented by Groisman et al. [19]. They identified mean annual SCE decreases of ~10% over the prior two decades (1972–1992), with high spring melt rates having major implications on the radiation balance. Two decades later, continuing declines in SCE are observed both regionally and hemispherically, with a strong trend toward decreased SCE in the spring and fall [20•, 21], and the strongest reductions occurring in May and June [22–25]. The most recent estimates show May and June SCE decreasing at rates of 3.1% and 13.6% per decade over the past half-century (1967–2018) [2•] based on the NOAA snow chart climate data record (NOAA CDR) [26]. While the NOAA CDR provides the longest data record, it is difficult to properly assess observational uncertainty from a single dataset. In a recent assessment using an ensemble of 7 datasets, Thackeray et al. [25] found that spring (March–June) SCE declined at a rate of approximately 3.3 ± 1.2% per decade from 1981 to 2010. The large observational uncertainty arises from uncertainties relating to the satellite retrievals, the performance of physical snow models, and biases in reanalysis-based forcing used in some products. During October, a positive trend in the NOAA CDR is inconsistent with all other products [20•, 27], illustrating the importance of using an observational ensemble whenever possible. Furthermore, various long-term datasets indicate a robust trend of later snow onset (2 days/decade) across the high Arctic [21].

Large documented SWE losses have been reported across the NH [28, 29]. Mudryk et al. [30] show that recent decreases in winter SWE are evident across five different datasets from 1981 to 2010, while more strongly negative spring trends occur in 4 of 5 datasets (Fig. 1). These reductions are evident when data are continentally averaged, but there remains a large amount of variability in the spatial trend patterns. Because of the high spatial variability when it comes to SWE, we will focus on studies that assess regional changes. For example, station data across Europe shows that there has

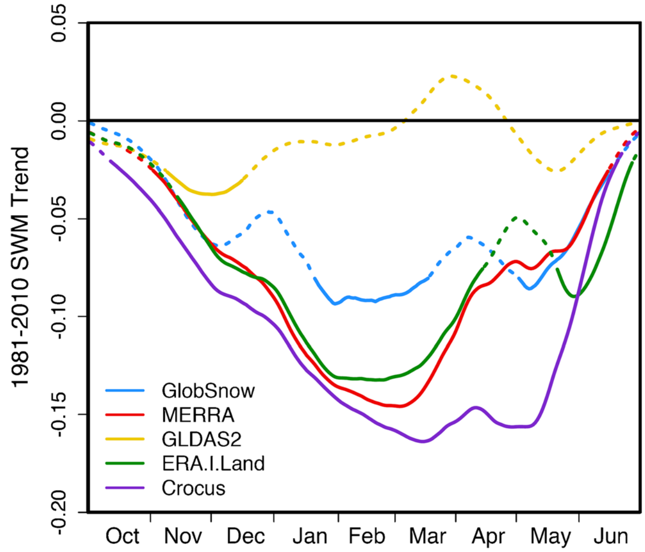

Fig. 1 Adapted from Mudryk et al. 2015. Trends in Northern Hemisphere Snow Water Mass (SWM) for five datasets over 1981–2010. The average trend of the four reanalysis-derived datasets over alpine regions has been added to the trend of the GlobSnow product. A 30-day running mean is used to smooth the data. Statistically significant trends (at the 95th confidence interval) are shown with solid lines, while non-significant trends are dashed. Units are $\times 10^{15}$ kg/decade. © American Meteorological Society. Used with permission

been a widespread mean snow depth decrease of ~12% per decade from 1951 to 2017, with the strongest trends at lower latitudes [31]. Similarly, SWE has decreased substantially across much of the Western United States [32–37]. According to Mote et al. [36], 92% of all long-term stations exhibit decreasing trends over the last six decades, with an average decline in April 1 SWE of 15–30%. It has recently been proposed that the decline in Western US SWE would be even more dramatic if not for contemporaneous atmospheric circulation changes that have acted to limit warming-induced snow loss [38]. Elsewhere, peak SWE trends of −5 to −10% per decade are found across Eastern and Northern Canada since 1981 with isolated pockets of increased SWE in the west where local spring cooling has occurred [39]. The latter is likely indicative of natural variability over the relatively short trend period. Lastly, in high-mountain Asia most catchments exhibit sharp decreases in spring and summer SWE [40]. Trends in snow mass can be more difficult to track in mountainous areas, but it is believed that the largest observed decreases are found in mid-elevation zones, which typically store the greatest snow water totals [40].

The general exception to this widespread snow loss pattern is in parts of the Arctic, where rising temperatures, which increase the moisture-holding capacity in the air, are driving increased precipitation in both solid and liquid phases (discussed more below) [41]. It is believed that increased snowfall in sufficiently cold climates may be capable of offsetting shorter snow seasons [42]. Robust analyses in these remote areas can be difficult, but increased SWE is evident for the coldest climates in Northern Scandinavia [31, 43•], whereas this trend is not evident across much of Northern Canada [39], possibly due to the large variability and short data record available there.

How Will Snow Change in the Future?

It is virtually certain that large-scale losses in terrestrial snow across the NH will be observed by the end of the twenty-first century. (The following examples are for high-emission scenarios unless otherwise stated [44].) Increasing surface temperatures will push the onset of the snow season later and promote an earlier melt period [42], with the greatest changes in spring. For example, the snow season around 1500 m across the Alps is projected to start 2–4 weeks later and end 5–10 weeks earlier than it does currently [45]. Similarly, NH SCE is projected to decline drastically in the shoulder seasons, with spring snow loss of $-3.7 \pm 1.1\%$ per decade from the CMIP5 models under a high-emission scenario [25, 46]. The largest reduction of SCE is expected at the southern snow line, where winter temperatures are close to freezing in the current climate [46]. There are, however, a number of factors that contribute to the fairly large model uncertainty seen in these projections. Much of the intermodel variability in SCE trends stems from differences in simulated future warming (especially for early-spring trends) and the climatological SCE (especially for late-spring trends) [25]. In addition, differences in future precipitation, climate feedbacks, and vegetation changes can all play a role.

Decreases in SWE are also expected across much of the hemisphere, although the magnitude differs greatly by region. Mid-century snow reductions are greatest across the Western US (~ 45%), while changes of 20–30% are likely across Europe, Eastern North America, and Western Canada plus Alaska [47]. Smaller SWE loss is projected across central Asia (~ 10%) and Northern Canada (~ 5%) [47, 48], but agreement between model simulations is low in Northern Canada due to the dual influences of increasing winter snowfall and warming [39]. The exception to this decreasing trend is extremely cold climates such as Siberia, where SWE is projected to increase by mid-century for both middle- and high-emission scenarios [21, 47, 48]. This is because temperatures during most of the snow season remain cold enough for a large fraction of precipitation (which increases drastically) to fall as snow [41]. Sospedra-Alfonso and Merryfield [49] show that these areas reside below the − 20 °C winter isotherm in the current climate, where SWE is nearly insensitive to temperature variability.

Because of the major implications that changing SWE has for water resources, numerous studies have assessed the outlook for specific regions, often using high-resolution modeling frameworks. Despite their geographic differences, many of them reach the same conclusion: we can expect dramatic declines in SWE. For example, Marty et al. [45] use regional model simulations to show that a decrease in future snowpack across the Alps is projected for all elevations, time periods, and emission scenarios. They find that areas below 1200 m are the most vulnerable and may see complete snow loss by the end of the century. Similarly, large decreases are expected across Northern Europe, with the exception of the highest elevations in Northern Scandinavia [50]. When it comes to North America, the future of Western US snowpack has been the focus of many recent studies [51, 52•, 53]. Fyfe et al. [52•] find mid-century losses of up to 60% in a high-emission scenario, whereas Rhoades et al. [53] estimate a more conservative 20–40% loss. The coastal mountain ranges are expected to experience the greatest impacts. Recent studies focusing on the Sierra Nevada suggest that snowpack declines ranging from 60 to 85% are likely by the end of the twenty-first century [54–57]. These large projected decreases are also expected for other mountainous regions featuring Mediterranean climates (e.g., Pyrenees, Atlas), where mid-century mean SWE could decline by 40–60% [58].

Changes to snow accumulation and melt will drastically impact runoff characteristics, with major impacts in semi-arid regions that are dependent on mountain snow. In many locations, we can anticipate decreased summer flows, higher streamflow earlier in the water year as a result of decreased snow storage, an earlier start to the melt season, and greater occurrence of winter rainfall [59, 60]. Changes to runoff patterns will likely be shaped by a combination of latitude and elevation, which determine the magnitude of the change in the proportion of precipitation falling as snow and the shift in melt timing. Decreasing snowfall will reduce the role that the snowpack plays as a natural reservoir (preserving water in frozen form during the warm phase of the seasonal cycle when demand is increased) with large implications on water availability during summer [9, 60]. One somewhat unexpected result is the suggestion that seasonal snowmelt may occur more slowly in a warmer world [61•] since an earlier start to the melt season coincides with a time of lower incoming solar energy. Additional changes to the winter snowpack may also stem from an altered risk of rain-on-snow events, which are projected to become more frequent at high elevations in the Western US [62] and less frequent across the Eastern US [63]. These rain-on-snow events can encourage flooding with important implications for water resources.

Drivers of Change

Here, we discuss the primary drivers of past and future changes in terrestrial snow. The most evident factor controlling snow cover variability is near-surface air temperature over land areas. It is well known that NH land is rapidly warming, with high-latitude surface temperatures increasing at the fastest rate globally [4, 64]. These temperature changes have the largest impact during the shoulder seasons, where climatological temperatures are closer to the freezing point. This coincides with the time when recent extratropical warming has been the largest (fall and spring) [20•]. The sensitivity of SCE to warming is approximately 1.9×10^6 km^2 lost for each degree of extratropical land warming on hemispheric scales (Fig. 2) [24, 25, 27]. Snow in the mid-latitudes—where the majority of the world's snowlines are located—appears to be most sensitive to climate warming [20•]. Consistent with this, Pederson et al. [34] suggest that recent Western US snowpack depletion is primarily driven by warmer spring temperatures, but that natural variability from large-scale teleconnections also plays a role. Additionally, snowpack loss over Western Canada and hemispheric snow cover retreat have both been attributed to anthropogenic forcing [65••, 66].

Precipitation also plays a critical role in driving changes in snow, particularly for SWE. There is a general consensus among projections from models that total precipitation and precipitation intensity will increase across high latitudes as the climate warms [67–69], primarily through hydrologic balance as evaporation increases into warmer air. However,

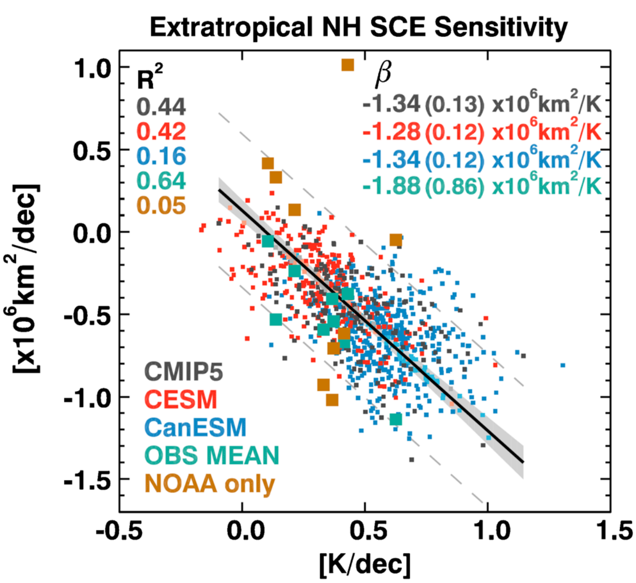

Fig. 2 SCE versus temperature (T_s) trends for individual months from October to June for individual realizations from CMIP5 (gray), the Community Earth System Model (red), and Canadian Earth System Model (blue) ensembles. Least products regression line (solid) with 95th confidence bounds (shading) shown based on CMIP5 trends; dashed lines indicate twice the standard deviation of residuals. Squares indicate individual monthly observation-based trends for the T_s ensemble mean versus the SCE ensemble mean (green) and for the T_s ensemble mean versus NOAA Climate Data Record trends (brown). Regression slopes (sensitivities) and R^2 values are colored according to the ensemble with twice the standard error on the regression slopes (β) in parentheses (from Mudryk et al. 2017). Reprinted with permission from John Wiley and Sons

historical precipitation changes are difficult to track due to the highly variable nature of precipitation over short distances and large observational uncertainties [70]. Additionally, several satellite-derived products do not observe at high latitudes (e.g., TRMM, PERSIANN), and atmospheric reanalyses are often inconsistent across these regions [71, 72]. Despite these issues, previous assessments have suggested that high-latitude precipitation has increased by between 2.7 to 5.8 mm/decade over the period of 1951 to 2008 [73, 74]. Increased precipitation may not directly translate to greater snowfall, however, as warming shortens the snow season and alters the fraction of precipitation that falls as rain and snow [41, 47]. Over most of the extratropics, the fraction of snow will decrease significantly [47, 75]. Similarly, studies suggest that precipitation is the main factor controlling snowpack variability in cold mountainous areas above ~ 1500 m [76, 77]. This is because locations above this elevation tend to be sufficiently cold to support snowfall even during anomalously warm periods. Similarly, on a hemispheric scale, there appears to be a mean winter temperature threshold of roughly − 5 °C, below which precipitation is the main driver of SWE and above which temperature is the dominant factor [49]. Thus, the strong interrelation between these factors makes it difficult to generally rank their relative importance to SWE variability.

Snowmelt can be accelerated through deposition onto the surface of light-absorbing particles such as black carbon (BC) and dust. The direct radiative forcing from BC deposition on the snowpack is estimated at 0.04 W m^{-2}, while the effective climate forcing is roughly three times larger because the warming associated with the reduced snow albedo promotes additional snow cover loss [78]. Atmospheric BC concentrations increased dramatically following the industrial revolution, and the largest source is currently from biomass burning [79••]. Recent increases in Western US wildfires are also linked to locally increased deposition of light-absorbing particles [80•]. Similarly, atmospheric dust concentrations approximately doubled over the twentieth century [81] likely as a result of human land use practices and increased rates of soil erosion under more frequent drought conditions [79••]. Increasing dust on snow concentrations in recent years has helped drive earlier snowmelt and runoff in the Western US [82–84] and the European Alps [85]. Therefore, the accumulation of light-absorbing impurities alters snowmelt dynamics and contributes to observed variability in snow and runoff.

High-latitude snow cover is in close proximity to Arctic sea ice, which itself has experienced significant losses over recent decades [86, 87]. The close nature of these two environments makes it plausible that changes to one may impact the other. In particular, receding ice cover along the Arctic coast reveals more open water which can act as a large moisture source [88]. Model simulations suggest that the greatest contribution to future Arctic precipitation increases stems from intensified local surface evaporation over newly open ocean [89].

Finally, snow accumulation may be impacted by changing vegetation on longer timescales, particularly in the Arctic. Arctic snow accumulates to the height of the prevailing ground vegetation after which it is redistributed by wind to topographic depressions and drifts [90, 91]. Despite improved process understanding, estimates of sublimation loss during blowing snow events remain a key uncertainty in the mass budget of the Arctic snowpack. Increased shrub cover influences snow capture and soil temperatures [92, 93], but changes in vegetation cover across the Arctic (at the coherent regional scales needed to impose an impact on the hydroclimatic system) are not uniform and the drivers are poorly understood [94]. A recent assessment of North American vegetation found that nearly 30% of Canada and Alaska has experienced significant greening from 1984 to 2012, while only 3% had experienced robust browning [95]. Vegetation changes can also influence spring snowmelt via changes to albedo (α) [80•, 96].

Snow-Climate Feedbacks

Long-term changes in snow cover influence the climate system primarily through the snow albedo feedback (SAF). SAF is characterized by the reduction in surface albedo associated with melting snow, which increases shortwave surface absorption and amplifies warming [97–100]. (Note that SAF can also operate in the reverse direction in a cooling climate.) This process also occurs each spring when seasonal warming is enhanced by albedo decreases associated with seasonal snow retreat (referred to as the seasonal SAF) [99]. SAF makes up approximately half of the NH surface albedo feedback [3, 98, 101], which includes changes to sea ice. SAF is the largest climate feedback operating over the NH extratropics during the melt season [102, 103]. However, because of its limited extent and seasonal timing, it is not as important on a global scale as the water vapor and cloud feedbacks [104]. The global mean SAF is ~0.1 W m^{-2} K^{-1} [5], whereas the global mean water vapor and cloud feedbacks are ~1.2 W m^{-2} K^{-1} and ~0.5 W m^{-2} K^{-1} [104], respectively. Despite this, SAF and the larger surface albedo feedback are key drivers of Arctic amplification [105–107], although there remains some debate as to where exactly it ranks in terms of the biggest contributors [108, 109]. Meanwhile, SAF is central to amplification of warming at mid- to high altitudes [110, 111] and over NH extratropical land [5].

The observed or simulated SAF can be calculated through a differential equation relating changes in near-surface air temperature and albedo to changes in the shortwave radiation, which quantifies the change in net shortwave radiation (Q_{net}) at the top of the atmosphere as a result of changes in surface albedo caused by a temperature perturbation (Eq. (1)).

$$\frac{\partial Q_{\mathrm{net}}}{\partial T_{\mathrm{s}}} = \frac{\partial Q_{\mathrm{net}}}{\partial \alpha_{\mathrm{s}}} \frac{\Delta \alpha_{\mathrm{p}}}{\Delta T_{\mathrm{s}}} = -Q \frac{\partial \alpha_{\mathrm{p}}}{\partial \alpha_{\mathrm{s}}} \frac{\Delta \alpha_{\mathrm{s}}}{\Delta T_{\mathrm{s}}} \tag{1}$$

One factor in this equation relates planetary albedo changes with surface albedo variability ($\partial\alpha_{\mathrm{p}}/\partial\alpha_{\mathrm{s}}$), while a second factor relates changes in surface albedo and near-surface air temperature ($\Delta\alpha_{\mathrm{s}}/\Delta T_{\mathrm{s}}$) [99]. This latter term is commonly used to approximate SAF strength because it explains most of the intermodel variability in SAF [5, 112]. SAF can also be quantified using the radiative kernel method [103], which uses the radiative response to a 1% perturbation of albedo calculated in a climate model to translate the albedo sensitivity ($\Delta\alpha_{\mathrm{s}}/\Delta T_{\mathrm{s}}$, units % K^{-1}) into climate feedback (units W m^{-2} K^{-1}).

The SAF process in the earliest general circulation models (GCMs) was far too sensitive [113, 114] due to a lack of sophistication in their representation of the land surface (snow-covered surface albedo did not vary with vegetation). After decades of development, the current generation of earth system models (ESMs) is equipped with highly detailed land components, which represent a vast array of geophysical processes. In recent comparisons of ESMs with estimates of SAF derived from observations of the seasonal cycle, studies have shown that the ensemble mean agrees well with observations across the NH extratropics. However, there is a threefold intermodel spread, which has not decreased much over the past decade [5, 112]. This spread is consequential as it explains a significant portion of the variability in projections of future NH land warming [5]. In an effort to reduce SAF spread in future generations of ESMs, recent studies have explored the reasons why model estimates vary so greatly. The sensitivity of surface albedo to temperature changes ($\Delta\alpha_{\mathrm{s}}/\Delta T_{\mathrm{s}}$) is primarily driven by two physical mechanisms: snow cover loss (SNC) and temperature-dependent snow changes, such as metamorphism (TEM) [99]. SNC accounts for the decrease in surface albedo that occurs with the transition from snow-covered to snow-free conditions (revealing a less reflective surface). On the other hand, TEM relates to the change in snow albedo for fixed snow cover, which takes place as the snowpack ages. It has been shown that these mechanisms can explain nearly all of the total SAF [112]. The SNC component is the dominant factor across the entire NH, but the exact contribution varies depending on the methodology used to calculate these components (60–80% of the total) [5, 112]. The TEM component can be large on a regional scale, for example, over the Tibetan Plateau [115], but the dominance of SNC on the hemispheric scale means that the contrast between snow-covered and snow-free surface albedo is of great importance to SAF variability.

Several studies have since taken the approach of evaluating snow-covered surface albedo in regional and global models to better understand its controls. Thackeray et al. [116] investigate the specific structural and parametric sources of SAF bias across the CMIP5 ensemble. They find that the most common issues relate to the representation of vegetation characteristics, snow cover, and snow albedo. Several ESMs have large biases in vegetation distributions and densities [96, 117], which can lead to overestimated SAF in cases where leaf area index is too low, or underestimated SAF where leaf area index is too high. Beyond this, there is a clear relationship in models between canopy snow, the seasonal cycle of surface albedo, and the strength of SAF [118, 119]. Additionally, a subset of ESMs relies on outdated parameterizations for snow cover [116, 120] and the way in which snow-vegetation masking is resolved [99]. Other process-based studies have pointed to the depiction of sub-grid scale lakes as a factor in snow-covered surface albedo biases, but only for a single model [121]. Thus, a wide variety of factors has recently been uncovered as contributing to model uncertainty in SAF, but we see biases in vegetation characteristics and snow-vegetation interactions as having the greatest impact.

In recent years, we have also seen greater use of regional models to evaluate SAF in areas of complex terrain [122, 123]. The improved representation of topography in these models can better capture the distribution of snow across elevation ranges, with impacts on the seasonality of SAF [122]. These studies consistently find that SAF contributes to future alpine warming, which is otherwise missed by ESMs and statistical downscaling techniques [124]. Winter et al. [123] show that the contribution from SAF to end-of-century spring/summer warming in the Alps is around 10% during snowmelt, whereas analysis over the Colorado Headwaters region shows an average enhancement that is about three times larger (which translates to a warming increase of about 1.5 °C) [122]. Similar area averages are not provided by Walton et al. [124], but they use a different approach to illustrate that SAF can enhance end-of-century warming by more than 2 °C locally in the US Sierra Nevada. The incorporation of SAF into regional modeling projections is therefore an important development.

Lesser feedback comes from the dependence of outgoing longwave radiation on land surface temperature. The presence of snow cover keeps the ground temperature around the freezing point, but when snow cover recedes, the temperature can increase, thus emitting more longwave radiation [97]. This negative feedback acts to mute some, but not all, of the positive radiative effect of SAF. Other possible feedbacks include changes in cloud cover induced by melting snow and changes to turbulent heat fluxes associated with changes in snow cover. These processes are less studied but are also highly variable between models [97, 125].

Snow-Atmosphere Coupling

While the importance of snow as a contributor to surface radiative feedbacks is unquestioned, a more controversial line of research has examined the potential for terrestrial snow anomalies to drive variability in the large-scale atmospheric circulation, raising the prospect of an additional source of subseasonal-to-seasonal predictability. A widely studied example emerged from the work of Cohen and Entekhabi [126], who first reported a strong correlation between observed interannual variations in the spatial extent of September–November mean Eurasian snow cover, and the leading mode of NH atmospheric variability (the Arctic Oscillation or AO) in the following winter (December–February mean).

The controversy surrounding this link centers around the need for a robust physical mechanism to explain not only the snow-AO relationship but also the time delay of multiple months between the snow anomalies and the AO response. A mechanism involving a strengthening Siberian High, upward propagation of a Rossby wave teleconnection into the polar stratosphere, and subsequent downward propagation of stratospheric circulation anomalies into the troposphere, was first proposed by Saito et al. [127], and many studies since then have attempted to disentangle this mechanism using observations and models [128–132]. An important issue is that multiple generations of climate models have been unable to spontaneously reproduce snow-AO connections in their internal variability [133, 134], and models have had to be perturbed by unrealistically large snow anomalies to generate a realistic-looking AO response (e.g. [129]). As summarized in Henderson et al. [135••] recent work suggests strongly that the observed snow-AO link is non-stationary [136] and may be modulated by other sources of climate variability such as the Quasi-Biennial Oscillation and/or the Pacific Decadal Oscillation [137].

On a related theme, for more than a century, anomalous Himalayan snow cover has been linked with variations in the Indian summer monsoon. Blandford [138] originally proposed the idea after observing several years where higher winter/spring snowfall was followed by drier conditions over India associated with a weakened monsoon. Since then many studies have pursued this link, with earlier work confirming Blandford's original hypothesis (e.g. [139]), while more recent work has shown that the relationship appears to have weakened or even changed sign [140, 141]. Some authors have also proposed that the snow-monsoon link is not robust and/or may be explained through a connection to ENSO [142]. The apparent non-stationarity and contradictory results from observational analyses have motivated substantial modeling efforts to elucidate the mechanisms underpinning the snow-monsoon link. Turner and Slingo [143] confirmed Blandford's hypothesis using a suite of sensitivity experiments with an atmospheric GCM and showed that the monsoon circulation is weakened due to a reduced meridional temperature gradient in years of high Himalaya snow. Incorporating this mechanism into a seasonal forecast system through improved initialization of Himalayan snow has been shown to delay the simulation of the onset of the Indian monsoon by approximately 1 week [144].

Finally, the coupling between snow and the atmosphere is typically strongest during spring melt. Snow anomalies are thought to produce a lasting impact on the surface climate through a delayed effect caused by excessive soil moisture from melting snow [145]. Recent work suggests that non-stationarity in the snow-monsoon link may be caused, in part, by compensating effects between increased albedo and excess soil moisture during high-snow years [146]. However, other authors have concluded that snow cover anomalies do not influence soil moisture, or the Indian monsoon, due to the short timescale of soil moisture feedbacks [147]. It is clear that substantial "memory" in the land surface of climate models is provided by soil moisture anomalies, which in cold regions during spring/summer are intrinsically linked to melting snow [148]. Yet, it remains an open question whether, and to what extent, such memory exists in the real climate system, and how/if it can be harnessed to improve understanding and/or predictability.

How Well Do Climate Models Capture These Changes?

ESMs from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) tend to underestimate recent extratropical reductions in spring SCE, with the ensemble mean being about 20% weaker ($-2.5 \pm 1.0\%$ per decade from 1981 to 2010) [25]. A similar conclusion was also reached for the early-spring period [46]. The discrepancy between ESMs and observations is thought to be greatest for June SCE [24], although observational uncertainty is larger than April and May during this month [20]. Recent studies have also evaluated why climate models underestimate observed trends. The main culprit appears to be an underestimation of the amount of snow loss that occurs with warming (defined as snow cover sensitivity) (Fig. 2). Mudryk et al. [20•] show that the largest differences in snow cover sensitivity take place in mid-latitude and alpine areas. Models also underestimate the amount of boreal spring land temperature change [46]. During late spring, model underestimates of climatological SCE may also be impacting the trends [25].

It is more challenging to assess model simulations of recent SWE changes on a hemispheric scale because of larger observational uncertainties in potential precipitation forcing of SWE trends and the coarse resolution of ESMs. The Community Earth System Model (CESM) underestimates observed losses in winter-spring over North America and like observations exhibit a mixed response over Eurasia [28]. On a more regional scale, Fyfe et al. [52•] show that a different model well captures decreases in peak SWE across the Western US from an average of reanalysis products, despite overestimating climatological SWE. The overestimation of climatological SWE also appears in much of the CMIP3 and CMIP5 ensembles across the rest of the NH [42, 149]. Therefore, ESMs are capable of qualitatively capturing SWE trends, but their overly simplistic underlying topography likely limits their usefulness for understanding large-scale SWE changes.

Conclusions

The literature assessed here demonstrates the broad research interest in how snow is changing and will continue to evolve under future climate change. There is high confidence that widespread NH snow loss is occurring [20, 25, 30, 43•], particularly in spring (Fig. 1). These changes are being primarily driven by temperature, but a number of other factors also play a role, including precipitation, vegetation, light-absorbing impurities, and sea ice melt. Changes in snow cover can also feedback on climate through SAF to enhance regional surface warming. Future snow seasons will very likely be dramatically shorter as a result of warming, while changes in SWE are expected to decline across all but the coldest (and high elevation) regions [45, 47, 52•]. These projected changes lead to considerable freshwater availability concerns in many densely populated regions where water supplies may already be stretched thin [9, 59, 150].

Sparse station data and difficulties monitoring snow from space make for large differences between various observation-based estimates of recent change. Furthermore, many of these datasets rely on reanalysis and snow models rather than direct surface observations (e.g., [151]). This highlights the need for better earth observation when it comes to snow mass [152], particularly in forested areas which make up a large fraction of the NH extratropics and where snow-vegetation interactions are strongest, and in mountainous areas where the deepest and most spatially variable snow occurs. For example, recent work estimates that the mountains of North America store 60% of the continent's annual peak snow water [153]. In the meantime, we encourage the use of a multi-dataset approach to properly capture the uncertainties associated with observed snow trends.

When it comes to the modeling of snow, we are encouraged by the greater emphasis on land surface modeling in the past decade, but note that there are still some essential snow processes that are not commonly represented, such as blowing snow. The representation of many other processes dates back several decades and is still often too simple (e.g., one-layer implicit snow schemes, type 4 snow-vegetation masking as defined by Qu and Hall [99]). For many snow-related questions in areas of intense topography, inherent limitations in ESMs due to their coarse resolution (at least 100 km by 100 km) make it necessary to consider alternative regional modeling approaches. Recent developments in variable-resolution modeling are particularly encouraging for answering questions relating to mountain snowpack [53]. Forthcoming analysis of CMIP6 output will determine whether reduced uncertainty in model projections of snow will emerge from the latest generation of earth system models. Additionally, ongoing collaborative modeling efforts should provide a significant advance in our knowledge of the role snow plays in the climate system. For example, ESM-SnowMIP is an international effort specifically aimed at this purpose. It will provide insight into the processes and characteristics that need to be improved in modeling of snow at both local and global scales [154•].

Given the aforementioned limitations and uncertainties, what can be done to improve projections of future snow from ESMs? Since projected SCE trends are predominantly controlled by NH extratropical land surface temperature changes [25], taking steps to ensure reduced intermodel variability in warming should help narrow the spread in model projections of future snow cover. An important contributor to the spread in extratropical land warming is SAF. Therefore, taking steps to reduce uncertainty in seasonal SAF, which should translate to reduced spread under climate change [5], is essential. We have known of the large SAF spread across ESMs for more than a decade. Although many ESMs did make notable improvements to better represent SAF from CMIP3 to CMIP5 [116], there has been little spread reduction in SAF from one ensemble to the next. This highlights the need for better communication of these and similar findings to individual modeling centers. There is a variety of further model development related to snow and land surface modeling going from CMIP5 to CMIP6 [116], but it remains to be seen if these activities lead to greater realism in SAF and reduction in SAF spread.

In closing, snow is a critical component of the NH ecology and climate and is a significant freshwater resource for a significant fraction of the world's population. Robust monitoring of snow cover and snow mass variability and change, continued model development, and well-constrained projections of future snow conditions are required to ensure societal and ecosystem resiliency.

Acknowledgments We would like to thank Lawrence Mudryk for providing the data to reproduce Fig. 1. We also thank the editor and two anonymous reviewers for their helpful comments. On behalf of all authors, the corresponding author states that there is no conflict of interest.

Funding information C.W.T. and A.H. would like to thank the funding from the National Science Foundation grant (#1543268) titled "Reducing Uncertainty Surrounding Climate Change Using Emergent Constraints."

References

Papers of particular interest, published recently, have been highlighted as:
- • Of importance
- •• Of major importance

1. Robinson D, Frei A. Seasonal variability of northern hemisphere snow extent using visible satellite data. Prof Geogr. 2000;52:307–15.
2.• Bormann KJ, Brown RD, Derksen C, Painter TH. Estimating snow-cover trends from space. Nat Clim Chang. 2018;8:924–8 **This review highlights the uncertainty associated with observing snow cover from satellite-based sensors.**
3. Flanner MG, Shell KM, Barlage M, Perovich DK, Tschudi M a. Radiative forcing and albedo feedback from the Northern Hemisphere cryosphere between 1979 and 2008. Nat Geosci. 2011;4:151–5.
4. Serreze MC, Barry RG. Processes and impacts of Arctic amplification: a research synthesis. Glob Planet Chang. 2011;77:85–96.
5. Qu X, Hall A. On the persistent spread in snow-albedo feedback. Clim Dyn. 2014;42:69–81.
6. Lawrence DM, Slater AG. The contribution of snow condition trends to future ground climate. Clim Dyn. 2010;34:969–81.
7. Ruosteenoja K, Markkanen T, Venäläinen A, Räisänen P, Peltola H. Seasonal soil moisture and drought occurrence in Europe in CMIP5 projections for the 21st century. Clim Dyn. 2018;50:1177–92.
8. Barnett TP, Adam JC, Lettenmaier DP. Potential impacts of a warming climate on water availability in snow-dominated regions. Nature. 2005;438:303–9.
9. Mankin JS, Viviroli D, Singh D, Hoekstra AY, Diffenbaugh NS. The potential for snow to supply human water demand in the present and future. Environ Res Lett. 2015;10:114016.
10.• Sturm M, Goldstein MA, Parr C. Water and life from snow: a trillion dollar science question. Water Resour Res. 2017;53:3534–44 **This is a detailed review of the hydrological importance of snow.**
11. Diffenbaugh NS, Pal JS, Trapp RJ, Giorgi F. Fine-scale processes regulate the response of extreme events to global climate change. Proc Natl Acad Sci U S A. 2005;102:15774–8.
12. Westerling AL. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philos Trans R Soc B Biol Sci. 2016;371:20150178. https://doi.org/10.1098/rstb.2015.0178.
13. Cohen JL, Furtado JC, Barlow MA, Alexeev VA, Cherry JE. Arctic warming, increasing snow cover and widespread boreal winter cooling. Environ Res Lett. 2012;7:014007.
14. Cohen J, Screen JA, Furtado JC, et al. Recent Arctic amplification and extreme mid-latitude weather. Nat Geosci. 2014;7:627–37.
15. Zou Y, Wang Y, Zhang Y, Koo JH. Arctic sea ice, Eurasia snow, and extreme winter haze in China. Sci Adv 2017;3:e1602751
16. Liu H, Liu X, Dong B. Influence of central Siberian snow-albedo feedback on the spring east Asian dust cycle and connection with the preceding Winter Arctic Oscillation. J Geophys Res Atmos. 2018;123:13,368–85.
17. Damm A, Greuell W, Landgren O, Prettenthaler F. Impacts of +2 °C global warming on winter tourism demand in Europe. Clim Serv. 2017;7:31–46.
18. Steiger R, Scott D, Abegg B, Pons M, Aall C. A critical review of climate change risk for ski tourism. Curr Issues Tour. 2017;22:1343–1379.
19. Groisman P, Karl TR, Knight RW, Stenchikov GL. Changes of snow cover, temperature, and radiative heat balance over the Northern Hemisphere. J Clim. 1994;7:1633–56.
20.• Mudryk LR, Kushner PJ, Derksen C, Thackeray C. Snow cover response to temperature in observational and climate model ensembles. Geophys Res Lett. 2017. https://doi.org/10.1002/2016GL071789 **This paper provides the most robust snow cover trend analysis to date by utilizing an ensemble of observational products.**
21. Brown R, Vikhamar-Schuler D, Bulygina O, Derksen C, Luojus K, Mudryk LR, Wang L, Yang D (2017) Chapter 3. Arctic Terrestrial Snow Cover. Snow, Water, Ice and Permafrost in the Arctic (SWIPA) 2017.
22. Brown RD, Derksen C, Wang L. A multi-data set analysis of variability and change in Arctic spring snow cover extent, 1967–2008. J Geophys Res. 2010;115:D16111.

23. Brown RD, Robinson DA. Northern Hemisphere spring snow cover variability and change over 1922–2010 including an assessment of uncertainty. Cryosph. 2011;5:219–29.
24. Derksen C, Brown R. Spring snow cover extent reductions in the 2008-2012 period exceeding climate model projections. Geophys Res Lett. 2012;39:L19504.
25. Thackeray CW, Fletcher CG, Mudryk LR, Derksen C. Quantifying the uncertainty in historical and future simulations of Northern Hemisphere spring snow cover. J Clim. 2016;29:8647–63.
26. Estilow TW, Young AH, Robinson DA. A long-term Northern Hemisphere snow cover extent. Earth Syst Sci Data. 2015;7:137–42.
27. Brown RD, Derksen C. Is Eurasian October snow cover extent increasing? Environ Res Lett. 2013;8:024006.
28. Mudryk LR, Kushner PJ, Derksen C. Interpreting observed northern hemisphere snow trends with large ensembles of climate simulations. Clim Dyn. 2014;43:345–59.
29. Kunkel KE, Robinson DA, Champion S, Yin X, Estilow T, Frankson RM. Trends and extremes in northern hemisphere snow characteristics. Curr Clim Chang Rep. 2016;2:65–73.
30. Mudryk LR, Derksen C, Kushner PJ, Brown R. Characterization of Northern Hemisphere snow water equivalent datasets, 1981-2010. J Clim. 2015;28:8037–51.
31. Fontrodona Bach A, van der Schrier G, Melsen LA, Klein Tank AMG, Teuling AJ. Widespread and accelerated decrease of observed mean and extreme snow depth over Europe. Geophys Res Lett. 2018;45:12,312–9.
32. Clow DW. Changes in the timing of snowmelt and streamflow in Colorado: a response to recent warming. J Clim. 2010;23:2293–306.
33. Kapnick S, Hall A. Causes of recent changes in Western North American snowpack. Clim Dyn. 2012;38:1885–99.
34. Pederson GT, Betancourt JL, McCabe GJ. Regional patterns and proximal causes of the recent snowpack decline in the Rocky Mountains, U.S. Geophys Res Lett. 2013;40:1811–6.
35. Mote PW, Rupp DE, Li S, Sharp DJ, Otto F, Uhe PF, et al. Perspectives on the causes of exceptionally low 2015 snowpack in the Western United States. Geophys Res Lett. 2016;43:10980–8.
36. MMote PW, Li S, Lettenmaier DP, Xiao M, Engel R. Dramatic declines in snowpack in the western US. npj Clim Atmos Sci. 2018;1. https://doi.org/10.1038/s41612-018-0012-1.
37. Zeng X, Broxton P, Dawson N. Snowpack change from 1982 to 2016 over conterminous United States. Geophys Res Lett. 2018;45:12,940–7.
38. Siler N, Proistosescu C, Po-Chedley S. Natural variability has slowed the decline in Western U.S. snowpack since the 1980s. Geophys Res Lett. 2019;46:346–55.
39. Mudryk LR, Derksen C, Howell S, Laliberté F, Thackeray C, Sospedra-Alfonso R, et al. Canadian snow and sea ice: historical trends and projections. Cryosph. 2018;12:1157–76.
40. Smith T, Bookhagen B. Changes in seasonal snow water equivalent distribution in high mountain Asia (1987 to 2009). Sci Adv. 2018;4:e1701550. https://doi.org/10.1126/sciadv.1701550.
41. Bintanja R, Andry O. Towards a rain-dominated Arctic. Nat Clim Chang. 2017;7:263–7.
42. Brown RD, Mote PW. The response of Northern Hemisphere snow cover to a changing climate. J Clim. 2009;22:2124–45.
43.• Beniston M, Farinotti D, Stoffel M, et al. The European mountain cryosphere: a review of its current state, trends, and future challenges. Cryosph. 2018;12:759–94 **This review highlights regional changes to snow across Europe in great detail.**
44. Collins M, Knutti R (2013) Long-term Climate Change: Projections, Commitments and Irreversibility. In: Stocker TF, Qin D, Plattner GK, Tignor M, Allen SK, Doschung J, Nauels A, Xia Y, Bex V, Midgley PM (eds) Clim. Chang. 2013 Phys. Sci. Basis. Contrib. Work. Gr. I to Fifth Assess. Rep. Intergov. Panel Clim. Chang. Cambridge University Press, Cambridge, UK, pp 1029–1136.
45. Marty C, Schlogl S, Bavay M, Lehning M. How much can we save? Impact of different emission scenarios on future snow cover in the Alps. Cryosph. 2017;11:517–29.
46. Brutel-Vuilmet C, Ménégoz M, Krinner G. An analysis of present and future seasonal Northern Hemisphere land snow cover simulated by CMIP5 coupled climate models. Cryosph. 2013;7:67–80.
47. Mankin JS, Diffenbaugh NS. Influence of temperature and precipitation variability on near-term snow trends. Clim Dyn. 2015;45:1099–116.
48. Krasting JP, Broccoli AJ, Dixon KW, Lanzante JR. Future changes in Northern Hemisphere snowfall. J Clim. 2013;26:7813–28.
49. Sospedra-Alfonso R, Merryfield WJ. Influences of temperature and precipitation on historical and future snowpack variability over the Northern Hemisphere in the second generation Canadian Earth System Model. J Clim. 2017;30:4633–56.
50. Räisänen J. Twenty-first century changes in snowfall climate in Northern Europe in ENSEMBLES regional climate models. Clim Dyn. 2016;46:339–53.
51. Ashfaq M, Ghosh S, Kao S-C, Bowling LC, Mote P, Touma D, et al. Near-term acceleration of hydroclimatic change in the Western U.S. J Geophys Res Atmos. 2013;118:10,676–93.
52.• Fyfe JC, Derksen C, Mudryk L, et al. Large near-term projected snowpack loss over the Western United States. Nat Commun. 2017;8:14996 **This paper used a large ensemble to better understand the role of natural variability in recent snowpack loss.**
53. Rhoades AM, Ullrich PA, Zarzycki CM. Projecting 21st century snowpack trends in Western USA mountains using variable-resolution CESM. Clim Dyn. 2018;50:261–88.
54. Berg N, Hall A. Anthropogenic warming impacts on California snowpack during drought. Geophys Res Lett. 2017;44:2511–8.
55. Huang X, Hall AD, Berg N. Anthropogenic warming impacts on today's Sierra Nevada snowpack and flood risk. Geophys Res Lett. 2018;45:6215–22.
56. Rhoades AM, Jones AD, Ullrich PA. The changing character of the California Sierra Nevada as a natural reservoir. Geophys Res Lett. 2018;45. https://doi.org/10.1029/2018GL080308.
57. Sun F, Berg N, Hall A, Schwartz M, Walton D. Understanding end-of-century snowpack changes over California's Sierra Nevada. Geophys Res Lett. 2019;46:933–43.
58. Lopez-Moreno JI, Gascoin S, Herrero J, et al. Different sensitivities of snowpacks to warming in Mediterranean climate mountain areas. Environ Res Lett. 2017;12.
59. Donnelly C, Greuell W, Andersson J, Gerten D, Pisacane G, Roudier P, et al. Impacts of climate change on European hydrology at 1.5, 2 and 3 degrees mean global warming above preindustrial level. Clim Chang. 2017;143:13–26.
60. Jenicek M, Seibert J, Staudinger M. Modeling of future changes in seasonal snowpack and impacts on summer low flows in alpine catchments. Water Resour Res. 2018;54:538–56.
61.• Musselman KN, Clark MP, Liu C, Ikeda K, Rasmussen R. Slower snowmelt in a warmer world. Nat Clim Chang. 2017;7:214–9 **This paper proposes the idea of slower snowmelt in the future, which has major implications for hydrology.**
62. Musselman KN, Lehner F, Ikeda K, Clark MP, Prein AF, Liu C, et al. Projected increases and shifts in rain-on-snow flood risk over Western North America. Nat Clim Chang. 2018;8:808–12. https://doi.org/10.1038/s41558-018-0236-4.
63. Wachowicz LJ, Mote TL, Henderson GR. A rain on snow climatology and temporal analysis for the eastern United States. Phys Geogr. 2019;00:1–16.

64. Fyfe JC, Von Salzen K, Gillett NP, Arora VK, Flato GM, McConnell JR. One hundred years of Arctic surface temperature variation due to anthropogenic influence. Sci Rep. 2013;3:1–7.
65.•• Najafi MR, Zwiers FW, Gillett NP. Attribution of the spring snow cover extent decline in the Northern Hemisphere, Eurasia and North America to anthropogenic influence. Clim Chang. 2016. https://doi.org/10.1007/s10584-016-1632-2 **This paper applies detection and attribution techniques to find anthropogenic forcing behind observed NH snow cover losses.**
66. Najafi MR, Zwiers FW, Gillett NP. Attribution of the observed spring snowpack decline in British Columbia to anthropogenic climate change. J Clim. 2017;30:4113–30.
67. O'Gorman PA, Schneider T. The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. Proc Natl Acad Sci. 2009;106:14773–7.
68. Kharin VV, Zwiers FW, Zhang X, Wehner M. Changes in temperature and precipitation extremes in the CMIP5 ensemble. Clim Chang. 2013;119:345–57.
69. Westra S, Alexander LV, Zwiers FW. Global increasing trends in annual maximum daily precipitation. J Clim. 2013;26:3904–18.
70. Kidd C, Becker A, Huffman GJ, Muller CL, Joe P, Skofronick-Jackson G, et al. So, how much of the earth's surface is covered by rain gauges? Bull Am Meteorol Soc. 2017;98:69–78.
71. Serreze MC, Barrett AP, Stroeve J. Recent changes in tropospheric water vapor over the Arctic as assessed from radiosondes and atmospheric reanalyses. J Geophys Res Atmos. 2012;117:1–21.
72. Henn B, Newman AJ, Livneh B, Daly C, Lundquist JD. An assessment of differences in gridded precipitation datasets in complex terrain. J Hydrol. 2018;556:1205–19.
73. Callaghan TV, Johansson M, Brown RD, Groisman PY, Labba N, Radionov V, et al. The changing face of arctic snow cover: a synthesis of observed and projected changes. Ambio. 2011;40:17–31.
74. Hartmann DJ, Klein Tank AMG, Rusticucci M, et al (2013) Observations: atmosphere and surface. Clim Chang 2013 Phys Sci Basis Contrib Work Gr I to Fifth Assess Rep Intergov Panel Clim Chang. https://doi.org/10.1017/CBO9781107415324.008.
75. Räisänen J. Warmer climate: less or more snow? Clim Dyn. 2008;30:307–19.
76. Morán-Tejeda E, López-Moreno JI, Beniston M. The changing roles of temperature and precipitation on snowpack variability in Switzerland as a function of altitude. Geophys Res Lett. 2013;40:2131–6.
77. Sospedra-Alfonso R, Melton JR, Merryfield WJ. Effects of temperature and precipitation on snowpack variability in the Central Rocky Mountains as a function of elevation. Geophys Res Lett. 2015;42:4429–38.
78. Bond TC, Doherty SJ, Fahey DW, Forster PM, Berntsen T, DeAngelo BJ, et al. Bounding the role of black carbon in the climate system: a scientific assessment. J Geophys Res Atmos. 2013;118:5380–552.
79.•• Skiles SM, Flanner M, Cook JM, Dumont M, Painter TH. Radiative forcing by light-absorbing particles in snow. Nat Clim Chang. 2018;8:964–71 **This review summarizes the radiative impact that light-absorbing impurities such as black carbon and dust have on snow.**
80.• Gleason KE, McConnell JR, Arienzo MM, Chellman N, Calvin WM. Four-fold increase in solar forcing on snow in Western U.S. burned forests since 1999. Nat Commun. 2019;10:1–8 **This paper links increases in wildfires to earlier snowmelt across parts of the Western US.**
81. Mahowald NM, Kloster S, Engelstaedter S, Moore JK, Mukhopadhyay S, McConnell JR, et al. Observed 20th century desert dust variability: impact on climateand biogeochemistry. Atmos Chem Phys. 2010;10:10875–93.
82. Painter TH, Deems JS, Belnap J, Hamlet AF, Landry CC, Udall B. Response of Colorado River runoff to dust radiative forcing in snow. Proc Natl Acad Sci. 2010;107:17125–30.
83. Skiles SM, Painter TH, Deems JS, Bryant AC, Landry CC. Dust radiative forcing in snow of the upper Colorado River Basin: 2. Interannual variability in radiative forcing and snowmelt rates. Water Resour Res. 2012;48:1–11.
84. Painter TH, McKenzie Skiles S, Deems JS, Tyler Brandt W, Dozier J. Variation in rising limb of Colorado River snowmelt runoff hydrograph controlled by dust radiative forcing in snow. Geophys Res Lett. 2017;45:797–808.
85. Di Mauro B, Garzonio R, Rossini M, et al. Saharan dust events in the European Alps: role on snowmelt and geochemical characterization. Cryosph. 2019;13:1147–65.
86. Stroeve JC, Kattsov V, Barrett A, Serreze M, Pavlova T, Holland M, et al. Trends in Arctic sea ice extent from CMIP5, CMIP3 and observations. Geophys Res Lett. 2012;39:1–7.
87. Stroeve J, Notz D. Changing state of Arctic sea ice across all seasons. Environ Res Lett Res Lett. 2018;13:103001.
88. Kopec BG, Feng X, Michel FA, Posmentier ES. Influence of sea ice on Arctic precipitation. Proc Natl Acad Sci. 2015;113:46–51.
89. Bintanja R, Selten FM. Future increases in Arctic precipitation linked to local evaporation and sea-ice retreat. Nature. 2014;509:479–82.
90. Sturm M, Stuefer S. Wind-blown flux rates derived from drifts at arctic snow fences. J Glaciol. 2013;59:21–34.
91. Bokhorst S, Pedersen SH, Brucker L, Anisimov O, Bjerke JW, Brown RD, et al. Changing Arctic snow cover: a review of recent developments and assessment of future needs for observations, modelling, and impacts. Ambio. 2016;45:516–37. https://doi.org/10.1007/s13280-016-0770-0.
92. Gouttevin I, Menegoz M, Dominé F, Krinner G, Koven C, Ciais P, et al. How the insulating properties of snow affect soil carbon distribution in the continental pan-Arctic area. J Geophys Res Biogeosci. 2012;117:1–11.
93. Druel A, Peylin P, Krinner G, Ciais P, Viovy N, Peregon A, et al. Towards a more detailed representation of high-latitude vegetation in the global land surface model ORCHIDEE (ORC-HL-VEGv1.0). Geosci Model Dev. 2017;10:4693–722.
94. Myers-Smith IH, Elmendorf SC, Beck PSA, et al. Climate sensitivity of shrub growth across the tundra biome. Nat Clim Chang. 2015;5:887–91.
95. Ju J, Masek JG. The vegetation greenness trend in Canada and US Alaska from 1984-2012 Landsat data. Remote Sens Environ. 2016;176:1–16.
96. Loranty MM, Berner LT, Goetz SJ, Jin Y, Randerson JT. Vegetation controls on northern high latitude snow-albedo feedback: observations and CMIP5 model simulations. Glob Chang Biol. 2014;20:594–606.
97. Randall DA, Cess RD, Blanchet JP, Chalita S, Colman R, Dazlich DA, et al. Analysis of snow feedbacks in 14 general circulation models. J Geophys Res. 1994;99:757–71.
98. Hall A. The role of surface albedo feedback in climate. J Clim. 2004;17:1550–68.
99. Qu X, Hall A. What controls the strength of snow-albedo feedback? J Clim. 2007;20:3971–81.
100. Thackeray CW, Fletcher CG. Snow albedo feedback: current knowledge, importance, outstanding issues and future directions. Prog Phys Geogr. 2016;40:392–408.
101. Colman RA. Surface albedo feedbacks from climate variability and change. J Geophys Res Atmos. 2013;118:2827–34.

102. Bony S, Colman R, Kattsov VM, Allan RP, Bretherton CS, Dufresne JL, et al. How well do we understand and evaluate climate change feedback processes? J Clim. 2006;19:3445–82.
103. Soden BJ, Held IM, Colman RC, Shell KM, Kiehl JT, Shields C a. Quantifying climate feedbacks using radiative kernels. J Clim. 2008;21:3504–20.
104. Dessler AE. Observations of climate feedbacks over 2000-10 and comparisons to climate models. J Clim. 2013;26:333–42.
105. Pithan F, Mauritsen T. Arctic amplification dominated by temperature feedbacks in contemporary climate models. Nat Geosci. 2014;7:181–4.
106. Walsh JE. Intensified warming of the Arctic: causes and impacts on middle latitudes. Glob Planet Chang. 2014;117:52–63.
107. Boeke RC, Taylor PC. Seasonal energy exchange in sea ice retreat regions contributes to differences in projected Arctic warming. Nat Commun. 2018;9:1–14.
108. Screen JA, Simmonds I. The central role of diminishing sea ice in recent Arctic temperature amplification. Nature. 2010;464:1334–7.
109. Graversen RG, Langen PL, Mauritsen T. Polar amplification in CCSM4: contributions from the lapse rate and surface albedo feedbacks. J Clim. 2014;27:4433–50.
110. Pepin N, Bradley RS, Diaz HF, et al. Elevation-dependent warming in mountain regions of the world. Nat Clim Chang. 2015;5:424–30.
111. Palazzi E, Mortarini L, Terzago S, von Hardenberg J. Elevation-dependent warming in global climate model simulations at high spatial resolution. Clim Dyn. 2019;52:2685–702.
112. Fletcher CG, Thackeray CW, Burgers TM. Evaluating biases in simulated snow albedo feedback in two generations of climate models. J Geophys Res Atmos. 2015;120:12–26.
113. Wetherald R, Manabe S. The effects of changing the solar constant on the climate of a general circulation model. J Atmos Sci. 1975;32:2044–59.
114. Lian MS, Cess RD. Energy balance climate models: a reappraisal of ice-albedo feedback. J Atmos Sci. 1977;34:1058–62.
115. Guo H, Wang X, Wang T, Ma Y, Ryder J, Zhang T, Liu D, Ding J, Li Y, Piao S. Spring snow-albedo feedback analysis over the Third Pole: results from satellite observation and CMIP5 model simulations. J Geophys Res Atmos. 2018:123:750–763.
116. Thackeray CW, Qu X, Hall A. Why do models produce spread in snow albedo feedback? Geophys Res Lett. 2018;45:6223–31.
117. Wang L, Cole JNS, Bartlett P, Verseghy D, Derksen C, Brown R, et al. Investigating the spread in surface albedo for snow-covered forests in CMIP5 models. J Geophys Res Atmos. 2016;121:1–16.
118. Thackeray CW, Fletcher CG, Derksen C. The influence of canopy snow parameterizations on snow albedo feedback in boreal forest regions. J Geophys Res Atmos. 2014;119:9810–21.
119. Thackeray CW, Fletcher CG, Derksen C. Quantifying the skill of CMIP5 models in simulating seasonal albedo and snow cover evolution. J Geophys Res Atmos. 2015;120:5831–49.
120. Slater AG, Schlosser A, Desborough CE, et al. The representation of snow in land surface schemes: results from PILPS 2 (d). J Hydrometeorol. 2001;2:7–25.
121. Verseghy D, Brown R, Wang L. Evaluation of CLASS Snow Simulation over Eastern Canada. J Hydrometeorol. 2017;18:1205–25.
122. Letcher TW, Minder JR. Characterization of the simulated regional snow albedo feedback using a regional climate model over complex terrain. J Clim. 2015;28:7576–95.
123. Winter KJPM, Kotlarski S, Scherrer SC, Schär C. The alpine snow-albedo feedback in regional climate models. Clim Dyn. 2017;48:1109–24.
124. Walton DB, Hall A, Berg N, Schwartz M, Sun F. Incorporating snow albedo feedback into downscaled temperature and snow cover projections for California's Sierra Nevada. J Clim. 2017;30:1417–38.
125. Cess RD, Potter GL, Zhang MH, Blanchet J, Chalita S, Colman R, et al. Interpretation of snow-climate feedback as produced by 17 general circulation models. Science (80-). 1991;253:888–92.
126. Cohen J, Entekhabi D. Eurasian snow cover variability and Northern Hemisphere climate predictability. Geophys Res Lett. 1999;26:345–8.
127. Saito K, Cohen J, Entekhabi D. Evolution of atmospheric response to early-season Eurasian snow cover anomalies. Mon Weather Rev. 2001;129:2746–60.
128. Gong G, Entekhabi D, Cohen J. Modeled Northern Hemisphere winter climate response to realistic Siberian snow anomalies. J Clim. 2003;16:3917–31.
129. Fletcher CG, Hardiman SC, Kushner PJ, Cohen J. The dynamical response to snow cover perturbations in a large ensemble of atmospheric GCM integrations. J Clim. 2009;22:1208–22.
130. Allen RJ, Zender CS. Forcing of the Arctic Oscillation by Eurasian snow cover. J Clim. 2011;24:6528–39.
131. Peings Y, Saint-Martin D, Douville H. A numerical sensitivity study of the influence of Siberian snow on the northern annular mode. J Clim. 2012;25:592–607.
132. Henderson GR, Leathers DJ, Hanson B. Circulation response to Eurasian versus North American anomalous snow scenarios in the Northern Hemisphere with an AGCM coupled to a slab ocean model. J Clim. 2013;26:1502–15.
133. Hardiman SC, Kushner PJ, Cohen J. Investigating the ability of general circulation models to capture the effects of Eurasian snow cover on winter climate. J Geophys Res Atmos. 2008;113:1–9.
134. Furtado JC, Cohen JL, Butler AH, Riddle EE, Kumar A. Eurasian snow cover variability and links to winter climate in the CMIP5 models. Clim Dyn. 2015;45:2591–605.
135.•• Henderson GR, Peings Y, Furtado JC, Kushner PJ. Snow–atmosphere coupling in the Northern Hemisphere. Nat Clim Chang. 2018;8:954–63 **This review extensively details the possible ways in which snow may influence atmospheric variability.**
136. Peings Y, Brun E, Mauvais V, Douville H. How stationary is the relationship between Siberian snow and Arctic Oscillation over the 20th century? Geophys Res Lett. 2013;40:183–8.
137. Peings Y, Douville H, Colin J, Saint-Martin D, Magnusdottir G. Snow–(N)AO teleconnection and its modulation by the quasi-biennial oscillation. J Clim. 2017;30:10211–35.
138. Blandford HF. On the connection of the Himalaya snowfall with dry winds and seasons of drought in India. Proc R Soc Lond. 1884;37:3–22. https://doi.org/10.1098/rspl.1884.0003.
139. Hahn DG, Shukla J. An apparent relationship between Eurasian snow cover and Indian monsoon rainfall. J Atmos Sci. 1976;33:2461–2.
140. Kripalani RH, Kulkarni A, Sabade SS, Khandekar ML. Indian monsoon variability in a global warming scenario. Nat Hazards. 2003;29:189–206.
141. Zhang T, Wang T, Krinner G, Wang X, Gasser T, Peng S, et al. The weakening relationship between Eurasian spring snow cover and Indian summer monsoon rainfall. Sci Adv. 2019;5:1–8.
142. Peings Y, Douville H. Influence of the Eurasian snow cover on the Indian summer monsoon variability in observed climatologies and CMIP3 simulations. Clim Dyn. 2010;34:643–60.
143. Turner AG, Slingo JM. Using idealized snow forcing to test teleconnections with the Indian summer monsoon in the Hadley Centre GCM. Clim Dyn. 2011;36:1717–35.

144. Senan R, Orsolini YJ, Weisheimer A, Vitart F, Balsamo G, Stockdale TN, et al. Impact of springtime Himalayan–Tibetan Plateau snowpack on the onset of the Indian summer monsoon in coupled seasonal forecasts. Clim Dyn. 2016;47:2709–25.
145. Xu L, Dirmeyer P. Snow-atmosphere coupling strength in a global atmospheric model. Geophys Res Lett. 2011;38:1–5.
146. Halder S, Dirmeyer PA. Relation of Eurasian snow cover and Indian summer monsoon rainfall : importance of the delayed hydrological effect. J Clim. 2017;30:1273–89.
147. Robock A, Mu M, Vinnikov K. Land surface conditions over Eurasia and Indian summer monsoon rainfall. J Geophys Res. 2003;108. https://doi.org/10.1029/2002JD002286.
148. Koster RD, Suarez MJ. Soil moisture memory in climate models. J Hydrometeorol. 2002;2:558–70.
149. Shi HX, Wang CH. Projected 21st century changes in snow water equivalent over Northern Hemisphere landmasses from the CMIP5 model ensemble. Cryosph. 2015;9:1943–53.
150. Marx A, Kumar R, Thober S, Rakovec O, Wanders N, Zink M, et al. Climate change alters low flows in Europe under global warming of 1.5, 2, and 3°C. Hydrol Earth Syst Sci. 2018;22:1017–32.
151. Brun E, Vionnet V, Boone A, Decharme B, Peings Y, Valette R, et al. Simulation of northern Eurasian local snow depth, mass and density using a detailed snowpack model and meteorological reanalysis. J Hydrometeorol. 2013;14:203–19.
152. Girotto M, Essery R, Musselman K (2019) New terrestrial snow observations and modelling and importance in climate change. Submitted to Curr Clim Chang Rep.
153. Wrzesien ML, Durand MT, Pavelsky TM, Kapnick SB, Zhang Y, Guo J, et al. A new estimate of North American Mountain snow accumulation from regional climate model simulations. Geophys Res Lett. 2018;45:1423–32.
154.• Krinner G, Derksen C, Essery R, et al. ESM-SnowMIP: assessing models and quantifying snow-related climate feedbacks. Geosci Model Dev. 2018;11:5027–49 **This paper details a series of proposed model experiments that will go a long way to improving our understanding of snow-climate interactions.**