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Assessment of Arctic Seasonal Snow Cover Rates of Change

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Abstract. Arctic snow cover extent (SCE) trends and rates of change reported across recent climate assessments vary due to the time period of available data, the selection of snow products, and methodological considerations. While all reported trends are strongly negative during spring, more uncertainty exists in autumn. Motivated to increase the confidence in SCE trend reported in climate assessments, we quantify the impact of (1) year-over-year increases in time series length over the past two decades, (2) choice of reference period, (3) the application of a statistical methodology to improve inter-dataset agreement, (4) the impact of dataset ensemble size, and (5) product version changes. Results show that the rate of change during May and June has remained consistent over the past decade as time series length has increased, and is largely insensitive to the choice of reference period. Although new product versions have increased spatial resolution, use more advanced reanalysis meteorology to force snow models, and include improved remote sensing retrieval algorithms, these enhancements do not result in any notable changes in the observed rate of Arctic SCE change in any month compared to a baseline set of older products. The most impactful analysis decision involves the scaling of dataset climatologies using the NOAA snow chart climate data record as the baseline. While minor for most months, this adjustment can influence the calculated rate of change for June by a factor of two relative to different climatological baselines.

1 Introduction

As comprehensively assessed in the Intergovernmental Panel on Climate Change (IPCC) Special Report on Oceans and Cryosphere in Changing Climate (SROCC) changes to the Arctic cryosphere driven by the response to warming surface temperatures are unequivocal (Meredith et al., 2019). Sea ice extent reductions are occurring in all months of the year (Stroeve and Notz, 2018), and are most dramatic in the late summer and early autumn as earlier melt onset and subsequent enhanced ice loss results in increased heat stored by the ocean which in turn delays ice formation (Stroeve et al., 2014). Near surface permafrost temperatures have reached record highs in the observational period (Biskaborn et al., 2020). Warmer summer air temperature, and hence soil temperature, induces a deeper active layer with implications for thermokarst events, changes to surface hydrology, and carbon release (Turetsky et al., 2020). Arctic seasonal snow cover on land is responding directly to warming temperatures (Mudryk et al., 2020).

Unlike the proportion of sea ice cover that presently survives the summer melt season (at least for the immediate future), snow disappears completely from the Arctic land surface every summer. The most climate-sensitive indicators are therefore

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Arctic snow extent during the onset (autumn) and melt (spring seasons). Variability and trends in snow phenology have important implications for the surface energy budget (Flanner et al., 2011), snow-related impacts on permafrost (Walvoord and Kurylyk, 2016), the timing of snow melt contributions to streamflow (Dery et al., 2016) and impacts on the habitat of flora and fauna (Bokhorst et al., 2016). Given this importance, the strong sensitivity of snow to surface temperature (Mudryk et al., 2017), and one of the longest historical data records from satellite (Estilow et al., 2015), spring snow cover is a compelling indicator of climate change impacts on the Arctic. As such, it is commonly included as part of climate assessments (e.g. Meredith et al., 2019; Mudryk et al., 2021; AMAP, 2021).

In this study, we examine Arctic snow cover trends through the lens of these climate assessments. The motivation comes from our participation in two different types of assessments. The Arctic Report Card (ARC) is published annually by NOAA (https://www.arctic.noaa.gov/Report-Card). The purpose of the ARC is to provide an annual update on long-term trends of key Arctic climate indicators, with an emphasis on placing the most recent year in the context of historical variability and trends. We have led the 'Terrestrial Snow' contribution to the ARC every year since 2009 (e.g. Mudryk et al., 2021). We also participated in the IPCC SROCC Polar Regions chapter (Meredith et al., 2019), and contributed snow cover trend information to the IPCC Sixth Assessment Report. Unlike the annually updated ARC, assessments like the SROCC and AR6 cover literature and data up to a specific cut-off date.

The SROCC SPM assessment statement assigned 'high confidence' to observed changes to Arctic snow cover extent (IPCC, 2019; IPCC calibrated uncertainty language is described in Mastrandrea et al., 2010). Inconsistent autumn trends due to the choice of snow dataset (e.g. Brown and Derksen, 2013) and large inter-product differences in spring snow extent magnitude and trends (e.g. Brown et al., 2010) precluded the attribution of 'very high confidence'.

The snow cover – climate literature communicates snow cover changes in different ways depending on the context and motivating science questions. To assess how conditions in one particular year differ from the long-term average, the anomaly is the relevant calculation. To determine the long-term change in a specific snow quantity, the trend is the appropriate metric. To understand the pace of observed changes, the rate of change is insightful. In both the ARC and the SROCC, change in spring snow cover extent was communicated as a rate, expressed as % decade^{-1}. This approach is common, and is applied in widely-cited and public-facing assessments of change for other variables, such as Arctic sea ice extent (http://nsidc.org/arcticseaicenews/). Change expressed as % decade^{-1} is attractive because it is straightforward for non-expert interpretation, facilitates comparison between different variables (e.g. snow cover versus sea ice) and is easily applied to both historical observations and climate model projections. There are limitations, however, because a rate change is sensitive to the reference period against which the change is determined and large proportional changes are exaggerated when absolute values are small.

In this study we determine the sensitivity of the commonly used metric of change in snow cover extent (expressed as % decade^{-1}) to year-over-year changes in time series length, choice of reference period, the application of a statistical methodology to improve inter-dataset agreement, version-to-version changes in snow products, and snow product ensemble

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size. Results quantify the sensitivity to the range of choices available to investigators, thereby increasing confidence in reported Arctic snow extent changes.

2 Data

2.1 Snow Products

Snow is a deceptively difficult variable to measure, model, and remotely sense. It is challenging to characterize using surface observations because of local scale variability driven by interactions between snow, wind, vegetation, and topography. It is generally accepted that a single point in space (e.g. snow depth as is typically measured at automatic weather stations) provides some locally-relevant information, which decreases in value with distance from that point. Uncertainty arises from extrapolation. Gridded datasets (remotely sensed; modeled) also have limitations by providing a single value over some integrated area; conventional wisdom is that uncertainty increases as resolution gets coarser. Uncertainty arises from aggregation and the inability to resolve spatial variability. Because point (or short transect) observations are generally used to validate gridded datasets, uncertainty is circular.

Despite these issues, evaluation with snow course measurements shows that ensembles of gridded snow products exhibit more skill than individual datasets (provided certain poorly performing datasets are excluded from the averaging as described in Mortimer et al., 2020). There is clear value in averaging multiple independent snow products together to reduce uncertainty. Unfortunately, maintaining up to date multi-product snow time series is difficult: some products fail to be updated, products inevitably transition to new versions, and new datasets emerge. In this study, we update the available set of snow products in order to determine the sensitivity to various analysis scenarios and choices as outlined in Section 3. We also maintain two generations of the products to allow an assessment of the impact of version changes.

As summarized in Table 1, the snow products are:

(1) output from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) (Gelaro et al., 2017), which follows from MERRA (Rienecker et al., 2011). Both datasets employ an intermediate complexity snow scheme (within the Catchment land surface model) forced by MERRA meteorology.

(2) snow accumulation determined by a simple temperature index model after Brown et al. (2003) driven by ERA-interim or ERA5 reanalysis. While the index model itself remains the same, the output is sensitive to the reanalysis version used to drive the model.

(3) the Crocus physical snow model driven by ERA-interim (Brun et al., 2013) or ERA5 reanalysis.

(4) the European Space Agency Snow CCI SWE dataset (version 1) derived from a combination of satellite passive microwave data and climate station snow depth observations (Luojus et al., 2021), which is an update of the ESA GlobSnow dataset (Takala et al., 2011). There are several versions of GlobSnow; we use version 2.1 as it was the product used in previous analysis (e.g. Mudryk et al., 2017) and its algorithm differs more from the recent advances implemented in Snow CCI.

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(5) the NOAA snow chart Climate Data Record (NOAA-CDR) derived primarily from optical satellite imagery. The NOAA CDR is a 180 km resolution binary snow extent product (Estilow et al., 2015). While the product switched to the 24 km Interactive Mapping System (IMS) data starting in 1998, the standard CDR was degraded to 180 km spacing to maintain consistency with snow charts from before IMS period (Helfrich et al., 2001). Recently, a re-gridding of the CDR data sources used during the 1980-1997 period changed the resolution to 24 km to match that of IMS data. This process produced a revised snow extent time series with improved grid spacing (Robinson and Estilow, 2021).

(6) the JAXA JASMES snow extent product, derived from objective analysis of AVHRR and MODIS imagery (Hori et al., 2017) Only a single version of this product is available.

Gridded daily snow cover is determined directly from datasets 5 and 6, and estimated for datasets 1-4 by applying a 5 mm SWE threshold to determine snow extent. These daily fields are averaged over each month to produce monthly snow cover fraction (SCF). Finally, Arctic snow extent is calculated by summing monthly SCF over land north of 60° latitude.

Table 1. Summary of snow datasets. Analysis group 2 represents the newest product versions relative to analysis group 1.

Variable	Family	Analysis Group	Version	Time Period	Grid Spacing	Model	Forcing Data	Reference
Snow Water Equivalent (SWE)	Brown	1	Brown-ERAint	1981-2018	0.75 deg	Temp-index	ERA-interim	Brown et al., 2003
		2	Brown-ERA5	1981-2020	0.25 deg	Temp-index	ERA5	
	Crocus	1	Crocus-ERAint	1981-2017	0.5 deg	Crocus	ERA-interim	Brun et al., 2013
		2	Crocus-ERA5	1981-2018	0.5 deg	Crocus	ERA5	
	GlobSnow	1	GlobSnow v2.1	1981-2018	25 km		PMW + in situ	Takala et al., 2011
		2	Snow CCI v1	1981-2018	25 km		PMW + in situ	Luojus et al., 2021
	MERRA	1	MERRA	1980-2015	0.5x0.67 deg	Catchment	MERRA	Rienecker et al., 2011
		2	MERRA2	1980-2020	0.5x0.5 deg	Catchment	MERRA2	Gelaro et al., 2017
Snow Cover Extent (SCE)	NOAA Snow Charts	1	Climate Data Record	1967-2020	190 km			Estilow et al., 2015
		2	Rutgers 24 km	1981-2020	24 km			Robinson and Estilow, 2021
	JAXA	2	JASMES V1	1981-2018	5 km			Hori et al., 2017

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2.2 Time Series Adjustment

In previous studies (e.g. Mudryk et al., 2020), the climatology and standard deviation of multiple snow extent datasets were adjusted before analysis by employing a methodology described in Brown et al. (2010) and Brown and Robinson (2011). We followed this process to create 'adjusted' versions of each dataset that differed from the raw versions by two factors. First, each climatology was replaced by the climatology of the Rutgers 24 km product. Second, each dataset's variability was scaled towards the average of all datasets. The first adjustment was made by calculating anomalies using each dataset's own climatology and adding those anomalies to the Rutgers 24 km climatology. The second adjustment was made by standardizing the anomalies using the standard deviation of each data set, but then "de-standardizing" using the average standard deviation of all datasets (see equations in section 3.2 for further details). These decisions were made under the assumption that the NOAA record represents the best estimate of the 'true' historical snow extent and that the variability of the six-component dataset is more accurate than any single dataset. This approach is justified by the analysis in Mudryk et al (2017) which showed that variability in the NOAA dataset may be artificially high during spring. These adjusted time series were averaged over the 1981–2017 period and this average time series was merged with the adjusted NOAA time series over the 1967–1980 period. This methodology allows the 'scaled' versions of datasets which start in 1981 to be extended back to 1967, and ensures that the transition between the pre- and post-1981 periods does not contain any discontinuities due to changes in climatology or variability.

The impact of the adjustment process as applied to each snow extent dataset is shown in Figure 1 for the month of May. We focus on the set of six most recent product versions (including JASMES). The raw time series (Figure 1a) cover a range of approximately 6 million km^2 (between 6 and 12 million km^2). This is a sobering number (not far below the mean May snow cover extent of ~8 million km^2 from all the products), and approximately the same as the product range for the older family of datasets (not shown). The inter-product range slightly exceeds the value calculated from an even older product set described in Brown et al (2010), although there are some methodological differences in how snow extent was defined. Regardless, there is no evidence of increased agreement in the absolute climatological extent of snow amongst the most recent product versions compared to previously published analysis. The adjustment process as described in Section 2 enforces climatological agreement, while retaining the interannual variability of each dataset (Figure 1b). This yields a mean May SCE between 1981-2018 of 10.6 (±0.76 stdev) million km^2, very similar to Brown et al (2010). The SCE rate of change since 1981, calculated for end years starting in 2000 (e.g. 1981-2000, 1981-2001, and so on), is shown in Figure 1c. The inter-product range is -2 to -5% decade^{-1}. The rate of May snow cover loss increased from 2005 through 2015 in all datasets, and has stabilized in recent years.

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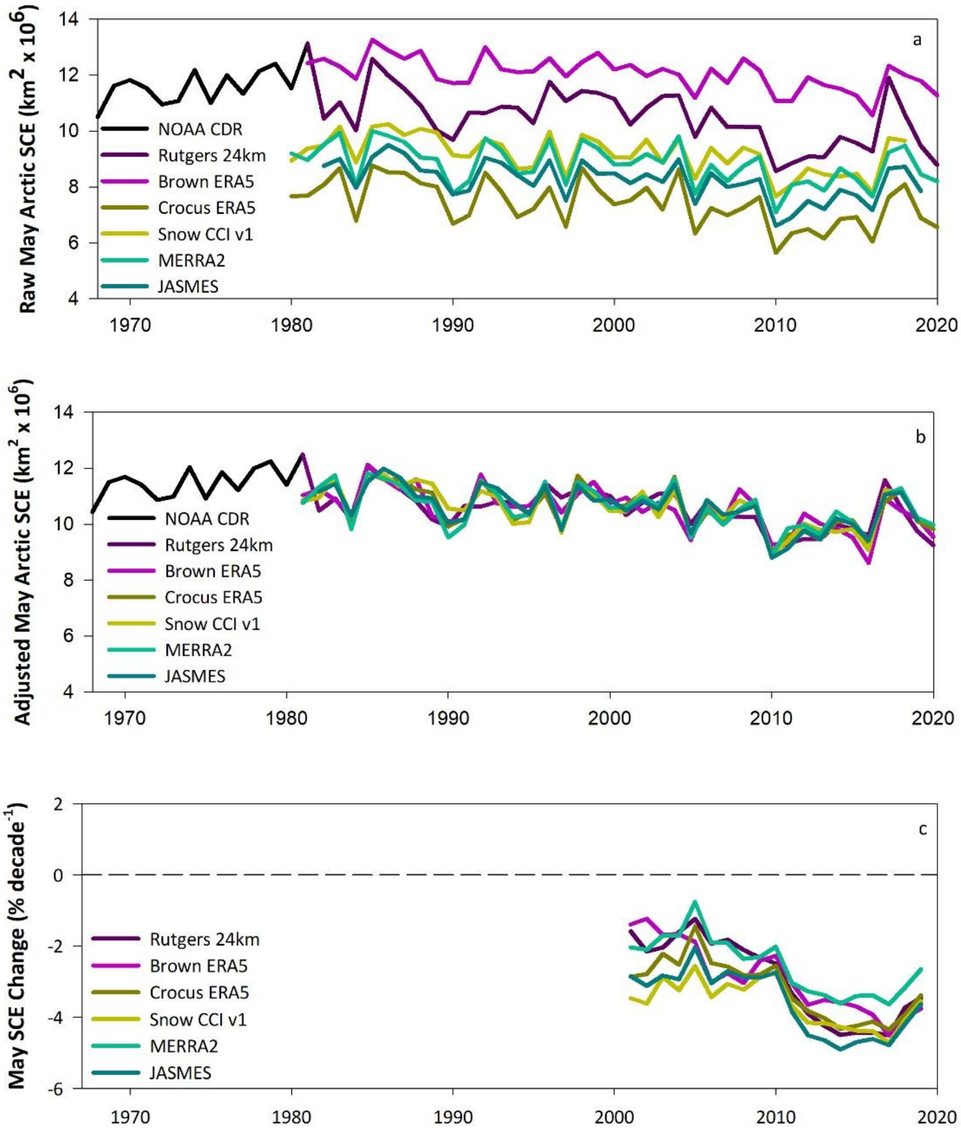

Figure 1. Raw time series of May Arctic snow extent (a), scaled to the NOAA CDR climatology (b), and rate of change since 1981 (c).

The impact of dataset adjustment is similar for the month of June (Figure 2a and 2b). The large range of raw snow extent values includes some datasets with very little snow (<2 million km^2), with others showing over 4 million km^2. Extensive June SCE in the NOAA dataset before 1980 explains the strong negative trends in June reported in studies which analyzed the NOAA record on its own (Derksen and Brown, 2012; Mudryk et al., 2017). Since 2000, the inter-product range in SCE reductions is -4 to -12 % $decade^{-1}$ (Figure 2c).

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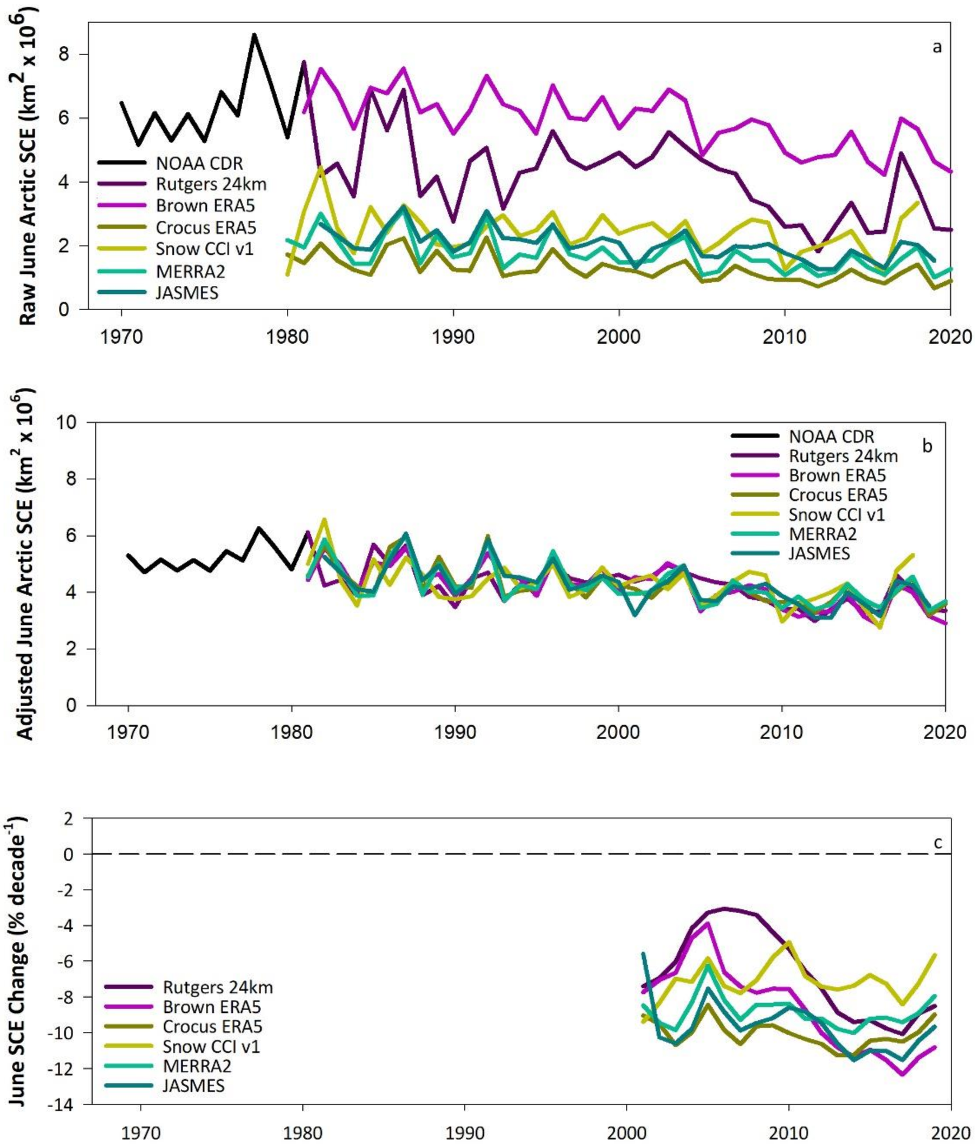

Figure 2. As in Figure 3, but for June.

October snow cover trends have long been of interest because an apparent increase in snow extent evident in the NOAA CDR was identified as the trigger to a sequence of feedbacks during the northern hemisphere winter (Cohen et al., 2012; Furtado et al., 2016). Assessment has shown, however, that other datasets do not exhibit a positive snow extent trend in October (Brown and Derksen, 2013) so the NOAA CDR trend is a significant outlier (Mudryk et al., 2017). Like May, the raw snow extent time series span a large range in October (~8 million km^2 ; Figure 3a). The adjustment process by definition aligns the absolute magnitude at an average of 10.5 million km2 (±0.87 stdev; Figure 3b), but because the NOAA trend does

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not agree with the other products, a larger inter-product spread is evident in the October SCE rates of change (Figure 3c). Unlike May and June, there is disagreement in the trend direction between datasets through approximately 2005. After that point, all datasets indicate a loss of October snow cover with the exception of the NOAA CDR.

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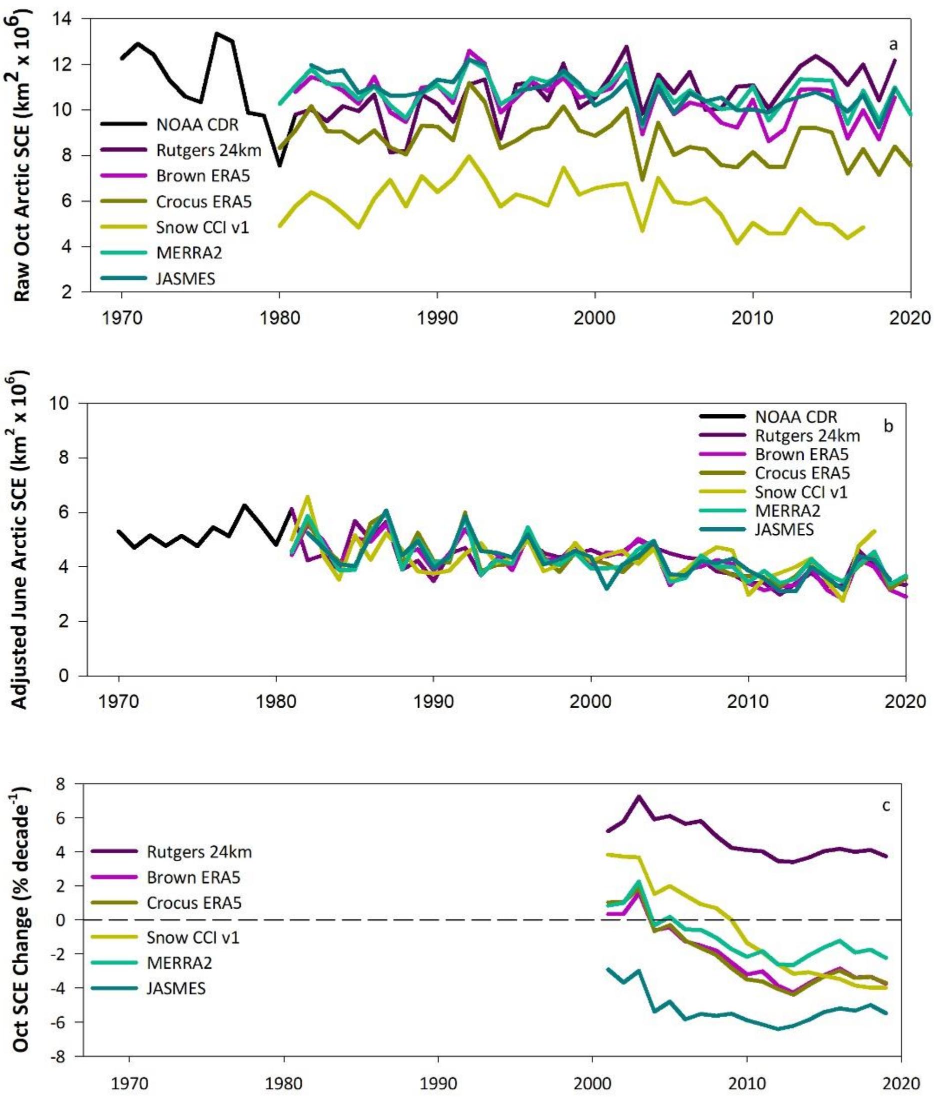

Figure 3. As in Figure 3, but for October.

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3 Methods

3.1 Rate of change calculations

We use the following notation for a time series:

$$x_i = \bar{x}_P + \Delta x_i \quad (1)$$

where x_i represents a snow extent time series for a given month (e.g. June SCE), $\bar{x}_P$ represents the climatological mean for the choice of reference period, and Δx_i are the yearly anomalies. A linear trend for the above series can be determined by ordinary least squares regression. The rate of change of the time series r_i (its slope) depends only on the anomalies (the selection of years considered), not on the choice of reference period used to determine $\bar{x}_P$. In what follows we will use *time window* to denote the selection of yearly anomalies considered, and *reference period* to denote the years used to determine $\bar{x}_P$.

To calculate a percent rate of change (for example, to cite a trend in units of % decade^{-1}) we use a normalized time series:

$$\tilde{x}_i = 1 + \frac{\Delta x_i}{\bar{x}_P} \quad (2)$$

with a percent rate of change $\tilde{r}_{i,P}$ that now depends not only on the anomaly time window, but also on the choice of reference period, P.

All our calculations use time windows that begin in 1981 so in the following we label rates of change with the final year of the time window, and a reference period taken from Table 2. For example $\tilde{r}_{2000,P2}$ denotes the percent rate of change calculated using anomalies from 1981-2000 but normalized with respect to a climatological period of 1991-2010.

Table 2. Summary of reference periods.

Reference	Years
P0	1981-2010
P1	1981-2000
P2	1991-2010
P3	2001-2017

The adjusted time series have the following form:

$$X_i = \bar{a}_p + \Delta x_i \frac{\langle SD \rangle}{SD_x} \quad (3)$$

where $\bar{a}_p$ is the climatology of the NOAA-CRD and $\langle SD \rangle / SD_x$ is the ratio of the standard deviation from the dataset under consideration (denoted SD_x) to the average standard deviation of all datasets (denoted $\langle SD_x \rangle$). While this ratio will vary if

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sampled over drastically different periods, it is approximately constant for the selection of years considered here (not shown); hence, we compute it for the 1981-2017 time period and take it to be constant in what follows. The normalized form can be written as:

$$\tilde{X}_i = 1 + \frac{\Delta x_i}{\bar{x}_p} \frac{\bar{x}_p}{\bar{a}_p} \frac{\langle SD \rangle}{SD_x} \tag{4}$$

This time series differs from its unadjusted version by two factors, $f_1 = \bar{x}_p / \bar{a}_p$ and $f_2 = \langle SD \rangle / SD_x$. At times we will express the percent rate of change of this time series using these two parameters $\tilde{R}_{i,P}(f_1, f_2)$, so that the percent rate of the change of the unadjusted time series is obtained by setting both, $f_1$and f_1 to unity viz., $\tilde{r}_{i,P} = \tilde{R}_{i,P}(1,1)$.

3.2 Year-over-year increases in time series length

We determined the impact on the percent rate of change due to year over year increases in the length of the time series. An initial rate of change was first calculated for adjusted time series anomalies in the 1981-2000 time window (20 years). Subsequent differences in the rate from the previous value were then calculated for each new year in the time series (difference between 1981-2001 and 1981-2000; difference between 1981-2002 and 1981-2001 and so on) through 1981-2017, the consistent time series covered by all six datasets. All calculations used the 1981-2017 reference period (P0 in Table 2). This procedure yields the following 17 differences:

$$\Delta\tilde{R}_{i1} = \tilde{R}_{2001,P0} - \tilde{R}_{2000,P0} \tag{5}$$

$$\Delta\tilde{R}_{i2} = \tilde{R}_{2002,P0} - \tilde{R}_{2001,P0} \cdots$$

$$\Delta\tilde{R}_{i17} = \tilde{R}_{2017,P0} - \tilde{R}_{2016,P0}$$

which are repeated for each of the six datasets to yield an ensemble of 102 differences.

3.3 Reference period

To compare the impact of the reference period on the rate of SCE change, three blocks of approximately 20 years were identified (Table 2). While shorter than the standard climatological 'normal' of 30 years, these shorter periods facilitate the comparison of three different periods within the total available time series of 1981 to 2017. The metric was calculated as the absolute difference in the rates of change between reference period P3 and reference period P1 obtained by holding the anomaly time window:

$$\Delta\tilde{R}_{P1} = \left|\tilde{R}_{2000,P3} - \tilde{R}_{2000,P1}\right| \tag{6}$$

$$\Delta\tilde{R}_{P3} = \left|\tilde{R}_{2001,P3} - \tilde{R}_{2001,P1}\right|$$

$$\ldots$$

$$\Delta\tilde{R}_{P18} = \left|\tilde{R}_{2017,P3} - \tilde{R}_{2017,P1}\right|$$

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The absolute difference is used because the effect of the normalization is to change the magnitude of the existing trend. If the later reference period has a smaller (larger) climatology than the earlier period, the trend magnitude is increased (decreased). These 18 calculations are performed for each of the six datasets to yield an ensemble of 108 differences.

Dataset Adjustments

The impact on the SCE rate of change from adjusting both the climatology and variability of each dataset was identified by comparing the scaled to unscaled versions of each dataset. For a given choice of dataset, time window and reference period three metrics are calculated as

$$\Delta\tilde{R}_{X1} = \tilde{R}_{2000,R0}(f_1, f_2) - \tilde{R}_{2000,R0}(1, f_2) \tag{7}$$

$$\Delta\tilde{R}_{X2} = \tilde{R}_{2000,R0}(f_1, f_2) - \tilde{R}_{2000,R0}(f_1, 1)$$

$$\Delta\tilde{R}_{X3} = \tilde{R}_{2000,R0}(f_1, f_2) - \tilde{R}_{2000,R0}(1, 1)$$

The first, $\Delta\tilde{R}_{X1}$describes the trend difference due to substituting the dataset's climatology with that of the NOAA-CRD, the second, $\Delta\tilde{R}_{X2}$describes the difference due to scaling the dataset's variability andthe last, $\Delta\tilde{R}_{X3}$describes the full difference between the adjusted and unadjusted time series.

4 Results

4.1 Impact of dataset adjustment procedure, time series length, and reference period

A key factor underpinning confidence in reported changes in Arctic snow cover is understanding the impact of various data processing and analysis decisions. To address this, we focus on the rate of change in Arctic snow extent (expressed as % decade^{-1}) because this is a widely used metric in climate assessments. As described in Section 3, we performed a series of calculations to isolate the sensitivity in this rate to a number of factors:

1. year-over-year increases in the length of the time series as time passes, relevant to annually updated assessments such as the Arctic Report Card;
2. the choice of reference period (Table 2 provides a summary of the different reference periods using in the calculations) which evolves from decade to decade as new updated climate normals are determined;
3. the decision to adjust the climatology and standard deviation of each dataset (as described in Section 2).

#1 is unavoidable: assuming datasets are maintained, time series length will always increase year-over-year. #2 and #3 are analytical choices based on expert judgement. To help conceptualize our analysis, Figure 4 provides an overview of the sensitivity of the change in Arctic SCE calculation (% decade^{-1}) for May. The impact of year-to-year increases in time series length, reference period differences, and changes due to dataset adjustments are noted, and represent the first three factors outlined above.

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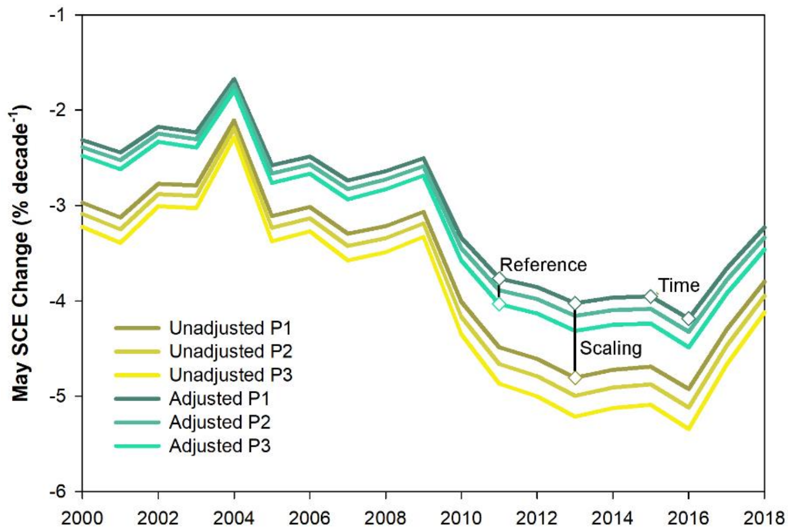

Figure 4. Change in Arctic SCE (% decade^{-1}) for May since 1981 relative to three reference periods (P1, P2, P3, see Table 2) and scaled versus unscaled datasets since 1981 through the year noted on the x-axis. The impact of year-to-year increases in time series length, reference period differences, and changes due to dataset adjustments are noted.

Descriptions of metrics that reflect each these factors are provided in Section 3.2. We focus on the months of April through June and September through November because Arctic land areas are always 100% snow covered between December and April, and essentially snow free during July and August. Figure 5 illustrates that the impact of additional years in the time series is small, peaking at approximately 2% in September and falling to within +/-1% for the remaining months. The net effect of additional years over the past decade is a slight weakening in the rate of change during the autumn season because SCE values reached a minimum in approximately 2015 and have not decreased further. Were current trend estimates for all months to remain stable going forward, the average value of this metric should tend to zero since it only reflects year-to-year variability. The second factor illustrated in Figure 5, the choice of reference period, only has a noticeable effect in September and June. Focusing on June, the most recent reference periods considered (1991-2010; 2001-2017; see Table 2) have less snow extent than the reference periods which include 1981-2000. When expressed as a % change relative to these different baselines, the rates appear weaker relative to the most recent reference period. The magnitude of this effect is small, but does reach 3% decade-1 in June. Furthermore, the magnitude will grow if snow cover reductions continue and new 30-year normal periods are progressively used into future decades. Finally, the dataset adjustment process has no net effect during the fall, but weakens SCE rates of change in the spring, reaching 5% decade^{-1} in June.

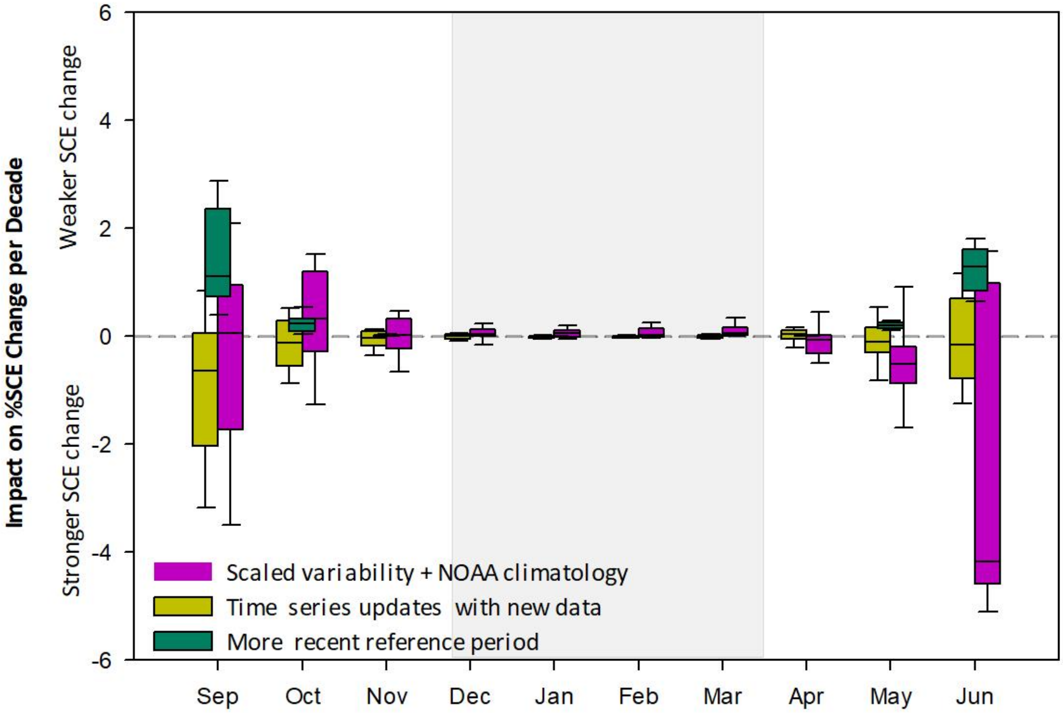

Figure 5. Sensitivity of Arctic snow cover extent rate of change calculations (expressed as % decade^{-1}) to changes in the available time series length, selection of reference period, and scaling to the NOAA climatology. Values above zero indicate a stronger SCE rate of change; values below zero indicate a weaker SCE rate of change.

Overall, the results in Figure 5 suggest the previously published rates of change in Arctic snow cover are comparable regardless of analytical decisions such as the choice of reference period and any adjustments made to the data. June remains the month most sensitive to the inter-dataset scaling used to achieve product consistency in absolute SCE values. We produced similar plots to Figure 5 for each individual dataset (not shown). The relatively narrow range of results when all six products are considered together reflects the generally consistent inter-dataset behaviour to the various metrics employed in this study, with the largest inter-product spread associated with normalizing the trends using the NOAA climatology in June and September.

4.2 Ensemble size

The impact of ensemble size was determined by calculating the rate of SCE change over 1981-2017 (relative to 1981-2000) for all datasets individually, all possible combinations of random groups of three datasets, and all datasets averaged together. Results for the new product set are shown in Figure 6. For all months, the rate of SCE change narrows with an increase in ensemble size. This reduction in spread with increased ensemble size is consistent with an increase in the skill of SWE

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estimates with an increase in ensemble size (evaluated using reference snow course measurements) identified by Mortimer et al. (2020).

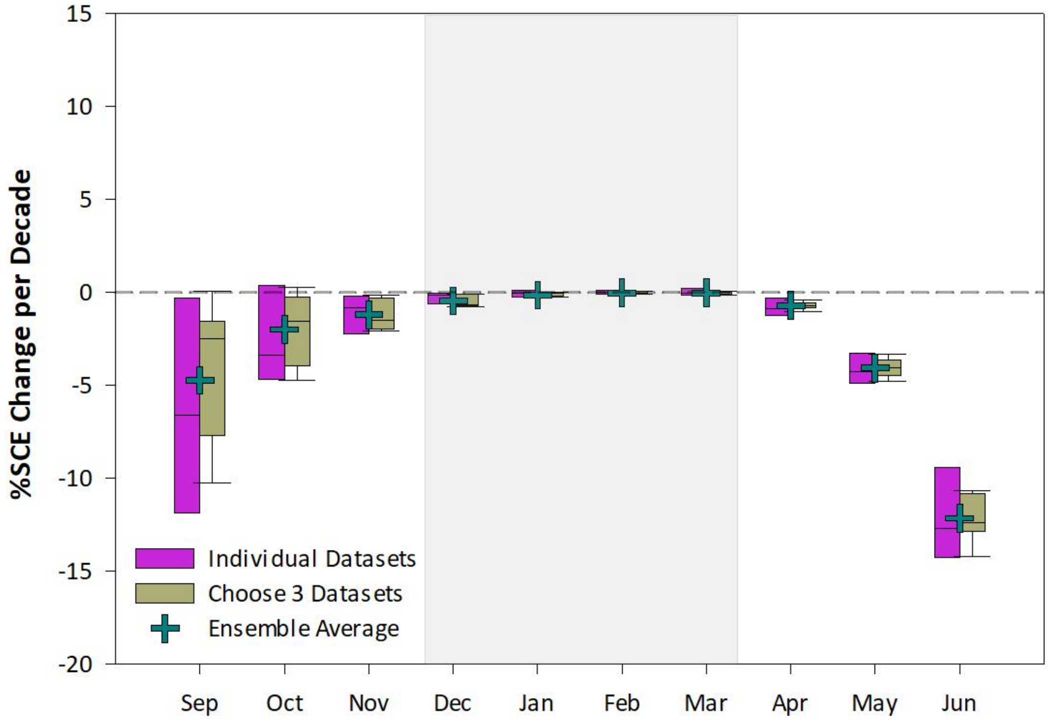

Figure 6. The impact of dataset averaging (new product set) on rates of change in Arctic SCE.

4.3 Dataset version changes

Figures 1a, 2, and 3a showed that although the interannual variability is strongly correlated, raw snow extent time series are very different between products in absolute terms. Large absolute differences in snow extent also exist when subsequent versions from the same product are compared to each other (Figure 7). We examined the four months during which Arctic snow extent is the most dynamic: May and June during the snow melt season, and October and November during initial snow accumulation. During spring, product version differences reach nearly 4 million km^2. The Brown temperature index model is clearly sensitive to the change in forcing from ERA-interim to ERA5 meteorology, with much greater spring snow extent in the ERA5 version. The change from GlobSnow v2.1 to Snow CCI v1 produces a large difference after 2010 in May, which requires further exploration. Product version differences are much smaller during the period of snow line advance, particularly by November when nearly all of the Arctic land surface is snow covered.

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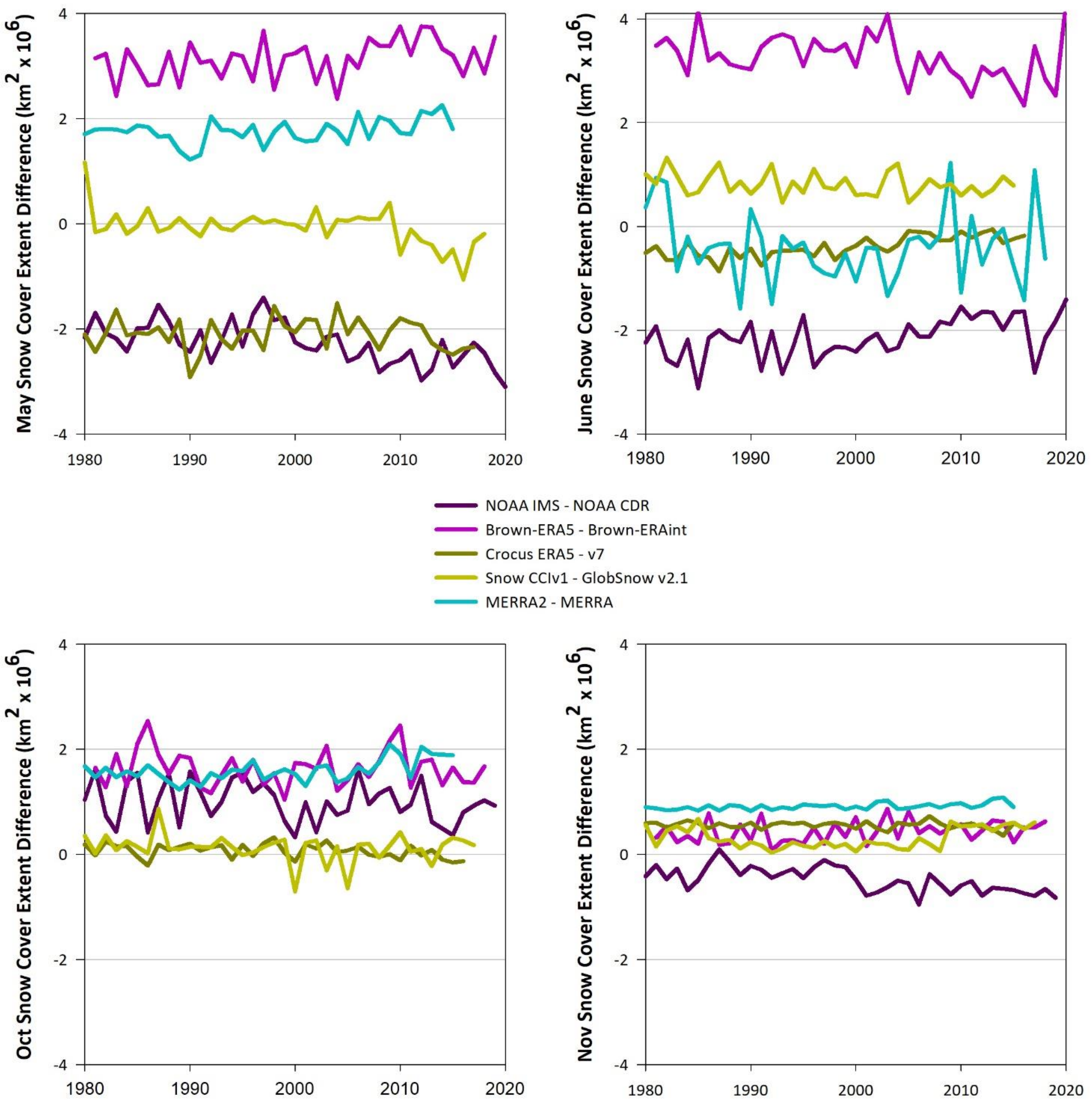

310 **Figure 7. Product version differences in snow extent (new version minus previous version) for (a) May, (b) June, (c) October, and (d) November.**

Mean snow extent trends for the entire northern hemisphere and Arctic land areas for the two product groups summarized in Table 1 are shown in Figure 8a (old product set) and Figure 8b (new product set). There is very little difference in both

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hemispheric and Arctic SCE trends over the common 1981-2017 period covered by both product sets. Arctic snow extent trends are virtually zero over the December through April period when there is consistently complete snow cover over land areas north of 60N. The negative SCE trends observed for the northern hemisphere during these months is by necessity driven by mid-latitude regions. Discounting the Arctic summer months when the absolute Arctic snow covered area is very small (July, August, September), the proportional contribution of the Arctic to the northern hemisphere trend is greatest in May, June, and October. During these months, the Arctic contributes the majority of the trend signal, with some contributions from mid-latitude high elevation areas (mountain areas; Tibetan plateau).

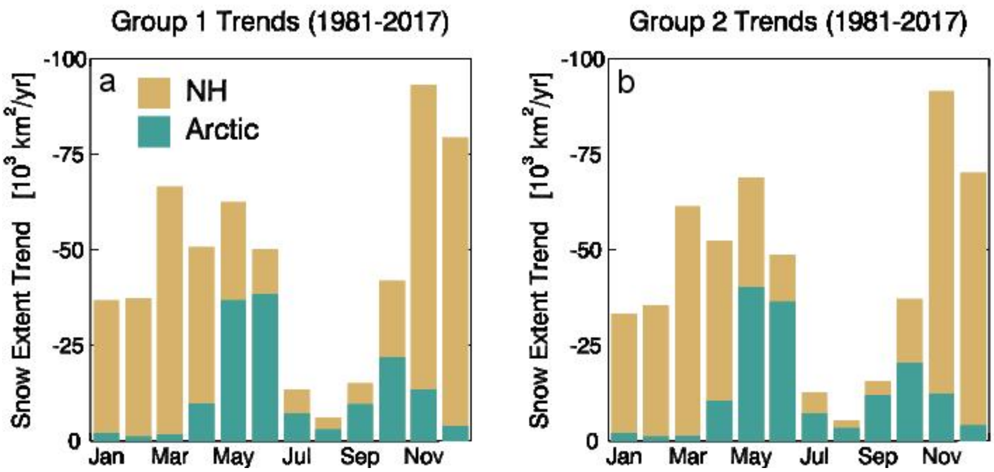

Figure 8. Snow extent trends over the 1981-2017 from multi-product groups outlined in Table 1: older product versions (a) and updated product versions (b).

5 Conclusions and Discussion

We have quantified the impact of increasing time series length, choice of reference period, the application of a statistical methodology to improve inter-dataset agreement, product version changes, and dataset ensemble size on Arctic SCE rates of change. In general, estimates of the rate of change in Arctic snow cover extent have remained consistent over the past two decades as time series length has increased, and are broadly insensitive to the choice of reference period. New product versions include enhancements in spatial resolution, more advanced reanalysis meteorology to force snow models, and enhanced remote sensing retrieval algorithms. Overall, these improvements result in only small changes in the observed monthly rates of Arctic SCE change. The most impactful analysis decision involves the scaling of dataset climatologies using the NOAA data record as the baseline. This results in a small impact in the estimated rate of change for October and May, but reaches 5% decade^{-1} June. This result reinforces that spring trends in the NOAA record are stronger compared to other products.

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In the IPCC SROCC Polar Regions chapter, sea ice trends were attributed '*very high confidence*' while seasonal snow extent trends were assigned '*high confidence*'. We believe the analysis in this study now supports the use of stronger confidence language underpinning Arctic snow extent trends because we have documented understanding of how analysis is affected by changes in time series, reference periods, and product versions. The evolution of estimates of Arctic spring snow cover extent rates of change from various studies over the past decade are summarized in Figure 9. In the context of annual assessment updates through the Arctic Report Card, May and June Arctic SCE exhibit stable rates of change over the past decade:

- The rate of May snow extent change has remained very consistent over the past decade at approximately -4% decade^{-1}. Overall, we have tighter constraints on May snow cover loss compared to June. Inter-dataset agreement is stronger in May than June, inter-version differences are smaller in May than June, and sensitivity to changes in time series length, reference period, and normalizing to the NOAA climatology are smaller in May than June.
- The calculated rates of June snow extent have weakened slightly over the past decade, compared to the estimate from just the NOAA CDR from Derksen and Brown (2012).
- Improvements in analysis in recent years to include multi-product ensembles allowed improved quantification of trend uncertainty, as illustrated by the error bars in Figure 9.

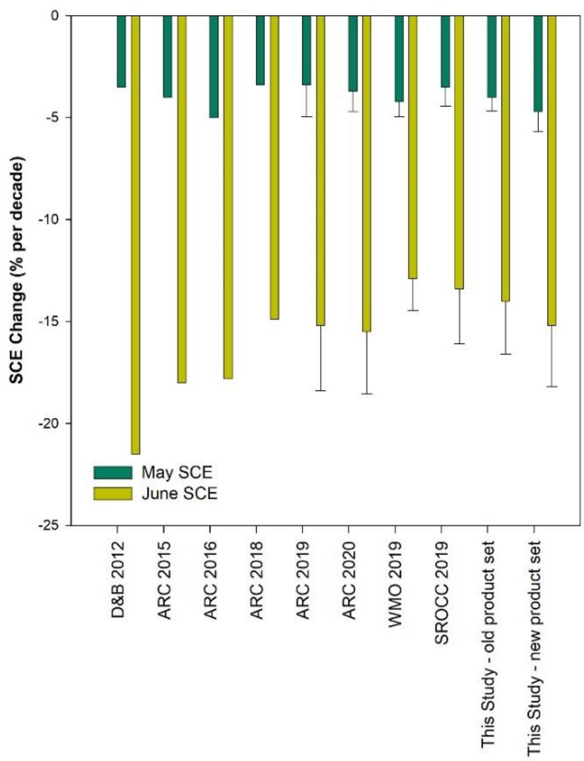

Figure 9. May and June Arctic snow cover extent rates of change from various assessments over the past decade.

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We make the following recommendations based on the analysis presented in this study:

1. We focused on better understanding the sensitivity of the rate of snow extent change expressed as % decade^{-1} because this a widely used metric. It is important to point out, however, that % change is less useful when absolute snow extent values become very small. While June snow cover remains the month with the greatest rate of snow extent loss, we will eventually need to drop June from assessments due to a lack of snow cover, in the same way September is presently ignored.
2. The analysis of data averaged to calendar months is common (e.g. the widely cited change in September sea ice extent), but of course this creates arbitrary and non-physical temporal boundaries to the data. The snow products assessed in this study are all available at a daily time step. The most dynamic period of Arctic snow extent change spans late May into early June, and late October into early November. Temporal precision is thereby lost through the use of monthly averaged data. At the very least, analysis should shift to weekly averaged data.
3. It is very difficult to work with raw time series from a multi-product ensemble, not just because of inter-product differences, but because of differences between versions of the same product. The adjustment procedure employed in this (and previous studies such as Mudryk et al., 2020) is an effective way to standardize time series and quantify uncertainty. Still, normalizing to the NOAA time series introduced notable impacts in June. This confirms that June Arctic snow extent trends are slightly more uncertain than May.
4. This study focused exclusively on snow extent because it is the variable most commonly used in climate assessments. Snow extent is conceptually straightforward, with variability and trends directly forced by surface temperature (Mudryk et al., 2020). Snow mass is arguably more important given processes related to insulation of underlying soil and snow melt release. Seasonal maximum snow water equivalent (SWEmax) is a commonly cited metric (assessed in detail for the Arctic in Brown et al. 2017), but SWE/snow mass is a conceptually trickier variable for snow non-experts to digest in an assessment context. It integrates both temperature and precipitation through the entire snow season, so the attribution of the drivers of variability and trends are more complicated than snow extent. The timing of when SWEmax occurs is another necessary consideration. Despite these challenges, additional effort should be placed into the provision of robust SWEmax trends for climate assessment. The underlying assumption in the snow community has always been that snow mass products have a higher uncertainty than snow extent. While the spread in absolute snow mass between products is high (Mudryk et al., 2015; Mortimer et al., 2020), especially in mountain regions (Wrzesien et al., 2019), the large spread between snow extent products evident in Figures 1, 2, and 3 shows that this conventional wisdom may be misplaced.

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Data availability

Snow products are available from the data originators: Météo-France (Crocus), NASA Goddard Earth Sciences Data and Information Services Center (MERRA/MERRA2), European Centre for Mid-range Weather Forecasts (ERA-Interim/ERA-5), Finnish Meteorological Institute (GlobSnow), European Space Agency Climate Change Initiative (Snow-CCI), Rutgers University Global Snow Laboratory (NOAA-CDR/NOAA-IMS) and the Japan Aerospace Exploration Agency (JASMES). Processed datasets analyzed in this study will be accessible through the Environment and Climate Change Canada open data catalogue.

Author Contributions

CD conducted the analysis and drafted the manuscript; LM processed data, contributed to analysis, and revised the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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