Quantifying and Diagnosing Sources of Uncertainty in Midcentury Changes in North American Snowpack from NARCCAP[®]

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ABSTRACT

The NARCCAP RCM–GCM ensemble is used to explore the uncertainty in midcentury projections of snow over North America that arise when multiple RCMs are used to downscale multiple GCMs. Various snow metrics are examined, including snow water equivalent (SWE), snow cover extent (SCE), snow cover duration (SCD), and the timing of the snow season. Simulated biases in baseline snow characteristics are found to be sensitive to the choice of RCM and less influenced by the driving GCM. By midcentury, domain-averaged SCE and SWE are projected to decrease in all months of the year. However, using multiple RCMs to downscale multiple GCMs inflates the uncertainty in future projections of both SCE and SWE, with projections of SWE being more uncertain. Spatially, the RCMs show winter SWE decreasing over most of North America, except north of the Arctic rim, where SWE is projected to increase. SCD is also projected to decrease with both a later start and earlier termination of the snow season. For all metrics considered, the magnitude of the climate change signal varies across the RCMs. The ensemble spread is large over the western United States, where the RCMs disagree on the sign of the change in SWE in some high-elevation regions. Future projections of snow (both magnitude and spatial patterns) are more similar between simulations performed with the same RCM than the simulations driven by the same GCM. This implies that climate change uncertainty is not sufficiently explored in experiments performed with a single RCM driven by multiple GCMs.

1. Introduction

Seasonal snow cover is an important component of the climate of North America. It plays a direct role in the surface energy budget through its high albedo and low thermal conductivity, which have important implications for the snow–albedo feedback (Qu and Hall 2007) and permafrost (Lawrence and Slater 2010). The spatial extent of snow cover over North America influences the atmospheric circulation on monthly to seasonal time scales (Cohen and Entekhabi 2001; Sobolowski et al. 2010). Snow plays a critical role in ecology as well. It provides an important habitat for Arctic vegetation and foraging mammals, such as caribou (Lemmen et al. 2008), and enables ground temperatures that support active winter soil ecology (Campbell et al. 2005). The seasonal cycle of vegetation is highly dependent on the

timing of snowmelt and the duration of snow-free periods (Parida and Buermann 2014; Cayan et al. 2001; Gottfried et al. 2011). In its role as a natural reservoir for winter precipitation, peak snowpack amount and the timing of snowmelt have important implications for water supply (Stewart et al. 2005; Christensen et al. 2004) and hydroelectric power generation (Lemmen et al. 2008; Vicuna et al. 2008; Brown 2010). Variations in snow conditions also affect travel (Lemmen et al. 2008) and tourism (Scott et al. 2004), especially the ski industry (Scott et al. 2008; Bark et al. 2010; McCusker and Hess 2018).

Over the past 60 years, the characteristics of snow have shown marked changes over the North America. Broad decreases have been observed in snow cover extent (SCE; Brown and Robinson 2011), the length of the snow cover season (Brown and Mote 2009; Knowles 2015), mean snowfall (Kunkel et al. 2009), and snow water equivalent (SWE; Mote et al. 2005; Kapnick and Hall 2012; Fassnacht et al. 2016; Gan et al. 2013). The only robust exception to these large-scale decreases occurs at high latitudes, where snowfall and

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SWE have increased due to enhanced moisture in the atmosphere (Vincent and Mekis 2006; Brown 2010; Frappart et al. 2011).

Observed changes in snow have been significant for the western United States, where they have been linked to increases in droughts, heat waves, and wildfires (Westerling et al. 2003; Mahanama et al. 2012). Snow declines in this region have been formally attributed to anthropogenic climate change (Pierce et al. 2008), indicating further increases in greenhouse gas concentrations could lead to more snow decreases. Continued losses will negatively impact water storage and supply, natural ecosystems, hydroelectric power production, and recreation. These impacts will have severe economic consequences for the United States (Sturm et al. 2017). Furthermore, areas with snow cover loss will be subject to additional warming due to the snow–albedo feedback (Qu and Hall 2014) and snow cover loss has the potential to impact weather systems and large-scale climate variability (Cohen and Entekhabi 2001).

Observed year-to-year variations and long-term trends in snow are linked to variations in temperature and/or precipitation, depending on the region. In general terms, lower-elevation and lower-latitude regions, which have relatively warm winter temperatures, have been found to be highly sensitive to temperature variations and moderately influenced by precipitation (e.g., Mote et al. 2005; Gonzales et al. 2018). In contrast, over high-elevation and high-latitude regions, winter temperatures tend to be well below freezing and variations in snow are mostly sensitive to precipitation.

Given the important role that snow plays in the climate of North America, it is critical to examine future changes in snow, their drivers, and their uncertainties. Large-scale projections of future climate change from global and regional climate models show continued increases in surface temperature over all of North America, with amplified warming in the high latitudes (Christensen et al. 2007; Collins et al. 2013; Mearns et al. 2013; Maloney et al. 2014; Wuebbles et al. 2017). These same models also agree that winter precipitation amounts will increase everywhere except the southwest United States. Regionally, future changes in snow will be driven by the complex interaction between increasing temperatures and changing precipitation patterns, both of which are in turn coupled to changes in snow itself. Projections for snow over North America from previous GCMs, RCMs, and statistical downscaling studies are aligned with observations and indicate that snow variables will continue to decrease over much of the continent in the future including reduction in snow cover, earlier snowmelt, and changes in the efficiency of snowmelt (Brown and Mote 2009; Klos et al. 2014;

Solander et al. 2017). Studies suggest low-elevation sites with historical near-freezing winter temperatures will be the most sensitive to change (Elsner et al. 2010). Also, some studies have shown there is uncertainty about the sign of the changes in peak SWE over high latitudes (Räisänen 2008; Brown and Mote 2009; Maloney et al. 2014) and high elevations (Brown and Mote 2009; Rasmussen et al. 2014) where increases in precipitation drive increases in SWE as long as winter temperatures remain below freezing.

The previous studies that have examined future changes in snow and their uncertainties over North America have used coarse GCM ensembles (Brutel-Vuilmet et al. 2013; Krasting et al. 2013; Diffenbaugh et al. 2012; Räisänen 2008), single RCMs driven with boundary conditions from one or more GCMs (Rauscher et al. 2008; Rasmussen et al. 2011; Musselman et al. 2017; Plummer et al. 2006; Ashfaq et al. 2016), or bias-corrected and statistically downscaled climate model output applied to land surface and snow models (Notaro et al. 2014; Demaria et al. 2016).

Each method above has its own strengths and weaknesses. GCM ensembles allow for the exploration of multiple sources of uncertainty (internal variability, model uncertainty, and scenario uncertainty; Hawkins and Sutton 2009), but their credibility for snow-related projections are limited in regions of complex topography due to the coarse resolution of raw GCM output (Fig. 1; Leung et al. 2004; Brown and Mote 2009; Walton et al. 2017). Higher-resolution RCM studies have the potential to add value to projections of snow due to their ability to better capture orographic precipitation processes (Rasmussen et al. 2011), extratropical cyclones (Poan et al. 2018), and finer resolution coupling between the land surface and the atmosphere (e.g., the snow–albedo feedback; Walton et al. 2017). However, RCM experiments are computationally expensive, and most existing studies over North America have only used a single RCM to explore changes in snow. This means the model uncertainty associated with the choice of RCM has not been explored. Also, while RCMs can generate higher-resolution simulations, they can still contain significant biases that affect the fidelity of snow simulations. Bias correcting and statistically downscaling GCM or RCM output and applying the results to an impact model can produce high-resolution projections of snow, but the coupling between the land surface and atmosphere is removed in such simulations and many additional uncertainties are added to the climate change signal corresponding with the quality of observations (Maraun et al. 2017), the choice of downscaling method (Teutschbein and Seibert 2012), and the choice of impacts model (Mendoza et al. 2015, 2016).

FIG. 1. Midcentury changes in January–March (JFM) SWE for three climate model ensembles. Shown is the median response from each ensemble. The three climate model ensembles are (a) NARCCAP, which has a spatial resolution of approximately 0.5° , (b) CMIP3, which has an average spatial resolution of $\sim 3^\circ$, and (c) CMIP5, which has an average spatial resolution of $\sim 2^\circ$.

What is missing from the literature on future projections of snow is an exploration of the combined uncertainty that results from using multiple RCMs to downscale multiple GCMs over North America. The goal of this study is to explore this type of model structural uncertainty using the NARCCAP ensemble of RCMs (Mearns et al. 2009, 2012), which consists of results from six RCMs that were driven with boundary conditions from four GCMs using a balanced factorial design (see section 2 for more details). As such, the NARCCAP ensemble is still the only downscaling ensemble for North America that adequately explores this dimension of uncertainty. We aim to quantify future changes in snow within the NARCCAP ensemble and diagnose where this uncertainty comes from. Although the NARCCAP model results will have biases due to inherited biases from the GCMs and biases from the RCMs themselves, we will nevertheless be able to examine future changes in snow, their drivers, and their uncertainties over North America with greater spatial and temporal detail and with increased confidence in regions of complex topography compared to studies that use raw GCM model output. Figure 1 demonstrates some of the value of the increased spatial resolution of the NARCCAP ensemble compared to the coarse CMIP3 (Meehl et al. 2007) and CMIP5 (Taylor et al. 2012) GCM ensembles. The high temporal frequency of the model output also provides a unique opportunity to study changes in duration of the snow cover as well as the timing of the start and end of the snow-covered period.

The NARCCAP models and observational datasets used for evaluation are described in section 2. Section 3 defines the methods used to calculate snow metrics and identify uncertainty. Model performance is examined in

section 4 and includes a discussion of the cause of model bias. The climate change response of the NARCCAP models is discussed in section 5. In section 6 we end with a brief summary and discussion of the overall conclusions.

2. Models and evaluation datasets

a. Models

NARCCAP is an ensemble of RCMs driven by different GCM simulations designed to study climate change processes and their uncertainties. In NARCCAP, 4 GCMs from the CMIP3 ensemble provided boundary conditions for 6 RCMs. A balanced fractional factorial design was used to statistically sample the full RCM–GCM matrix resulting in a total of 12 dynamically downscaled simulations at 50-km resolution (Mearns et al. 2009). Details about the RCMs and driving GCMs used in this study can be found in Tables 1 and 2. In NARCCAP, simulations for the current/historical period span 1971–99 and future simulations span 2041–60 (Mearns et al. 2007). Greenhouse gas projections in the future climate simulations are based on the Special Report on Emissions Scenarios (SRES; Nakićenović and Swart 2000) A2 scenario. Additionally, while all RCM simulations were performed at 50-km resolution, each model uses a distinct map projection; therefore, for ensemble calculations and estimation of bias the simulations were first interpolated to a common $0.5^\circ \times 0.5^\circ$ grid using the Earth System Modeling Framework (ESMF) patch recovery method (see Fig. 2 for the NARCCAP domain and representative topography). SWE was not saved from the HRM3-gfdl simulation so our RCM ensemble only has 11 members (Table 2). SWE was also not available for the HadCM3 GCM climate experiment.

TABLE 1. GCMs and RCMs used in NARCCAP, their identifying acronyms, and relevant references. All RCMs were run at a 50-km resolution. For the GCMs, horizontal resolution is listed.

	Acronym	Model	References
GCMs	CCSM	NCAR Community Climate System Model, version 3 (CCSM3), T85	Collins et al. (2006)
	CGCM3	Third Generation Canadian Coupled GCM, version 3 (CGCM3), T47	Flato et al. (2000)
	GFDL	GFDL Climate Model, version 2.1 (GFDL CM2.1), $2.0^\circ \times 2.5^\circ$	GFDL Global Model Development Team (2004)
	HadCM3	Hadley Centre Coupled Model, version 3 (HadCM3), $2.5^\circ \times 3.75^\circ$	Gordon et al. (2000); Pope et al. (2000)
RCMs	CRCM	Canadian RCM	Caya and Laprise (1999)
	ECP2	Experimental Climate Prediction Center's Regional Spectral Model	Juang et al. (1997)
	HRM3	Third-generation Hadley Centre RCM	Jones et al. (2003)
	MM5I	Fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model	Grell et al. (1994)
	RCM3	International Centre for Theoretical Physics RCM, version 3	Giorgi et al. (1993a,b); Pal et al. (2007)
	WRFG	Weather Research and Forecasting Model	Skamarock et al. (2005)

b. Evaluation datasets

1) SNOW WATER EQUIVALENT

As discussed in McCrary et al. (2017, hereafter MC17), a challenge for evaluating SWE in models is the lack of long-term, high-resolution (spatial and temporal), well-vetted observations. To overcome the poor spatial resolution of SWE observations, many studies use SWE from models; either atmospheric reanalysis products (Kapnick and Delworth 2013) or blended observational–model surface products (Frei et al. 2005). Unfortunately, model-derived SWE has large uncertainties in data-sparse areas where SWE is heavily influenced by model parameters. Following MC17 we created an ensemble of observation based SWE products to evaluate the NARCCAP models. Details of the datasets in the ensemble are outlined in Table 3. We required that all of the observation-based datasets in the ensemble be gridded SWE with finer than 1° latitude–longitude resolution, covering most, if not all, of North America, with at least 15 years of data between 1970 and 2000 (matching the NARCCAP RCM simulations), and with daily frequency data. All of the datasets are interpolated onto a common $0.5^\circ \times 0.5^\circ$ grid using the ESMF patch recovery method.

2) TEMPERATURE AND PRECIPITATION

Temperature and precipitation from the RCMs are compared against version 4 of the University of Delaware Air Temperature and Precipitation dataset (UDEL; Willmott and Matsuura 2001). In UDEL, temperature and precipitation are interpolated from surface stations to a $0.5^\circ \times 0.5^\circ$ grid covering the entire globe from 1901 to 2012. We make use of temperature and precipitation for the period 1970–2000 (to align with the GCM driven NARCCAP RCMs).

3. Methods

a. Estimation of snowfall and ablation

Snowfall and snowmelt were not archived for the NARCCAP simulations. We take advantage of the high-frequency output of NARCCAP to estimate snowfall and ablation (the loss of snow due to melt and evaporation/sublimation). Instantaneous values of SWE were saved from each NARCCAP model every 3 h. Within that 3-h window, SWE can either increase (snowfall > ablation), decrease (snowfall < ablation), or remain constant (snowfall = ablation; both are zero). While snowfall can immediately ablate from the surface, we make the assumption that this type of loss will be small. Therefore, we define snowfall as when SWE increases over the 3-hourly time step and ablation when SWE decreases over a 3-hourly time step. Snowfall is estimated from the evaluation datasets using a daily time step.

b. Calculation of snow cover metrics

To calculate snow cover from SWE, we apply a 2.54-mm (0.1 in.) threshold to the daily SWE field to produce a daily binary yes/no snow cover field. This is the threshold used for reporting SWE measurements in many in situ observation datasets. Results were shown

TABLE 2. NARCCAP RCM and GCM simulation combinations with SWE available. While the HRM3-GFDL simulation was performed, SWE was not archived.

	CCSM	CGCM3	GFDL	HadCM3
CRCM	X	X		
ECP2			X	X
HRM3			—	X
MM5I	X			X
RCM3		X	X	
WRFG	X	X

FIG. 2. Map showing the NARCCAP domain and representative topography at $0.5^\circ \times 0.5^\circ$ latitude-longitude grid resolution.

to not be sensitive to this threshold (not shown). Three metrics are then calculated from this field to examine changes in the timing of the snow season. These include 1) the snow cover duration (SCD), which is defined as the number of days per year with snow on the ground, 2) the first snow covered date, and 3) the last snow covered date. These three metrics are all calculated over a snow year defined from 1 August to 31 July.

The daily binary field is also used to calculate the monthly SCE, defined as the total snow-covered area over the NARCCAP domain. To calculate SCE the daily binary field is averaged over each month to produce a monthly snow cover fraction for each grid box. Monthly total SCE is then calculated by weighting the area of each grid box by the monthly snow cover fraction and summing over the entire domain. This is similar to the methods used in [Mudryk et al. \(2017\)](#), but using a different SWE threshold.

c. Measures of uncertainty

In this paper we seek to use NARCCAP to examine the combined uncertainties in changes in North American snow characteristics that arise when multiple GCMs are used to provide boundary conditions to multiple RCMs in dynamical downscaling experiments. Climate changes are calculated as the difference between the average values from the future time period (2041–69) and the average values from the current time period (1971–99). 1999 was chosen as the endpoint for the current time period, as the CCSM GCM simulation ends there.

We use the model spread to represent uncertainty in future climate. This uncertainty is displayed in two ways. First, the spatial patterns of the uncertainty in future change are highlighted using maps of the 25th, 50th, and 75th percentiles of the change. Following the methods outlined in Annex I of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change ([IPCC 2013](#)) the 25th, 50th, and 75th percentiles of the NARCCAP ensemble are calculated by ranking the climate change signal of each variable, from each model, at each grid point. Equal weight is given to each RCM in these rankings. This method smooths the spatial variability in the climate change response compared to individual model responses, but it also enables the visualization of what the range of possible future conditions might look like and improves upon the typical approach of displaying the mean and standard deviation of the response of the ensemble.

Second, we also show the uncertainty in the NARCCAP ensemble using time series plots of climate variables averaged over all of North America from each individual model. These time series plots are used to show the annual cycle of the model spread and highlight which models have the smallest or largest climate change response. This method is also used to examine the spread in

TABLE 3. Observation-based gridded SWE datasets used to create the observational SWE ensemble.

Name	Product	Resolution	Spatial coverage	Period	Reference
B03	North American AMIP3 Snow Depth and SWE analysis	$0.25^\circ \text{ lat} \times 0.25^\circ \text{ lon}$	North America	1979–98	Brown et al. (2003)
ERA1-R	ERA-Interim Snow Cover Reconstruction	$0.75^\circ \text{ lat} \times 0.75^\circ \text{ lon}$	North America, $30^\circ\text{--}90^\circ\text{N}$	1979–2010	R. Brown 2013, personal communication
ERA1-Land	ERA-Interim Land product	T255 spectral ($\sim 80 \text{ km}$)	Global	1979–2010	Balsamo et al. (2012)
MERRA-Land	MERRA Land product	$0.5^\circ \text{ lat} \times 0.67^\circ \text{ lon}$	Global	1980–2010	Reichle et al. (2011) ; Reichle (2012)
GLDAS-Noah	Global Land Data Assimilation System	$0.25^\circ \text{ lat} \times 0.25^\circ \text{ lon}$	Global	1948–2010	Rodell et al. (2004)
Livneh	Livneh daily North American derived hydrometeorological data	$0.0625^\circ \text{ lat} \times 0.0625^\circ \text{ lon}$ $\sim 6 \text{ km}$	North America, $\sim 10^\circ\text{--}53^\circ\text{N}$	1950–2013	Livneh et al. (2015)

the observations and the spread in the baseline or current climate simulations from the RCM and driving GCMs.

4. Observational SWE and model evaluation

We start by identifying biases in the NARCCAP models by comparing the simulated current climate conditions with observations. This is a critical step, as model bias may influence climate change response of each model.

a. Observed climatology

The observational climatologies of key snow-related metrics are shown in Fig. 3. The median value from the observational SWE ensemble is displayed on each map. These snow metrics include the average January–March (JFM) SWE, annual SCD, and the first and last snow covered dates. Winter SWE increases with latitude and elevation, corresponding with colder temperatures, higher precipitation rates, or both (Fig. 3a). Regions influenced by moist air masses, such as the coastal range along the Pacific and Newfoundland near the Atlantic, also have high winter SWE amounts. As with JFM SWE, SCD increases with elevation and latitude (Fig. 3b). Many high-latitude and high-elevation locations have snow on the ground for more than half, if not two-thirds of the year, while low-elevation and lower-latitude locations have more ephemeral snow cover, lasting less than 60 days in many regions. Snow first accumulates at the high-latitude and high-mountain regions in September and October (Fig. 3c) and stays on the ground until May or June (Fig. 3d), whereas many lower-latitude and -elevation regions only have snow cover between December and March.

When averaged over North America SWE follows a similar annual cycle in all of the observational datasets (Fig. 4a), with annual maximum SWE (or peak SWE) occurring in March in all but GLDAS, which peaks in February. The GLDAS simulation in this study uses the Noah land surface model (Koren et al. 1999), which is known to underestimate SWE and melts snow too early (MC17, and references therein). Spread across the observations is low in the fall and early winter (20–25 mm in December), as the observed datasets agree on the initial accumulation rate of SWE. Spread is large in winter (41–67 mm in March) and spring (5–28 mm in May), as total SWE accumulation and the timing of melt varies across the datasets.

While the observational datasets show considerable spread in SWE, they agree more about the annual cycle of SCE over North America (Fig. 4b). Five of the six observational SWE datasets provide adequate spatial

coverage over the domain to be included in the calculation of SCE. These datasets agree on SCE in fall, however they start to diverge in December. The largest spread occurs in spring (April and May), but the uncertainty in observed SCE is low compared with SWE.

b. Model bias

Simulated bias in SWE and snow cover corresponds with differences in the accumulation of snowfall and ablation of SWE. Both the accumulation and ablation of snow are related to temperature, precipitation, and the way snow processes are represented in the land surface models (LSMs). In these RCM experiments, biases in temperature and precipitation will be due to the compounding effects of inherited bias from the GCM and those generated within the RCMs themselves.

MC17 evaluated the reanalysis driven NARCCAP simulations and provides a detailed analysis of the cause of bias due to RCM configuration. Briefly, we summarize the information relevant to the present study. Snow in HRM3 is determined by the microphysics of the atmospheric model while the other RCMs all use a temperature threshold in the LSM to distinguish between rain and snow; CRCM, ECP2, MM5I, and WRFG use a 0°C threshold and RCM3 uses a 2.2°C threshold (see Table 1 for model acronym definitions). The LSM used in CRCM has the most sophisticated representation of snow, but it tends to retain snow on the surface for longer than observed resulting in positive SWE biases. Two mechanisms likely cause these positive SWE biases: CRCM is the only model where snowmelt and rainfall can percolate through the snowpack and freeze and CRCM uses a relatively low thermal conductivity (Verseghy et al. 2017), which leads to cold temperature biases and the retention of snow. RCM3 also overestimates SWE, and positive biases are linked to excessive precipitation and its high rain/snow temperature threshold. ECP2, MM5I, and WRFG use similar, but distinct, versions of the same LSM (predecessors to the Noah v3.0 model). MC17 found the simulation of snow varies across these models, but it was difficult to distinguish whether compensating biases from the atmospheric model or differences in the LSM configurations drove these changes. Consistent with other studies MC17 found WRFG loses snow quickly via melt and latent heat flux (e.g., Barlage et al. 2010). MC17 found that SWE was well captured in the MM5I simulation but underrepresented in ECP2 due to excessive sublimation immediately following snowfall.

Next we briefly identify the biases in the GCM-driven RCM simulations from NARCCAP, placing the biases

FIG. 3. Maps of the median value from the observational ensemble for climatological JFM average (a) SWE, (b) snow cover duration, (c) first snow date, and (d) last snow date. Median values are calculated across the six-member observational ensemble independently at each grid point, except at the high latitudes (above 53°N) and south of 30°N where only five ensemble members have data. See Table 1 for spatial coverage of each observation-based product.

found in these simulations within the context of previous results.

1) SPATIAL PATTERN OF SWE

Regional variations in winter SWE biases in the individual RCMs are highlighted in Fig. 5. Bias is calculated by removing the median JFM SWE (Fig. 3a) of the observational ensemble from the RCM current climate simulations. By inspection, it is evident that the regional patterns of SWE bias are more similar to each other in the simulations performed with the same RCM than in the simulations driven by the same GCM. The simulations performed with CRCM and

RCM3 have large positive SWE biases over the whole domain, but especially in the western mountains. Both WRFG simulations have negative SWE biases, especially the simulation forced by CGCM3. In the ECP2 simulations, there is a clear issue with SWE in the western mountains, with too much SWE on the windward side of the mountains, and too little SWE on the lee side. Bias in the one simulation available from HRM3 is mixed over the domain. MM5I is the only model that shows distinct differences in winter SWE patterns corresponding with the driving GCM. In both MM5I simulations SWE is overestimated in the Rocky Mountains and underestimated in the PNW. East of the Rocky Mountains, however, the

FIG. 4. The annual cycle of (a) SWE and (b) SCE averaged over the North American NARCCAP domain (see Fig. 2) for the individual observational ensemble members (colored lines), the median of the observations (black line), and the spread across the ensemble (gray shading). The median curve is calculated across the area averaged annual cycle time series from each observational ensemble member. SWE is averaged over North America (shown in mm) and SCE is summed over North America (in million square km).

CCSM driven simulation has negative SWE biases while the HadCM3-driven simulation has positive SWE biases.

Biases in SCD follow suit with JFM SWE biases (Fig. 6). In all but HRM3, in regions with positive

(negative) winter SWE biases the SCD is longer (shorter) than observed. This implies that the frequency of snow cover is coupled to the amount of snowfall and persistence of SWE. SCD biases are very large in a few models. For instance, in CRCM and RCM3 SCD is more than 90 days longer than observed over the western half of the domain. The only discrepancy for this correlation is in HRM3, where SCD is underestimated in spite of positive SWE biases. Evaluation of the bias in the first and last dates with snow cover highlights that biases in SCD occur on both ends of the season, whether positive or negative (Figs. S1 and S2 in the online supplemental material) in all of the models except WRFG-cgcm3. In WRFG-cgcm3, biases in SCD are primarily driven by a loss of snow too early in the season (Fig. S2e).

Across all the RCMs, there is a general trend for snow to occur farther south than is observed (light gray shading in Figs. 5 and 6). Inspection of winter temperature and precipitation biases suggest colder than observed temperatures may cause this bias (not shown).

2) ANNUAL CYCLE OF SWE

Examination of the annual cycle of SWE averaged over North America highlights that the RCM ensemble has noticeably more spread than the observational uncertainty (Fig. 7a). Five of the simulations (both simulations from RCM3 and CRCM as well as MM5I-hadcm3) drastically overestimate SWE throughout the year, while five (both simulations from ECP2, HRM3-hadcm3, MM5I-ccsm, and WRFG-ccsm) largely fall within or just above the spread of the observations, and one simulation (WRFG-cgcm3) greatly underestimates SWE. From Fig. 5 we see that the models that fall within the observational range do so because of compensating errors across the domain. Other than for the WRFG simulations, the annual maximum SWE for North America occurs in March, which corresponds with five of the six observational datasets. In both WRFG simulations SWE peaks one month too early. In WRFG-cgcm3, annual maximum SWE is 40% lower than the median of the observations and SWE declines to zero 2 months early. Supporting the results from spatial maps of SWE bias described above, the annual cycle of SWE is typically more similar between the simulations performed with the same RCM than by simulations driven by the same GCM.

Spread in SCE is also high across the RCMs. The timing of the annual cycle of SCE in the RCMs is similar to observations, however the magnitude of SCE in the RCMs differs from observations. As with SWE, the simulations from RCM3 and CRCM overestimate SCE throughout the year while WRFG-cgcm3 greatly underestimates SCE. The

FIG. 5. Bias in JFM climatological SWE for the current climate simulations of the 11 NARCCAP RCMs. Results are shown for each individual model. Models are organized by GCM driver (columns). Bias is calculated relative to the ensemble median JFM climatology (Fig. 1a). Colors indicate bias (mm). Light gray shading highlights regions where the RCMs have snow cover and the observations do not. Dark gray shading highlights where the observations have snow and the RCMs do not.

bias in the annual cycle of SCE in HRM3-hadcm3 is strikingly different from that found for the annual cycle of SWE. While SWE is well captured in HRM3-hadcm3, the spatial extent of snow cover is grossly underestimated. As discussed in MC17, a spatial investigation of HRM3 indicates a number of inconsistencies in snow cover. This patchy snow cover results in the low SCE values in HRM3-hadcm3.

3) SOURCES OF MODEL BIAS

Next we address the question of what drives the differences found in SWE across the RCMs. SWE is an accumulated field, which means average winter SWE amounts represent a cumulative summary of the weather that occurred in both fall and winter. To explore the primary drivers of differences in winter SWE across the RCMs we look at the relationship between average winter (JFM) SWE and average October–March (ONDJFM) temperature (Fig. 8a), precipitation (Fig. 8b), snowfall

(Fig. 8c), and what we have coined the cold-season ablation fraction (CAF; Fig. 8d). CAF is defined as the percent of ONDJFM snowfall that is subsequently lost via ablation over these same months. In essence, CAF is ablation normalized by snowfall. This helps to remove the influence of snowfall differences on our understanding of the role of ablation in simulated SWE differences. Due to the low frequency of their output, snowfall and ablation could not be estimated from the GCMs.

If we consider the RCMs, GCMs, and observations as a set, there is no correlation between ONDJFM surface temperatures and JFM SWE (Fig. 8a, $r = 0$). There is however a larger correlation between the ONDJFM precipitation and JFM SWE (Fig. 8b, $r = 0.51$). From these scatterplots it is clear that most of the models (RCMs and GCMs) are colder and wetter than the observations. The combined effect of colder, wetter conditions likely leads to the higher than observed winter

FIG. 6. As in Fig. 5, but for the bias in climatological SCD. Bias is calculated relative to the median of the observational ensemble SCD climatology (Fig. 1b). Colors indicate bias in number of days.

SWE values (when compared to the median of the observations) in all but the WRFG simulations.

Average surface temperature and total precipitation by themselves do not appear to drive differences in the simulated winter SWE values, but the combined impact of temperature and precipitation on snowfall and ablation are correlated with winter SWE values. Total snowfall from ONDJFM and JFM SWE are highly correlated (Fig. 8c, $r = 0.95$) and more snowfall leads to higher SWE values. There is also a large negative correlation between ONDJFM CAF and JFM SWE (Fig. 8d; $r = -0.79$). The models with a higher CAF have lower SWE values. For example, HRM3-hadcm3 has higher snowfall amounts than either ECP2 simulation, but comparable SWE values. The CAF in HRM3-hadcm3 shows that a greater percentage of cold-season snowfall melts in the cold season in this model, contributing to lower winter SWE values. For another example, CRCM has similar snowfall amounts to MM51-cgcm3 and HRM3-hadcm3, but considerably higher SWE values. Again, the CAF values from CRCM

highlight that fractional snow loss in this RCM is much lower than in the others, which contributes to its high SWE values.

Figures 5–8 highlight that differences in winter SWE in the RCMs (both the magnitude and spatial patterns) generally follow the RCM, rather than the driving GCM, especially for CRCM, RCM3, and ECP2. All of the models have biases, which may influence the simulation of future changes in snow.

5. Future change in SWE

In the future, changes in snow and snow related variables will be due to the complex interaction between increasing temperatures and changing precipitation patterns. Rising temperatures result in decreases in snow in two ways: they reduce the proportion of precipitation that falls as snow and they increase snow loss via ablation. In the absence of any temperature changes, changes in snowfall would be positively correlated with precipitation and increases (decreases) in precipitation

FIG. 7. Time series plots of the annual cycle of (a) SWE and (b) SCE. SWE is averaged over North America (shown in mm) and SCE is summed over North America (in million square km). Black lines and their corresponding dash patterns represent the GCMs. Colored lines represent the RCMs. Dash patterns of the colored lines signify the driving GCMs. Gray shading highlights the range of the observational ensemble. The thick yellow line shows the median of the observational ensemble.

would correspond with increases (decreases) in snowfall. In the future, temperature and precipitation will interact with each other in complex ways, resulting in regional variations in the sign and magnitude of changes in snowfall, SWE, and snow cover. It is also important to note that simulated biases in baseline temperature and precipitation may affect the sensitivity of SWE to changes in temperature and precipitation. For example, in a region where a RCM has a warm bias, small increases in temperature in the future will result in larger SWE losses compared to a model with a cold bias in the same region.

a. Mean change in SWE

1) SPATIAL PATTERNS OF CHANGE

By midcentury, the RCM ensemble projects that winter SWE will decrease over most of North America, except at high latitudes where SWE is projected to increase (Fig. 9). Increases in winter SWE at high latitudes is a robust climate response from the NARCCAP ensemble as all of the individual RCMs project that SWE will increase during winter over some portion of northern Canada (Fig. S3).

Over the domain the broad regional patterns of SWE change (absolute and percent) are relatively consistent across the interquartile range (IQR) of the ensemble, but there is considerable uncertainty in the magnitude of the change in SWE. Also, there is uncertainty about the sign of the change in SWE at a few points within the continental interior and over Northern Quebec. For the absolute change in SWE (Fig. 9, top row) the largest spread is found over the western mountains, where baseline SWE values in the current climate simulation differ greatly between the RCMs (Fig. 7). Biases in baseline temperature, precipitation and SWE values in these simulations likely play a large role in the spread in future changes in this region. Outside of the mountains, the magnitude of SWE losses is smaller and spread across the models is lower.

Percent losses in SWE (Fig. 9, bottom) highlight a different story and pattern of change. In the Rocky Mountains in Canada and the United States, the IQR of percent change is low and spans from a 3% increase to a 30% decrease. The largest percent losses occur in maritime regions along the coasts and at lower-latitude and lower-elevation regions over the United States. A number of models project 90%–100% losses of SWE along the southern margins of climatologically snow covered areas, although model agreement on the location of total snow loss is difficult to assess as the models disagree on the placement of snow cover in their baseline simulations (Figs. 5 and 6).

FIG. 8. Scatterplots of the historical relationship between average JFM SWE (mm) and average October–March (a) temperature (°C), (b) precipitation (mm), (c) snowfall (mm), and (d) the cool-season ablation fraction (CAF) (%). All variables have been averaged over North America. Results from the RCMs and observations are plotted on all panels. Values from the driving GCMs are displayed on the precipitation and temperature panels. For the observations, the median of the ensemble for SWE and snowfall is shown on the panels. In all plots, the shape of the marker is determined by the driving GCM and the color by the RCM. Black markers denote the GCMs. The yellow star represents the observations.

As referenced in the introduction, a few studies have used high-resolution RCMs to show that there is potential for SWE to increase at high elevations in the western half of the domain (Brown and Mote 2009; Rasmussen et al. 2014). In these studies, winter temperatures at high elevations remain below freezing and the effects of precipitation increases result in SWE increases. Output from raw GCMs do not show increases in SWE in the western mountains, likely due to their coarse resolution and the attendant lack of high elevations (e.g., Brown and Mote 2009). These previous dynamical downscaling studies have only examined changes in single RCM experiments, and the uncertainty

regarding the role that the RCM potentially plays in these changes has not been explored.

In Fig. 10, we zoom in over the western half of the domain to explore how the relationship between changes in winter SWE and elevation varies across the models. The general representation of topography at 0.5° resolution is shown in Fig. 2, but each RCM uses a unique 50-km grid and with a unique representation of the underlying topography (Fig. S4).

Future increases in winter SWE at high elevations are projected to occur in the simulations of CRCM and ECP2, although the location of these increases varies with RCM. In CRCM, SWE increases over the northern

FIG. 9. The 25th, 50th, and 75th percentiles of the (top) absolute change in SWE and (bottom) percent change in JFM SWE. Climate change values are calculated as the difference between the future climate simulations and the current climate simulations. Percentiles are calculated across the 11 NARCCAP models independently at each grid point. At each grid point, absolute and percent SWE changes are ranked from lowest (most negative) to highest (most positive).

Rocky Mountains in Canada, Montana, Idaho, and Wyoming. This is similar to the results found in [Brown and Mote \(2009\)](#), which used a similar version of CRCM run at 48 km. In the ECP2 simulations, SWE increases occur farther south over the mountains in Wyoming and Colorado. The remaining seven RCM simulations do not show any increase in SWE at high elevations. While the RCM3 runs do show increases in SWE occurring in Wyoming, Idaho, Utah, and Colorado, close inspection reveals that these increases occur to the south and east of the high-elevation mountains. Plotting JFM changes in SWE as a function of elevation (Fig. S5) further demonstrates that the choice of RCM can control the spatial distribution of changes in SWE. While biases in baseline SWE amounts likely drive some of these differences, the integrated effects of changes in temperature and precipitation within each RCM will also be different, thus driving differences in SWE changes ([section 5c](#)). We have demonstrated here that in dynamical downscaling experiments, the choice of RCM can lead to additional uncertainties in high-elevation regions.

As with the bias plots of SWE ([Fig. 5](#)), by inspection we see that the spatial pattern and magnitude of SWE change is more similar across the simulations performed with the same RCM than in the simulations driven by the same GCM ([Figs. 9 and 10](#)). This highlights the sensitivity of the climate change response of SWE to the choice of RCM used to perform dynamical

downscaling. Studies that only use one RCM to examine future changes in snow will not capture the structural differences that can arise from using different RCMs and may well underestimate the uncertainty of future changes in snow.

2) AREA AVERAGE CHANGE

To expand our analysis of the uncertainty in snow changes, [Fig. 11](#) shows the annual cycle of absolute and percent changes in SWE ([Figs. 11a,c](#)) and SCE ([Figs. 11b,c](#)). When averaged over North America both SWE and SCE are projected to decrease in all months of the year, in all of the models. The maximum absolute losses in SWE occur between March and May and range from a loss of 1.3 to 21.7 mm. The largest percent losses in SWE occur in late spring, summer, and early fall when total SWE is low and small absolute changes result in large percent changes. In winter, however, percent changes range from 7.3% to 26.2%. The absolute and percent changes in SWE are similar across the simulations performed with the same RCM and there are no readily apparent similarities in changes in SWE between models forced by the same GCM. Percent and absolute losses are large in the MM5I simulations and small in the WRF simulations. The WRF simulations have some of the lowest SWE amounts in the baseline climate, so small absolute losses are not

FIG. 10. Future change in absolute JFM SWE values for the western portion of the domain from the individual RCMs. Models are organized by GCM driver (columns) as shown in Table 2.

surprising. The RCM3 simulations have large absolute losses, but relatively small percent losses.

Maximum absolute SCE loss is found in November, with a secondary maximum in April/May. Percent SCE losses are largest in the spring, summer and fall, and

relatively small in winter (between December and March). While spread in the absolute losses is large in winter (~ 1.3 million km^2 between the highest and lowest models in most months), spread in the percent losses is small (a range of 10% between the models). Most snow

FIG. 11. Time series plots of the annual cycle of (a) the absolute change in SWE, (b) the absolute change in SCE, (c) the percent change in SWE, and (d) the percent change in SCE. Black lines and their corresponding dash patterns represent the GCM. Colored lines represent the RCMs. Dash patterns of the colored lines represent the driving GCMs.

cover loss occurs in the marginal snow zones along the southern edge of the snow boundary (Fig. 8).

Percent losses in winter SCE are smaller than percent losses in winter SWE. This indicates that while some of the total loss in snow cover extent contributes to the loss of SWE, the amount of water stored in the snowpack is also decreasing in regions where snow cover remains.

b. Change in the timing of the snow season

As temperatures increase and precipitation patterns shift, the timing and duration of the snow covered season

will also change (Fig. 12). Domain wide, the RCMs project that the annual SCD will decrease in the future (Fig. 12, top). There is considerable spread in the change in SCD in the western United States, ranging from ~ 30 to 50 days. Although SCD decreases are small in Northern Canada, the models agree that the SCD will decrease in spite of projected increases in winter SWE for this region (Fig. 9 and Fig. S3). SCD decreases correspond with a contraction of the snow-covered season. The models agree that the onset of the snow cover season will occur later in fall and

FIG. 12. Maps of the 25th, 50th, and 75th percentiles of the future change in (top) snow cover duration (SCD), (middle) first date with measurable snow on the ground, and (bottom) last date with measurable snow on the ground.

winter over all regions of North America, although the IQR is large east of the Rocky Mountains (Fig. 12, middle). This shift occurs because the first date with below freezing temperatures occurs later in the year (not shown). The RCMs also project that the termination of the snow cover season will occur earlier in spring, although there is uncertainty about the sign of the change in the continental interior (Fig. 12, bottom).

Over the central United States, the timing of the onset and termination of the snow cover season is highly variable from year to year (not shown) and the ~29-yr time slices for the current and future climate simulations may not be sufficient to capture robust changes in the timing of the snow season in this region. Thus, results

over the central United States may be more uncertain than the model spread suggests.

c. Drivers of change

Projected changes in winter SWE will correspond with changes in snowfall accumulation and ablation, which are linked to changes in temperature and precipitation. Figure 13 explores the regional variations in the drivers of SWE changes. Across the ensemble, temperatures are projected to increase over the entire domain, with the largest increases occurring in the arctic (Figs. 13a–c). In this region, temperature increases range from 3° to 5° in the IQR. Increasing temperatures will reduce the fraction of precipitation that falls as snow and increase melt efficiency.

FIG. 13. The 25th, 50th, and 75th percentiles of the absolute change in October–March (a)–(c) temperature, (d)–(f) precipitation, (g)–(i) snowfall, (j)–(l) the ratio of snowfall to precipitation, and (m)–(o) CAF. Percentiles are calculated across the 11 NARCCAP models independently at each grid point. At each grid point, the change in each variable is ranked from lowest (most negative) to highest (most positive). Variables are ranked independently from each other.

Total precipitation is also projected to increase over much of the domain, but there are large differences across the models in the western United States (Figs. 13d–f). In this region, the lower quartile and upper quartile of the ensemble disagree on the sign of the change in precipitation. The uncertainty in changes in precipitation may contribute to the uncertainty in SWE changes, however ultimately it depends on how changes in temperature and precipitation covary and result in changes in snowfall.

As one might expect, the spatial patterns of the change in average in snowfall (Figs. 13g–i) broadly agree with the spatial patterns of the change in SWE (Fig. 9). The models show widespread decreases in snowfall over much of the domain, except for the high-latitude regions where snowfall increases. In northern Canada, in spite of large increases in temperature, average winter temperatures remain well below freezing in winter and projected precipitation increases result in increases to snowfall and SWE.

That being said, warming temperatures are projected to decrease the proportion of total precipitation that falls as snow (Figs. 13j–l) everywhere over North America. While the magnitude of this shift varies across the ensemble there is general agreement that the largest changes will occur in the western half of the domain, particularly over the Great Basin of the United States and the Sierra Nevada. The smallest changes in the snowfall fraction are found at high latitudes over northern Canada and over the southeast United States.

Changes in winter SWE are also a function of enhanced snow loss due to ablation. Increases in temperature should result in melt occurring earlier and more frequently throughout the year. We focus on changes in the CAF to highlight changes in the timing of melt/ablation as the CAF removes the effects of simulated differences in snowfall across the models. From Figs. 13m–o we see that in most of the models, ONDJFM CAF is projected to increase in the future over the domain. This means that in a warmer climate, more of the total cold-season snowfall will also melt in the cold season than being retained in surface snowpacks to melt in spring. There is some uncertainty in the sign of the change of melt, and in the lower third of the models, however, most of the large decreases correspond with small number division and are not reliable. In sum these plots show that more precipitation is falling as rain than snow and the snowfall that does occur is melting away earlier in the year.

The relationship between changes in these same variables and SWE in the models can be further quantified by averaging over North America (Fig. 14). A clear negative relationship is found between changes in

temperature and changes in SWE ($r = -0.65$) and a 1°C increase in temperature corresponds with a 7.58% decrease in SWE (Fig. 14a). Losses in SWE appear to be mitigated by precipitation increases, and a positive relationship is found between SWE and precipitation changes ($r = 0.42$; Fig. 14b). When averaged over the domain, the models with larger precipitation increases tend to have smaller SWE losses. The combined effects of changes of temperature and precipitation on SWE show a strong positive relationship between snowfall and SWE ($r = 0.87$) and a 1% decrease in snowfall corresponds with a 1.2% decrease in SWE. The larger losses of SWE than snowfall correspond to increasing ablation. Averaged over the domain there is a negative relationship between changes in CAF and SWE ($r = -0.51$). Models with the largest increases in CAF (which indicates increased ablation fraction for ONDJFM and a shift in the timing of melt to earlier in the season) have the largest SWE losses.

6. Discussion and conclusions

The goal of this study was to use the NARCCAP RCM–GCM ensemble to quantify and diagnose the uncertainties in future projections of snow over North America that arise when multiple RCMs are used to dynamically downscale multiple GCMs. We believe this is the first study to explore this dimension of uncertainty in relationship to snow over North America. RCMs are regularly used to downscale coarse GCMs to add value to our understanding of climate change on regional scales. However, dynamical downscaling adds an additional layer of uncertainty onto our understanding of climate change, namely the structural uncertainty corresponding with the choice of RCM. We have explored that uncertainty in the context of snow.

Before identifying the climate change response of the RCMs, model performance was evaluated against an ensemble of gridded observation-based SWE products. In NARCCAP model biases are due to the combined effects of biases inherited from the driving GCM and biases generated within the RCM. Overall, from our analysis, no single model stands out as better or less biased than the others in this ensemble, but biases in snow were found to be highly sensitive to the choice of RCM and less influenced by the driving GCM. We demonstrated that dynamical downscaling adds uncertainty into the simulation of the baseline climate as the spread in domain averaged SWE and SCE is much larger in the RCMs than the spread found in the observational ensemble or the driving GCMs. While this result has been inferred in other studies (e.g., Wood et al. 2004) this is the first study to quantify this

FIG. 14. Scatterplots of the future change in JFM SWE (%) plotted against the change in average October–March (a) temperature (°C), (b) precipitation (%), (c) snowfall (%), and (d) CAF (%).

additional uncertainty across multiple RCMs over North America.

By midcentury, the NARCCAP ensemble projects that domain averaged SWE and SCE will decrease in all months of the year in all of the RCMs and their driving GCMs. The largest absolute losses in SWE are found in early spring while the largest percent losses occur in late spring, summer, and early fall. Absolute SCE losses on the other hand are largest in the transition seasons (fall and spring). As with the baseline climate values, spread in the climate change response of SWE and SCE is much larger in the RCMs than the GCMs. Some of the uncertainty in absolute SWE losses stems from differences in the baseline representation of SWE and the uncertainty decreases when considered as percent losses of SWE.

We found that the RCMs agree on the broad spatial patterns of change; winter SWE will decrease almost everywhere except at high latitudes north of 60°N. But, the magnitude, spatial details, and range of uncertainty of the projected changes vary greatly across the domain. Absolute winter SWE losses are projected to be largest over the western mountains and low over the remainder of North America and percent losses were found to be largest over the low-elevation, coastal, and southern portions of the domain and smallest over the Rocky Mountains. We also found considerable uncertainty between the NARCCAP RCMs regarding the sign of the change in SWE for northern Quebec, where half the models show moderate increases in SWE and half the models show moderate decreases. We also identified that there is RCM uncertainty regarding the sign of the

change in SWE at high elevations in the Rocky Mountain range, which we discuss more below.

The RCMs agree that over all regions of North America annual SCD will decrease, the onset of the snow season will start later in fall and the termination of the snow season will occur earlier in spring. Along the west coast, uncertainty for the projected changes in SCD is high. Spread in the onset of the snow season is highest in the Great Plains while spread in termination of the snow season is highest along the west coast.

In these simulations, the regions and seasons where total snow cover loss occurs, additional amplified warming is likely to arise because of the snow–albedo feedback. This local source of additional warming is a critical part of the climate change signal and a significant source of added value in dynamical downscaling experiments. Although GCMs capture the snow–albedo feedback, they do so on coarse scales such that the local effects of snow loss are missing in regions of complex topography. Statistical downscaling approaches can produce high-resolution climate change results, but they cannot capture the additional warming associated with the snow–albedo feedback, as it requires coupling between the land surface and the atmosphere (Walton et al. 2017). Statistical approaches assume the empirical relationships between the coarse and fine scales are stationary in time, and therefore do not capture the additional warming associated with local snow losses. Therefore, more complex models such as RCMs are needed for this process to be captured.

While the NARCCAP RCMs show a wide range of possible futures with regard to SWE, we have demonstrated that the variations in the magnitude of the change in winter SWE across the RCMs are physically consistent and correspond with changes in temperature, precipitation and their influence on snowfall and the timing of snowmelt. For example, regardless of driving GCM, MM5I shows the largest percent losses in winter SWE, and also has some of the largest temperature increases, the smallest precipitation increases, high snowfall loss, and the largest shift in the timing of melt to earlier in the season. WRFG-ccsm on the other hand has some of the smallest winter SWE losses, but it also has some of the smallest temperature increases, and the greatest increases in precipitation, which result in very small decreases in snowfall and almost no change in the timing of melt. These results indicate that the choice of RCM used for downscaling can have an important effect on the simulations of the future response of snow. It is worth noting that the sensitivity of SWE to future changes in temperature and precipitation might be misrepresented in regions with large biases in the baseline climate.

A few dynamical downscaling studies have shown that it is likely snowfall and SWE will actually increase at high elevations in the Rocky Mountains, a possibility that is not found in the raw output from coarse GCM experiments (e.g., Brown and Mote 2009). The arguments made in these RCM studies is that at higher spatial resolution, the high peaks will be resolved such that temperatures will remain below freezing and precipitation increases will result in more snow. As we demonstrated here, that result is dependent on the RCM, and not just a function of increased resolution and elevation. In fact, we demonstrated that the spatial patterns of changes in SWE in regions of complex topography are highly sensitive to the choice of RCM used to perform the dynamical downscaling and less controlled by the driving GCM. Therefore, the conclusions from previous studies that such increases are likely need to be reevaluated in the context of RCM uncertainty.

Although NARCCAP is currently the only existing RCM–GCM ensemble that has an adequate combination of simulations to study the role of the choice RCM in driving uncertainty in future projections over North America, it is arguable that the 50-km resolution of the simulations, while much higher than current GCMs, is still too coarse to fully resolve the variations in elevation small scale processes necessary to capture snow dynamics in high-latitude regions. A few studies have performed resolution sensitivity tests and demonstrated that very high-resolution (<13 km) simulations are needed to capture point observations of SWE (e.g., from SNOTEL) in regions of complex topography (Leung and Qian 2003; Garvert et al. 2007; Rasmussen et al. 2011). Very high resolution experiments are able to better capture the local orographic forcing of precipitation associated with local ridges and valleys. While NA-CORDEX (Mearns et al. 2017) might be able to answer some questions regarding the role of resolution on changes in the U.S. Mountain West, this ensemble does not use a balanced factorial design to span the RCM–GCM uncertainty space and RCM–GCM pairs are too inconstant to assess, even by inspection, the relative roles of the RCM versus driving GCM in driving biases or future changes. Furthermore, while increases in RCM resolution would likely change the results for each model, it is likely that the uncertainty would still be large in terms SWE as key processes such as cloud microphysics, radiation, and surface snowpack must still be parameterized at high resolution. This added uncertainty associated with the choice of RCM should be considered when studying features of climate change using RCMs.

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