Response to Editor

Thanks to all three reviewers for their constructive comments on the manuscript. Our revisions have resulted in the inclusion of additional datasets, and improved the clarity and impact of the paper.

As outlined in more detail in our responses to the review comments, we have incorporated both ERA5 and MERRA2 for the validation (comparison with snow course measurements). We retained both MERRA and ERA-land in order to show the difference in performance between subsequent generations.

For the dataset inter-comparison, we have replaced MERRA with MERRA2 and added ERA5. Because ERA5 represents a significant departure in many ways from ERA-land (optimal interpolation vs. Cressman, a number of bug fixes, data assimilation of IMS etc.) we have retained ERA-land in this analysis. In preparing ERA5 data for the inter-comparison analysis, we found a very strong negative trend since 1980, which is driven by a discontinuity in the time series starting in 2004. After following up with ECMWF, it is clear that this is caused by the assimilation of IMS snow extent data into ERA5, which starts in 2004. This means ERA5 cannot be used (without some form of correction) for snow mass trend analysis. This is an important finding to communicate to the snow community, which we now emphasize in the revised manuscript.

Our response to each comment is outlined below in **bold**. Revised text is in *red italics*. We hope these responses are clear, and we look forward to submitting the revised manuscript.

Anonymous Referee #1

Received and published: 3 January 2020

The authors discuss the evaluation of three types of Northern Hemisphere snow water equivalent (SWE) products, including (i) four reanalysis-based products, (ii) two stand-alone passive microwave remote sensing products, and (iii) one product based on a combination of passive microwave remote sensing data and in situ snow depth measurements.

The evaluation is primarily vs. a large number of independent snow course measurements from Russia, Finland, and Canada. The authors find that the performance of the stand-alone passive microwave remote sensing products is considerably worse than that of the other products, and only the passive microwave product constrained with surface observations provides comparable performance to the reanalysis-based products.

Among the reanalysis-based SWE products, MERRA and the Crocus/ERA-Interim product perform best, suggesting that these products should be included in any multi-product ensemble estimate.

The manuscript discusses an important and still active field of cryospheric research. The manuscript is not ground-breaking and hews closely to the datasets evaluated in Mudryk et al. (2015). However, it includes the AMSR-E stand-alone passive microwave remote sensing products and, if I am not mistaken, the performance evaluation vs. the snow course measurements. These new elements provide, in my opinion, sufficient novelty to warrant eventual publication of the paper in The Cryosphere. However, before I can recommend publication, the authors would need to address the MAJOR issues outlined in the comments below.

Major comments:

1) Dataset selection and period

a) Why evaluate MERRA data when MERRA-2 has now been available for 3+ years (Gelaro et al. 2017), and MERRA has been discontinued since early 2016??? There are some differences MERRA and MERRA-2 SWE (e.g., Reichle et al. 2017). As it stands, the reader has to assume that MERRA was used because that is the dataset that was ready to use from the earlier Mudryk et al. (2015) publication. At the very least, the authors need to discuss the existence of MERRA-2, point to the relevant literature and differences, and justify their use of MERRA instead of MERRA-2.

Gelaro et al. (2017), The Modern-Era Retrospective Analysis for Research and Applications, Version-2 (MERRA-2), Journal of Climate, 30, 5419-5454, doi:10.1175/JCLI-D-16-0758.1.

Reichle et al. (2017), Assessment of MERRA-2 land surface hydrology estimates, Journal of Climate, 30, 2937-2960, doi:10.1175/JCLI-D-16-0720.1.

> **This is an important comment, and this issue was raised by other reviewers as well. We have updated the analysis to now include both MERRA2 and ERA5; the manuscript was revised in many places (including Table 1 and all figures) to reflect this new analysis. The new versions of the figures are included at the end of this document. We retained both MERRA and ERA-land in the validation in order to show the difference in performance between subsequent generations of the same product. In the case of ERA5, there is noticeable improvement, especially across Eurasia where the positive SWE bias in ERA-land is corrected in ERA5. This difference is likely**

due in large part to the assimilation of weather station snow depth observations in ERA5, so text was added to emphasize the impact of this change. Changes from MERRA to MERRA2 are much more subtle, and based on the validation statistics it appears snow mass in MERRA2 is actually degraded slightly from MERRA.

For the dataset inter-comparison, we have replaced MERRA with MERRA2 and added ERA5 since it represents a significant departure in many ways to ERA-land. In preparing ERA5 data for the inter-comparison analysis, we found a very strong negative trend since 1980, which is driven by a discontinuity in the time series starting in 2004. After following up with ECMWF, it is clear that this is caused by the assimilation of IMS snow extent data into ERA5, which starts in 2004. This means ERA5 cannot be used (without some form of correction) for trend analysis. This is an important finding to communicate to the snow community, which we now include in the revised manuscript.

A similar comment applies to the paper's use of ERA-Land and "Crocus", which are both based on ERA-Interim, which has been replaced by ERA-5 and ERA-5/Land (albeit much more recently than the MERRA version change).

See our response above. We have revised the analysis to include MERRA2 and ERA5. Manuscript and figures have been revised to reflect this change.

While ERA5 is now available and could be used with Crocus, the most recent version of the Crocus dataset is still forced with ERA-interim. This will be changed in future versions of this product, but not until an evaluation is completed at Météo France on the impact of changes in the forcing dataset on the SWE simulations. The important attribute of the Crocus dataset is that it includes a more complex physical snow model compared to the other products. In that sense the forcing dataset is of secondary importance, so we have retained the Crocus product as part of the analysis.

b) Why does the analysis stop in 2010 (Table 1)? As far as I am aware, all of the SWE products should be available for several years beyond 2010 (given that AMSR2 extends the AMSR-E record to the present, with only a modest gap). Being a few years behind real-time was ok in Mudryk et al. (2015), but by now 2010 nearly a decade behind real-time, which at the very least requires justification.

The SWE products are not all available over a common time period. The 2002-2010 period was used to maximize commonality between datasets. The primary time series limitations are GLDAS-2 and ERA-Interim/Land (which both end in 2010) and v1 of the AMSR-E product (which only covers 2002-2011). While it is desirable in some ways to cover the most recent time period possible, the focus of this analysis is on the validation and inter-comparison of the products. In that sense, only a sufficiently long time period is required (in order to capture the range of naturally varying snow conditions) but the actual time period covered is less important. Text added (Line 100-102):

'The analyses described subsequently in Section 2.3 were conducted for the period 2002 –2010 to maximize temporal overlap between products.'

2) The discussion of the methodology needs to be improved.

a) As it stands, there are bits and pieces of the methodology in the Results section, and the Methods section is lacking a concise discussion of the various metrics. E.g., lines 193-196, 235-236, and 276-282 belong in the Methods section, and the Methods section needs a complete discussion of the metrics.

We have revised Section 2 to now cover both datasets and methods:

Section 2. Datasets and methods

Section 2.1. Gridded SWE products

Section 2.2. Snow course data

Section 2.3 Validation and intercomparison methods

This change included moving text that was previously in the Results (lines 193-196; 235-236, and 276-282) into Section 2. Additional clarification to the methods text in Section 2.3 was also added in response to other points mentioned in the review comments.

- **In Section 2.1, which describes the gridded SWE products, we added discussion of how snow depth observations are used in different reanalysis products.**
- **Section 2.2 provides a more comprehensive discussion of the snow course data than was previously included. We improved our explanation of snow course measurement protocol, added mention of snow course measurement uncertainty, and explicitly stated how we dealt with zero SWE values.**
- **Section 2.3 clearly outlines the two approaches we have taken to evaluating SWE products – validation and inter-comparison. Much of this text was either previously in the results section or is new in response to reviewer feedback. We use the term *validation* to represent the evaluation of gridded products against snow course data as a measure of ground truth; whereas *inter-comparison* is similar to the analysis of Mudryk et al. (2015) and quantifies the spatial and temporal anomaly correlations between datasets. Methods, including quantitative metrics, relevant to each of the two approaches are outlined separately.**

b) The **temporal and spatial resolution of the metrics calculations is a bit unclear.** Line128 states that all SWE products were regridded onto a 1-deg grid, whereas the snow course measurements are on the 25-km EASE grid (line 161). How are the 1-deg grid cells matched with the 25-km EASE grid cells?

The re-gridded (1°x1°) products were only used for inter-comparison. Native product resolutions were used for validation with the gridded snow course data. We have included more precise wording and additional clarification in the revised methods section – see response above. Relevant sections:

Line 211-214: *'For a given measurement date, each EASE grid cell with snow course data was paired with corresponding SWE values from each of the nine gridded products. The paired SWE values correspond to the grid cell at each product's native resolution that intersects with the centroid of the snow course EASE grid cell.'*

Line 226-227: *'The intercomparison analysis does not consider the snow course measurements, only the nine gridded SWE products. For this analysis, daily SWE from each product was interpolated to a regular 1° x 1° longitude–latitude grid.'*

And why introduce the 25-km EASE grid in the first place, given that the snow course data are not anywhere near that scale(transects range from 150 m to 4 km), and in any case the 25-km EASE grid is

different from the 1-deg grid of the SWE products. Why not use the same grid for the SWE products and the (gridded) transect data? At the very least, this requires justification and clarification.

> **We gridded the snow course measurements in order to reduce sampling bias due to concentrations of surveys in some areas (this is a particularly important issue for the Canadian data because snow courses are concentrated in heavily populated regions of southern Canada). We chose the 25 km EASE-Grid as a compromise resolution which reduced spatial sampling bias but didn't introduce too much uncertainty due to the representativeness of snow course measurements relative to the coarse grid cell resolution. We have clarified this in the revised methods section lines 199-217.**
>
> *'For the validation analysis, SWE product grid cells must be matched in both space and time with the snow course measurements. To achieve this, snow course observations from Canada and Finland were first grouped into bi-weekly periods using a 16 day window centred on the 1st or 15th of each month. Likewise, over Russia, observations were grouped into ten-day periods centred on the typical measurement dates (10th, 20th, 30th of each month). For each temporal grouping, snow course measurements falling within a given 25 x 25 km EASE grid cell (Brodzik et al., 2012) were averaged together, thereby forming a gridded snow course field (Fig. 2). Roughly 30% of these snow course grid cells had two or more separate snow courses which were averaged together while the remaining 70% had only one snow course observation. Grouping the snow course data had the largest impact over Canada and Russia where 35% and 20% of grid cells, respectively, had multiple snow courses. Although Finland's snow course network is representative of the landscape's different snow-climate classes(Sturm et al., 1995), in Canada, and to a lesser extent over Russia, tundra environments which are often remote, are under-sampled while maritime and alpine snow types are oversampled (Fig. 2).*
>
> *For the validation analysis, we included all nine products in Table 1, to consider the range of available products and show the difference in performance between subsequent product generations (e.g. MERRA to MERRA2). For a given measurement date, each EASE grid cell with snow course data was paired with corresponding SWE values from each of the nine gridded products. The paired SWE values correspond to the grid cell at each product's native resolution that intersects with the centroid of the snow course EASE grid cell. In order to fairly compare how the gridded products perform against one another, only snow course data from EASE grid cells with corresponding paired values from all nine of the SWE products were analysed. This means that regions of complex topography are implicitly excluded from the validation analysis because they are masked in GlobSnow.'*

c) The snow course data are available from once every 5 days to once every month (Section 2.1), whereas the SWE products are available between hourly and daily (which requires better clarification!). Lines 158-161 state that the snow course observations were "converted into bi-weekly [or (over Russia) ten-day] periods". How exactly are the SWE products and snow course data matched in time for the computation of the metrics? Are the SWE products sampled on a single day (1st and 15th of each month), or are two-week (or ten-day) average SWE values computed from the hourly/daily products before the metrics are computed? This needs to be clarified.

Part 1: The snow course data are available from once every 5 days to once every month (Section 2.1), whereas the SWE products are available between hourly and daily (which requires better clarification!).

> **We have added text describing how we used data from products with sub-daily values. Lines 97-100:**

'All the products provide SWE directly and are available at daily or sub-daily frequency. For the four products available at sub-daily frequency, we either obtained daily mean versions directly from the product's distribution site (MERRA, MERRA2) or sampled a consistent sub-daily snapshot for each calendar day (ERA-Interim/Land, ERA-5) which we consider to be representative of the daily mean value.'

Part 2: How exactly are the SWE products and snow course data matched in time for the computation of the metrics? Are the SWE products sampled on a single day (1st and 15th of each month), or are two-week (or ten-day) average SWE values computed from the hourly/daily products before the metrics are computed? This needs to be clarified.

Snow course measurements are compared with a single day from the SWE products. For example, SWE products from 1 February are compared with the gridded snow course data centered on 1 February. We have added additional clarification concerning the matching of SWE products and gridded in situ data and calculation of validation metrics:

Lines 199-204: *'For the validation analysis, SWE product grid cells must be matched in both space and time with the snow course measurements. To achieve this, snow course observations from Canada and Finland were first grouped into bi-weekly periods using a 16 day window centred on the 1st or 15th of each month. Likewise, over Russia, observations were grouped into ten-day periods centred on the typical measurement dates (10th, 20th, 30th of each month). For each temporal grouping, snow course measurements falling within a given 25 x 25 km EASE grid cell (Brodzik et al., 2012) were averaged together, thereby forming a gridded snow course field (Fig. 2).*

Lines 211-217: *'For a given measurement date, each EASE grid cell with snow course data was paired with corresponding SWE values from each of the nine gridded products. The paired SWE values correspond to the grid cell at each product's native resolution that intersects with the centroid of the snow course EASE grid cell. In order to fairly compare how the gridded products perform against one another, only snow course data from EASE grid cells with corresponding paired values from all nine of the SWE products were analysed. This means that regions of complex topography are implicitly excluded from the validation analysis because they are masked in GlobSnow.'*

d) Lines 138-141: Please clarify whether snow course data are measurements of snow depth or SWE. (The paragraph in question talks a lot about snow depth, but only in the context of the point-scale measurements used in GlobSnow.) Also, if snow course data are snow *depth* measurements, how are the measurements converted to SWE? Using local and contemporaneous snow density measurements? Or climatological snow density values?

Thank you for this comment as our description was not clear. Snow course measurements are not snow depth measurements but composed of a series of manual gravimetric snow corer measurements. The precise instrument and protocol differs by jurisdiction but a snow cylinder (snow corer) is used to collect a vertically integrated sample of the snowpack at a specific location that is then weighed. For a given snow course, the reported SWE is the average of the multiple gravimetric measurements (specific averaging protocol may vary (e.g. Brown et al., 2019; Haberkorn 2019). In contrast, the point snow depth measurements used in GlobSnow are single depth measurements from networks of climate/weather stations and do not contain any information about snow density nor SWE. These point snow depth values are assimilated

directly into some products (GlobSnow; ERA5) but are fully independent from the manual snow course measurements used for validation.

Brown, R., and Braaten, R.: Spatial and temporal variability of Canadian monthly snow depths, 1946-1995, Atmos.-Ocean, 36, 37–54. https://doi.org/10.1080/07055900.1998.9649605, 1998.

Haberkorn, A. (Ed.): *European Snow Booklet*, 363 pp., doi:10.16904/envidat.59, 2019.

We have revised the text (Lines 149-156) to better differentiate between the snow course SWE measurements and point snow depth measurements:

'The suite of gridded SWE products described in Section 2.1 are validated with a network of in situ snow course measurements from multiple national and regional agencies. These data consist of manual gravimetric snow measurements made at multiple locations along a pre-defined transect that are averaged to obtain a single SWE value for a given snow course on a given day. Measurements are collected along the same transect multiple times each snow season. By averaging multiple samples along a transect, the resulting SWE measurement provides better representation of sub-grid scale variability than a single point measurement and so is more suitable for evaluation of SWE at the scale of the gridded products. These snow course data are fully independent of the point snow depth measurements assimilated into GlobSnow and ERA5. Transect length, number of samples collected along each transect, and sample aggregation methods differ among reporting agencies as described below.'

e) Fig 2c: It is not clear how the correlation shown here was computed. Is this the spatial average of the temporal correlation coefficient at the individual grid cells? Or the spatial correlation of the time series average? Or all data points thrown into a single correlation coefficient calculation???

It is the latter. Correlation coefficient (r) is calculated from all data pairs. Line 177-179 in methods was added for clarification.

Line 217-219: *'Bias and root mean squared error (RMSE) were calculated for each product-snow course pair and then averaged over the full November 2002 – April 2010 time period; correlation was calculated from all data pairs for the November 2002 – April 2010 period.'*

f) Lines 235-236: "seasonality [metrics...] were computed at a bi-weekly time step for 2002 through 2010". This is unclear. Based on this statement, the metrics could have been computed in one of the following ways: - subset time series at each location, then throw all values into the metrics computation - subset time series at each location, then compute (temporal) metrics at each location, then spatially average metrics – subset time series at each location, then compute time-average SWE values, then compute (spatial) metrics Which is it?

Thank you for raising this. We agree this was not clear and have added clarification in Section 2.2. Metrics were computed from all data points for a given time step (1st or 15th of each month or 10, 20, 30th in the case of Russia) across all years. Revised text (Lines 219-221):

'To understand the influence of seasonality on product performance, bias, RMSE and correlation were also computed across all years for each biweekly period (10 day period for Russia).'

g) How were zero SWE values treated? Are SWE values excluded from the metrics computations if the snow course and/or SWE product indicated zero SWE? How about cross-masking

> **Snow course measurements are not made when there is no snow (zero snow measurements are not typically reported). To avoid the use of any potentially erroneous in situ SWE values, zero snow course measurements were removed prior to the spatiotemporal aggregation described in Section 2.3. For Nov-April 2002-2010 Russia had 17 zero SWE observations, Finland and Canada had none. Added text Lines 174-177:**
>
> *'Because snow course measurements are only acquired during the snow season and zero SWE values are not reported in a consistent manner across all jurisdictions, zero SWE is not a reliable measure of snow-free conditions. All zero snow course observations were therefore removed prior to spatiotemporal aggregation (Sect. 2.3); SWE product zero values were also excluded.'*

h) The number of grid cells ("locations") with snow course data is unclear. According to section 2.1, there are 517 snow course locations in Russia, 200 in Finland, and >1000 in Canada. However, the y-axis scale in Fig. 4d suggests that at most∼100 locations are used for Russia. The discrepancy between 517 and ∼100 needs to be discussed explicitly. Is this reduction due to insufficient length of time series, or because the snow course data are ultimately averaged into 25-km EASE grid cells (or 1-deg grid cells)??? How many sites (or grid cells?) were used for Finland and Canada?

> **We think there may have been some confusion about the y-axis. The number of grid cells (dashed line) is shown on the right-hand axis and ranges from ~600 for 1 November to >3000 in January-March.**

i) Lines 276-279: The text here is unclear. Is the metric discussed in line 277 different from that discussed in line 278? In Line 281, in which way are the "anomalous SWE fields" different from the "anomalous snow mass"??? Is not "SWE" synonymous with "snow mass"?? (Or does "snow mass" here refer to the spatially integrated SWE? If so, that is not clear.)

> **Clarification of anomalous snow mass is included in the improved methods section 2.3. Relevant lines:**
>
> **Line 228-230:** *'To determine the strength of agreement among datasets we use three metrics, all applied to SWE or snow mass anomalies (i.e. with the seasonal cycle removed).'*
>
> **Line 232-234:** *'First, we considered the correlation between each product's time series of daily Northern Hemisphere snow mass anomalies (SWE integrated over the entire Northern Hemisphere land area).'*

Also, throughout section 3.3 I was confused whether there were two different temporal correlation metrics (one using raw data including the seasonal cycle, and another using data with the mean seasonal cycle removed).

> **The seasonal cycle is removed for all metrics used in the inter-comparison section. All metrics (temporal correlation of domain-integrated snow mass, spatial correlation over the full domain, and temporal correlation of individual grid cell SWE) use anomalous SWE or snow mass which removes the seasonal cycle. We have clarified this in our improved methods section 2.3.**
>
> **Line 228-230:** *'To determine the strength of agreement among datasets we use three metrics, all applied to SWE or snow mass anomalies (i.e. with the seasonal cycle removed).'*

3) ERA-Land and Crocus similarities, and dependence on snow measurements

a) ERA-Land and Crocus use the same forcing data. Including the correlation of the two datasets in Fig 6 therefore artificially elevates the "R4" correlation. Should the ERA-Land/Crocus pair not be excluded from the correlation coefficients contributing to the "R4" value?

> **While ERA-land and Crocus both use the same reanalysis forcing, (ERA-interim) the objective of using both datasets is to show the impact of the different snow models used within each dataset. The land surface model in ERA-land is HTESSEL, which has a comparatively simple snow scheme compared to the Crocus snow model. Previous work (see Figure 11 in Mudryk et al., 2015) has shown that the same land surface model with different atmospheric forcing will result in different SWE. Likewise, the same forcing applied to different land surface models will result in different SWE. This latter case is readily apparently in the different validation statistics that we present for ERA-land versus Crocus. Despite using the same forcing, the resulting SWE datasets are quite different.**

b) Perhaps more importantly, ERA-Land and Crocus are *not* fully independent of insitu snow measurements. Both datasets rely on ERA-Interim surface meteorological forcing data. ERA-Interim includes a snow analysis that is based on snow cover data and on in situ snow depth measurements, which impacts the ERA-Interim surface meteorology estimates through, at the least, surface albedo feedback. This needs to be pointed out. (Note that there is no snow analysis in MERRA or MERRA-2.)

> **It's an important detail that the forcing meteorology from ERA-int includes explicit assimilation of snow information (even though the SWE produced by ERA-land and Crocus do not). For these products, the use of snow depth information is one step removed from the final SWE estimates compared to products like GlobSnow and ERA5, although the assimilation of snow information can improve variables such as lower tropospheric temperatures which obviously have an impact on snow. We have added text starting on line 137 to clarify this.**
>
> *'The impact of snow depth observations also differs between reanalysis products. Snow depth observations are directly assimilated into ERA5. For ERA-Interim/Land, however, only the forcing meteorology includes explicit assimilation of point snow depth measurements (the SWE produced by ERA-Land does not). Therefore, for ERA-Interim/Land, the use of snow depth information is one step removed from the final SWE estimates compared to ERA5, although the assimilation of snow information impacts variables such as lower tropospheric temperatures which obviously have an indirect impact on snow.'*

4) Lines 75-76 (implicitly) motivates the present study by saying that "[t]o date, these ensembles have relied heavily on models driven by atmospheric analysis and include only a single dataset (GlobSnow) which utilizes remote sensing." However, Line 263states that "[t]he two AMSR-E products were excluded from this comparison because of the low correlation with the snow course data [...]" That is, the present study is not really different from previous studies in this regard. This particular motivation of the present study seems therefore invalid.

> **In previous SWE ensembles used for climate studies, GlobSnow was the only component dataset which included earth observation data. This is explicitly noted on lines 81-82. So, a motivation of this study is to see if additional satellite-derived datasets (either or both of the AMSR-E products) are suitable for inclusion, but they must first be assessed, as noted on lines 86-87. The results of the validation and inter-comparison in this study clearly show that they**

should NOT be included as part of a historical SWE ensemble. We think this motivation is appropriate as described in the last paragraph of Section 1.

Minor comments: ——————

i) Line 52: Please add a reference for the "temporal inconsistencies" in reanalysis datasets, e.g., Robertson, F. R., M. G. Bosilovich, J. Chen, and T. L. Miller, 2011: The effect of satellite observing system changes on MERRA water and energy fluxes. J. Climate, 24, 5197–5217, doi:10.1175/2011JCLI4227.1

Reference to Robertson et al. 2011 added to end of sentence beginning on line 52: *'There may also be temporal inconsistencies in the forcing data related to changes in the observational streams assimilated in the reanalyses (Robertson et al., 2011).'*

Full citation has been added to the reference list:
Robertson, F. R., Bosilovich, M. G., Chen, J., and Miller, T. L.: The effect of satellite observing system changes on MERRA water and energy fluxes, J. Clim., 24, 5197–5217, doi:10.1175/2011JCLI4227.1, 2011

ii) Lines 53-61: Recent results using Sentinel-1 (active) radar data suggest that at least for deep mountain snow much higher spatial resolution snow depth estimates are achievable (Lievens et al. 2019). This should at least be pointed out here, and a clarification should be added that the present study focuses on passive microwave data only. The Lievens et al. (2019) results also suggest that the text in Line 77may need clarification. Lievens et al. (2019), Snow depth variability in the Northern Hemisphere mountains observed from space, Nature Communications, 10, 4629,doi:10.1038/s41467-019-12566-y.

The Lievens et al. (2019) manuscript presents positive results on the potential for C-band SAR to provide high spatial resolution snow depth estimates in mountain areas. It lacks, however, any physical explanation for how this is possible using cross-polarization C-band radar data. As such, we feel these results must be approached with some caution. Since cross-pol C-band radar data are only available since the launch of Sentinel-1A in 2014, there is limited potential to provide climate-relevant time series at the present time. Despite these limitations, we agree that it is appropriate to note the potential in this area, so we have added some text and a reference to the Lievens et al paper starting on line 62.

'There may be potential for cross-polarized C-band SAR to provide high spatial resolution snow depth information in mountain areas (Lievens et al., 2019), but these estimates currently lack a physical explanation. Since cross- polarized C-band SAR data are only available since the launch of Sentinel-1A in 2014, there is limited potential to provide climate-relevant time series.'

iii) The nomenclature "NASA Historical" and "NASA Operational" is a bit unfortunate. First, MERRA is (or rather, was) also a *NASA* (quasi-)operational product. Second, the use of *Historical* and *Operational* suggests that "Historical" is only for the retrospective period while "Operational" is for the present and future. However, if I understand the manuscript correctly, "Historical" is really an older version of the NASAAMSR-E retrieval product, and "Operational" is a newer version of that same product. Two of the authors of the present paper are also authors of the "NASA AMSR-E" product. They should know the appropriate version numbers of the NASA AMSR-E products discussed here, and these version numbers should be used in the paper.

We have revised the nomenclature throughout. 'NASA Historical' and 'NASA Operational' are now referred to as 'NASA AMSR-E SWE v1.0' and 'NASA AMSR-E SWE v2.0', respectively.

iv) In the context of **Figure 2** or the corresponding Methods discussion, the number of grid cells with snow course measurements contributing to the metrics should be provided. See also comment 2h) above.

The number of grid cells with snow course measurements contributing to the metrics in Fig.2 has been added to a revised Figure 2, which is now Figure 3 (see appendix).

v) Line 346: replace "idealized" with "ideal"

Change made.

vi) Lines 369-370: The term "NASA AMSR-E *operational* dataset" appears twice, once in each line. Should one of the two be the "historical" dataset?

The first instance of NASA AMSR-E operational should have read NASA AMSR-E historical. This line has been changed to use version numbers and reads (Line 482-484):

'…the NASA AMSR-E SWE v1.0 dataset and is available from the paper's authors upon request as is the NASA AMSR-E SWE v2.0 dataset.'

vii) Line 82: replace "to evaluation" with "to evaluate"

Change made.

viii) Lines 123-124: The paper should make it clear whether the SWE output from the reanalysis data was used or whether the snow depth output was used (with subsequent conversion to SWE using ancillary snow density values). This is a bit unclear.

SWE was the output variable used for analysis. This is now noted explicitly in line 226-227.

'For this analysis, daily SWE from each product was interpolated to a regular 1° x 1° longitude–latitude grid.'

Anonymous Referee #2

Received and published: 12 January 2020

Summary This manuscript performs an intercomparisons and evaluation of seven different northern hemisphere representations of daily Snow Water Equivalent: four reanalyses (CROCUS, ERA/Land, MERRA, and GLDAS, two products based on AMSRE passive microwave data, and the GlobSnow product, which is based on a combination of passive microwave and in situ snow data. The authors compare the products to one another and find broad similarities among all products except the passive microwave only products, which are quite different. Evaluation against in situ snow course data also suggest that all products other than the passive microwave only datasets provide similar levels of accuracy. The study has implications for any hemisphere-scale analysis that relies on understanding of snowpack.

Overall Review

I found this paper to quite well written, and I very much like the approach the authors took to their analysis. I kept finding myself wanting a particular type of analysis to be done and then, a few paragraphs later, the authors had done just what I'd hoped for (e.g. the ensemble analysis). However, there are a few points that I think would substantially improve the paper. The first one, and most major, is that the selection of reanalysis products is somewhat outdated. In particular, both MERRA and ERA-Interim/Land have been, at least to some degree, superseded by MERRA-2 and both ERA5 and ERA5-Land. In the latter case, the resolution of the data products is higher (30 km) and much higher (9 km). I anticipate that most users in the future will probably use these more recent datasets rather than the older ones listed here. So the current paper is useful, but it would be so much more useful if these additional datasets were included. I recognize that it would probably be a fair amount of work to add them in, but I really think it would probably be worth it. That said, this is a decision that should be made by the authors in consultation with the editor. I do think the paper is publishable as is, just not as useful as it could be.

> **As discussed in more detail in our response to Reviewer 1, we have revised the analysis to also include MERRA2 and ERA5.**

Second, I would like to see just a bit more discussion of snow in high-topography regions. I recognize that this is not the primary focus of the paper, but mountain snowpack is pretty important. There's been some really good work published on this recently. I'm thinking of the paper by Jessica Lundquist that talks about the utility of models vs. observations in understanding mountain snow and precipitation (https://doi.org/10.1175/BAMS-D-19-0001.1) and some of the work by Melissa Wrzesien that intercompares different global products in a way similar to what's done here (but explicitly for mountains), such as https://doi.org/10.1029/2019WR025350. I don't think this needs to be a very heavy lift, but I would like to see some mention in the abstract of the fact that mountains are (mostly) excluded in the analysis, along with a paragraph in the discussion addressing this point and related work.

> **We now more clearly state in our conclusions that non-alpine areas are the focus of this study. We have also added text with new references in Section 4 (starting on line 445) to highlight the key issues regarding mountain snow:**
> **-representativeness of surface observations in complex terrain**
> **-coarse resolution of gridded SWE products**
> **-uncertainty in meteorological forcing, particularly precipitation amount and phase**

Lines 445-451:

'As with any continental-scale evaluation, our results may (or may not) apply to small regions or local domains, and the validation results do not apply to alpine areas which contribute a large proportion (~30%) (Wrzesien et al., 2019) to the total northern hemispheric SWE. In areas of complex terrain, uncertainty in meteorological forcing within reanalyses, particularly precipitation amount and phase (Lundquist et al., 2019) must also be considered. Further, in alpine regions the coarse resolution of the gridded SWE products (25 km or more) does not lend itself to comparison with snow course observations because of limited representativeness of surface observations in complex terrain and across elevation gradients; a different validation approach is likely needed for mountain areas.'

Citations added to the reference list:

Lundquist, J., Hughes, M., Gutmann, E., and Kapnick, S.: Our Skill in Modeling Mountain Rain and Snow is Bypassing the Skill of Our Observational Networks. Bull. Amer. Meteor. Soc., 100, 2473–2490, https://doi.org/10.1175/BAMS-D-19-0001.1, 2019.

Wrzesien, M. L., Pavelsky, T. M., Durand, M. T., Dozier, J., and Lundquist, J. D.: Characterizing biases in mountain snow accumulation from global data sets, Water Res. Res., 55, 9873–9891, https://doi.org/10.1029.2019WR025350, 2019.

Specific comments

Line 34: "There is a growing number"

Change made.

Line 39: I think it would be good to cite the relevant paper by Meromy et al. (2013) here: https://doi.org/10.1002/hyp.9355

Added reference to Meromy et al. (2013) to line 41 and to reference list.

Line 40: *'However, both snow depth and snowfall measurements from single point locations are intrinsically limited by a lack of confidence in how they capture the landscape mean across coarse grid cells (Meromy et al., 2013).'*

New reference:

Meromy, L., Molotch, N. P., Link, T. E., Fassnacht, S. R., and Rice R.: Subgrid variability of snow water equivalent at operational snow stations in the western USA, Hydrological Processes, 27, 2383–2400, https://doi.org/10.1002/hyp.9355, 2012.

Line 60: I just want to say that I really like this sentence about gridded/in situ dataset comparisons

Thank you!

Line 76: Somewhere in here it would probably be good to mention the new Nature Communications paper by Lievens et al. (https://doi.org/10.1038/s41467-019-12566-y). Also would be good to mention it in the section on mountains that I suggest above.

See our response to Reviewer 1. While we have reservations about the physical mechanisms driving C-band radar response to SWE, we have added the citation with some new text to the Introduction (line 62).

Line 160: what fraction of the grid cells have at least one data point? How do these data represent (vs. not represent) different environments?

Thank you for raising this. We have addressed each question separately below.

Part 1: what fraction of the grid cells have at least one data point?

Only a small fraction of EASE grid cells have at least one snow course observation. This is one of the primary reasons for combining the validation and inter-comparison approaches in our overall methodology. Although more than one quarter (27%) EASE grid cells in Finland have at least one snow course observation, the situation is very different over Russia and Canada which are considerably larger and have more remote areas. Excluding permanent land ice and large water bodies but including alpine areas that are masked out in GlobSnow, only ~3-4% and 1-2% of Canada and Russia's land area, respectively, has a corresponding EASE grid cell with a snow course observation.

The majority of grid cells retained for our analysis only had one snow course measurement. Slightly less than one third (30%) had two or more snow courses, in these cases the grid cell in situ SWE value was the average of multiple snow courses. The proportion of grid cells with two or more snow courses was higher for Russia (35%) and Canada (20%) compared to Finland (7%). In Canada this occurs (primarily) because there are snow courses in close proximity to one another, this is especially the case near population centres. In contrast, the large proportion of grid cells having more than one snow course observation is attributed to there being multiple snow courses over different land cover types (field, forest, gulley) that are assigned the same WMO Id and thus have the same coordinates.

We have added a brief summary of these numbers to the end of Section 2.3 (204-206).

'Roughly 30% of these snow course grid cells had two or more separate snow courses which were averaged together while the remaining 70% had only one snow course observation. Grouping the snow course data had the largest impact over Canada and Russia where 35% and 20% of grid cells, respectively, had multiple snow courses.'

Part 2: How do these data represent (vs. not represent) different environments?

Snow course transects are several hundred metres to several kilometers in length and are often designed to sample multiple land cover types (e.g. the Finnish snow courses). This makes it difficult to assign each snow course to a single land cover type so instead we used the Sturm snow climate classes (Sturm et al., 1995). For each jurisdiction the proportion of each snow class (excluding permanent ice cover and large water bodies) that sampled is as follows:

<u>Table</u>. Percent of EASE grid cells that have at least one snow course observation by Sturm snow class [percent of grid cells with snow course observations by Sturm Snow Class / percent of land area by Sturm snow class] ** ^

Sturm Snow Class	Canada	Finland	Russia
Tundra	0.54 [5.59/36.17]	24.39 [7.25/8.03]	1.15 [20.82/31.80]
Taiga	2.16 [23.31/38.10]	22.11 [15.22/18.63]	1.38 [38.18/48.66]
Maritime	14.2 [47.01/11.69]	30.37 [42.03/37.45]	3.22 [4.12/2.26]
Prairie	3.27 [4.05/4.37]	42.11 [5.80/3.73]	3.02 [14.53/8.50]
Alpine*	8.14 [20.04/8.69]	25 [29.7/32.16]	4.53 [22.34/8.70]

***note: alpine snow class is not the same as the topographic mountain mask used in GlobSnow so presence of this snow type is not unexpected.**
****land area included in the mountain mask that is excluded in our analysis is included in the above calculations but snow courses falling in these areas are excluded.**
^there are no snow courses in the ephemeral snow zone which makes up <1% of both Canada and Russia so it is not included here.

From this analysis we see that Finland's snow course network does a good job of sampling the distribution of snow types. In Canada, tundra is heavily under-sampled while maritime and alpine snow are oversampled. The same is true over Russia but the over/under-sampling is less pronounced.

We have added a brief summary of these numbers to the end of Section 2.3 (lines 207-209) and a figure with locations of grid cells having snow course measurements overlaid on Sturm Snow Classes (new Figure 2).

'Although Finland's snow course network is representative of the landscape's different snow-climate classes (Sturm et al., 1995), in Canada, and to a lesser extent over Russia, tundra environments which are often remote, are under-sampled while maritime and alpine snow types are oversampled (Fig. 2).'

Sturm, M., Holmgren, J., and Liston, G.: A seasonal snow cover classification system for local to global applications, Journal of Climate, 8: 1261-1283, 1995.

Line 164 (Section 3.1): It would be great if you could get a little bit more quantitative in this section. Right now it seems like you're doing a visual comparison of the climatologies from the different datasets, but it wouldn't be difficult to also compare them quantitatively.

We could compare the climatologies quantitatively by producing difference plots, but we wanted to avoid adding too many panels to the figure. The purpose of Figure 1 is to frame the analysis that follows, and show that it is readily apparent visually that the AMSR-E products differ clearly from the other datasets.

Line 181: "The source of inability of the standalone passive microwave products" sounds a bit awkward. What about "The reason the standalone passive microwave products. . . " or something similar?

Thank you for this suggestion. Revised text (Line 264):
'The reason the standalone passive microwave products fail to capture higher SWE in western Siberia, Russia, northern Europe, and eastern Canada is less clear…'

Line 185: There should be a hyphen between observation and sparse.

Change made.

Line 203: I think it might make sense to include a metric such as relative RMSE or normalized RMSE to assess whether the performance in Canada is, in fact worse because there's more snow. I also wonder if it might not have something to do with the less systematic nature of the in situ measurements in Canada. You even make reference to relative RMSE later in the paper (Line 239), though no values are provided.

We have added a new panel to Figure 2 (now Figure 3, see appendix) showing the RMSE as a percentage of the mean observed SWE. Mean observed SWE was taken as the average observed SWE from grid cells having snow course measurements and coincident SWE product data for all nine products. There are different statistical approaches to this calculation, but we feel this most clearly illustrates how RMSE varies as a function of SWE magnitude as measured at the snow courses.

We have clarified the text in question (Lines 283-288):

'Larger absolute bias and RMSE over Canada may be attributed, in part, to a higher average SWE since the mean SWE of all snow course grid cells used for validation (Sect. 2.3) is 143 mm in Canada compared to 96 mm in Finland and 76 mm in Russia. However, the RMSE, expressed as a percentage of the mean observed SWE (of grid cells used in the analysis) is still higher over Canada for almost all products, indicative of poorer relative performance. The exception is ERA-Interim/Land which has poorer relative performance over Russia than over either Finland or Canada, consistent with product intercomparisons from Mudryk et al. (2015).'

We have also modified the layout of Figure 4 (now Figure 5) so that the RMSE is directly above the mean observed SWE to make it easier for the reader to quickly compare the two values.

Line 279: I had to read this sentence a bunch of times before I understood what you meant. Could you rewrite to try to be a bit clearer about what you did? I think you basically took the spatial correlations for all days and then averaged them. Also, could you clarify what difference, if any, there is between spatial correlations and pattern correlations? I think you're using them interchangeably, but it's not totally clear.

We have clarified the wording in our updated methods section 2.3, lines 232-245:

'First, we considered the correlation between each product's time series of daily Northern Hemisphere snow mass anomalies (SWE integrated over the entire Northern Hemisphere land area). Each product's time series was calculated using its respective climatology (determined for the snow season over the November 2002–April 2010 period). A correlation coefficient was calculated for each pair of datasets by correlating the two snow mass anomaly time series cropped to the snow season (November–April) over the April 2002 – November 2010 period. Secondly, we considered correlations between the patterns of anomalous SWE fields. Daily SWE anomalies were calculated for each product using its respective climatology. For each dataset pair, we calculated the daily pattern correlation between the two anomalous SWE fields and averaged the sequence of correlation values over the snow season for the 2002–2010 period. These first two metrics are bulk measures of agreement, specifically in their estimates of Northern Hemisphere snow mass anomalies and the average agreement of their pattern correlations. Finally, we also considered 'local' correlation maps of anomalous SWE. As above, we calculated daily anomalous SWE fields. Then for each dataset pair, we calculated the correlation coefficient between the daily time series of anomalous SWE at each location on the 1° x 1° grid. The correlation calculation only considers

the snow season (November – April) over the November 2002 – April 2010 period. This third metric allows us to consider which regions agree more and less among the various products.'

Line 283: If you look at the AMSR-E datasets in Figure 6, it sure looks like the mean pattern correlation is higher. Can you clarify?

Wording clarified (line 384-385):

'For the snow analyses and GlobSnow, the mean pattern correlation is lower than the corresponding temporal correlation of total snow mass (Fig. 7).'

Line 333: No need for the comma between Canada and show.

Comma removed.

Anonymous Referee #3

Received and published: 20 January 2020

General comments

The authors conducted a thorough analysis of various publicly-available SWE products. Continental SWE datasets based on reanalysis products, land surface modeling, and passive microwave satellite data are evaluated against (in-situ transect) snow course measurements. The standalone passive microwave-based datasets seem to perform poorly relative to the snow course measurements and the other SWE products. Although no 'best' dataset is identified, the product ensembles that contained Crocus or MERRA performed better.

The authors have provided a sufficiently explanatory literature review for readers who may be unfamiliar with SWE estimation techniques. This effort will benefit researchers who utilize SWE products as ancillary information in their models and help them understand the uncertainty associated with these products.

The paper is well-written and requires only minor modifications.

Specific comments

a) It would be helpful to add a figure showing the geolocation of the snow course data in Section 2.1. It will add topological context to the analysis.

We have added a figure (new Figure 2) showing the location of the snow courses, overlaid on the Sturm et al (1995) snow-climate classification.

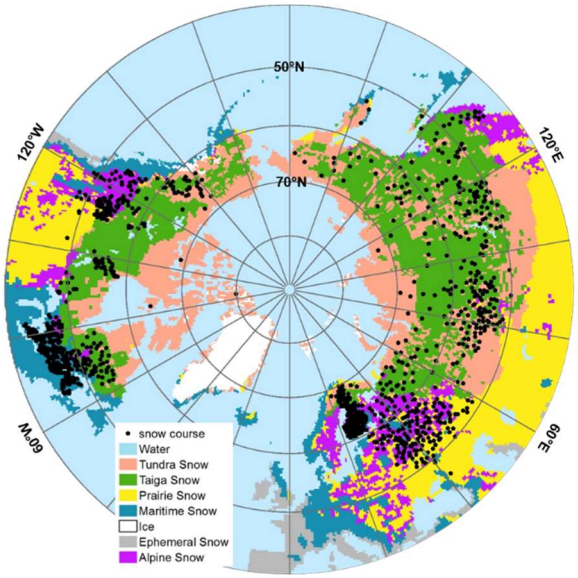

Figure 2. *Centroid of 25km EASE grid cells with snow course observations used in the analysis (Sect. 2.3) overlaid on Sturm et al (1995) snow classes; snow class dataset: Sturm et al. (2009).*

Data source added to reference list:

Sturm, M., Holmgren, J., Liston, G.: Global Seasonal Snow Classification System. Version 1.0. UCAR/NCAR - Earth Observing Laboratory. https://doi.org/10.5065/D69G5JX5, 2009. Accessed 14 Feb 2020.

b) Please add quantitative and/or qualitative information regarding the uncertainty or tentative precision of the snow course measurements used for evaluation in Section 2.1. A quantitative measure of uncertainty for each of the three datasets would be sufficiently descriptive.

It is difficult to attach specific uncertainty values to the snow survey measurements because non-standard sampling tools are used between snow course networks (e.g. no consistent snow corer diameter). Furthermore, error in the individual measurements is no doubt overwhelmed by uncertainty in how the snow course measurements represents the landscape mean at the scale of the gridded SWE products. We have added text which identifies the sources of uncertainty into the final paragraph of Section 2.2 (Lines 177-182):

'Finally, it is difficult to attach specific uncertainty values to the snow survey measurements because non-standard sampling tools are used between snow courses (e.g. no consistent snow corer diameter). Full discussion of snow course measurement protocols and instruments is available elsewhere (Goodison et al., 1981; Brown et al., 2019; Haberkorn et al., 2019), but there is no doubt that uncertainty associated with the individual measurements (± approximately 5%; Brown et al., 2019) is overwhelmed by uncertainty in how the snow course measurements represent the landscape mean at the scale of the gridded SWE products.'

Complete citation for the following references added to reference list:

Goodison, B. E., Ferguson, H. L., McKay, G. A.: Measurement and data analysis. In: Handbook of Snow (D. M. Gray and D. H. Male, eds.), pp. 191–274. Reprint. Caldwell, NJ, USA, The Blackburn Press, 1981.

Haberkorn, A. (Ed.): European Snow Booklet, 363 pp., doi:10.16904/envidat.59, 2019.

c) Increasing the size of individual stereographic maps will improve the visual clarity of the figures.

We have increased the size of the stereographic maps.

d) Please highlight in the conclusion (Line 341) that this analysis is for continental performance evaluation and may/may not apply to small regional or local domains.

We have added text to reflect your suggestion. Current Line 448-450*: 'As with any continental-scale evaluation our results may (or may not) apply to small regions or local domains and the validation results do not apply to non-alpine areas which constitute a large proportion (~30%) (Wrzesien et al., 2019) of the total hemispheric SWE.'*

Technical corrections

Abstract – A '0.1' increase in correlation does not seem very significant. Please provide justification of the significance of this increase in correlation using additional analysis (such as hypothesis testing). This

analysis can be included as a separate paragraph in Section 3.3. If no justification exists, then it would be advisable to remove the sentence from the abstract.

Sentence revised and reflects addition of ERA5 and MERRA2:

'Using a seven-dataset ensemble that excluded the standalone passive microwave products reduced the RMSE by 10 mm (20%) and increased the correlation from 0.67 to 0.78 compared to any individual product.'

Line 32 – Please define which seasonal forecasts the authors are eluding to. Being specific will make the discussion more accessible to the reader.

The statement on the verification of seasonal forecasts is followed by the reference to Sospedra-Alfonso et al. (2016). This citation provides details on the study which used various snow analyses to verify forecast from the Canadian Seasonal to Interannual Prediction System (CanSIPS).

Line 38 – Please define the difference between 'snow depth' and 'surface snowfall' measurements.

'Snow depth' refers to snow on the ground measured by a ruler, sonic snow depth instrument, etc.; 'surface snowfall' refers to snowfall measurements from a precipitation gauge. We removed the word 'surface' which clarifies the sentence (lines 37-39).

'Meaningful spatially continuous information can be derived from surface observations for regions and time periods with a sufficiently dense observing network (Dyer and Mote, 2006; Brown and Derksen, 2013); as an alternative to snow depth, snowfall measurements can also be integrated (Broxton et al., 2016).'

Line 40 – It isn't clear what 'coarse' grid cells means. Can you quantify what you mean by 'coarse'?

Good point. We re-phrased this sentence (lines 39-43):

'However, both snow depth and snowfall measurements from single point locations are intrinsically limited by a lack of confidence in how they capture the landscape mean across coarse grid cells (Meromy et al., 2013), which is particularly problematic in areas of mixed forest vegetation, open areas prone to wind redistribution, and complex topography (most snow covered regions fall into at least one of these categories).'

Line 83 – Replace evaluation with evaluate.

Change made. (Line 85)

Line 110 – Rephrase the sentence to highlight the difference between using separate brightness channels versus spectral difference for SWE estimation.

We feel it is too much technical detail to describe the difference between individual brightness temperature measurements and the spectral gradient. But we have modified the wording to clarify the sentence (line 119-121):

'The approach evolved from standalone passive microwave algorithms (it also relies on 19 and 37 GHz measurements), but the retrieval also integrates daily surface snow depth measurements.'

Line 162 – Please add an appropriate reference for the EASE2 grid.

Reference to Brodzik et al. 2012 added to line 202-204:

'For each temporal grouping, snow course measurements falling within a given 25 x 25 km EASE grid cell (Brodzik et al., 2012) were averaged together, thereby forming a gridded snow course field (Fig. 2).

Added to reference list:

Brodzik, M. J., Billingsley, B., Haran, T., Raup, B., & Savoie, M. H.: EASE-Grid 2.0: Incremental but significant improvements for Earth-gridded data sets, ISPRS International Journal of Geo-Information, 1, 32-45, https://doi.org/10.3390/ijgi1010032, 2012.

Line 220 – Please elaborate briefly on what the 'acceptable' uncertainty is for SWE. Please be specific in terms of quantitative (rather than qualitative) values of SWE uncertainty.

Added specific quantitative values. Revised (current) Line 358-361:

'Because the RMSE of even the best performing products is at the margins of acceptable uncertainty for operational (<15%; Rott et al., 2010; Larue et al. 2017) and scientific (10-25%; Derksen and Nagler, 2019) requirements, the increase in accuracy represents a simple method to yield performance gains.'

Line 225 – GlobSnow also underestimates SWE above values > 130mm. This statement needs to be included here.

Added statement regarding underestimation of GlobSnow above >130 mm, current Line 312:

'*GlobSnow overestimates SWE up to ~100 mm and underestimates above ~130 mm …'*

Line 239 – Figure 3g shows >70mm rather than >60mm as the pivot point.

Thank you for this observation, we have changed the text to reflect this. Current Line 313-314:

'The AMSR-E v1.0 product exhibits low sensitivity to SWE, especially for values >70 mm and overestimates low SWE values.'

Line 266 – contain is written twice.

Second 'contain' removed.

Figure – 1: Extra 'E' in AMSR-E in caption.

Extra 'E' removed from AMSR-E in caption.

Figure – 3:

a) Please define how Figure 3 was developed in the main text. Is the binning based on average SWE values for each grid cell or the average of bi-weekly values for all snow courses?

We have added additional text to explain how the binning was conducted. Reviewer 1 asked that we reorganize the description of methods that were interspersed with the results. The clarification about Figure 3 (now Figure 4) was added to this revised methods section.

Added to lines 222-225: '*Finally, to determine the influence of SWE magnitude on product performance, all snow course-product SWE pairs were binned into 10 mm increments according to the snow course SWE. For each 10 mm increment the average product SWE was plotted against the bin midpoint.'*

b) The term 'retrieval' is used in the caption. This term does not apply to all the different SWE datasets being evaluated. Please change the sentence from 'retrieval performance versus reference SWE ....' to 'Performance of SWE datasets versus reference SWE measurements .....'

Thank you for this suggestion. We have revised Figure 3's (now Figure 4) caption accordingly:

Figure 4. *Performance of SWE datasets versus reference SWE ± 1 standard deviation for (a) Crocus; (b) ERA-Interim/Land; (c) ERA5; (d) GLDAS-2; (e) GlobSnow v2.0; (f) MERRA; (g) MERRA2; (h) AMSR-E v1.0; (i) AMSR-E v2.0. SWE values above 300 mm are not shown.*

c) The figure labels for subplots f and g do not match the caption labels.

We have revise this figure caption. See previous response.

Figure – 4: In the text, a bi-weekly time step is specified while the caption describes a ten day time step. Please clarify this contradiction.

Although the use of 10-day steps for Russia is described in the methods section, we have clarified the text to specify that ten day time steps were used for Russia.

Revised methods lines 219-221:

'To understand the influence of seasonality on product performance, bias, RMSE and correlation were also computed across all years for each biweekly period (10 day period for Russia).'

Results lines 320-321:

'To quantify the influence of seasonality on product performance, validation statistics (RMSE, bias, correlation) were computed at a bi-weekly time step (10 days for Russia) for 2002 through 2010 (Sect. 2.3).'

Figure – 6: The figure title can be removed since the caption and labels are self explanatory.

Figure title removed.

Data availability – There seems to be a typing error in the data availability description.
The NASA AMSR-E operational dataset is mentioned twice.

Thank you for catching this. The first mention of NASA operational should have read NASA historical. We have revised the nomenclature surrounding the NASA products. NASA Historical is now NASA AMSR-E SWE v1.0 and NASA Operational is now NASA AMSR-E SWE v2.0. Data availability now reads:

'Data availability. Météo-France provided data from the Crocus snowpack model; the NASA AMSR-E SWE v1.0 dataset and is available from the paper's authors upon request as is the NASA AMSR-E SWE v2.0 dataset. The remaining datasets are available for download via the links and references provided in Sect. 2.'

Revised Figures and Table

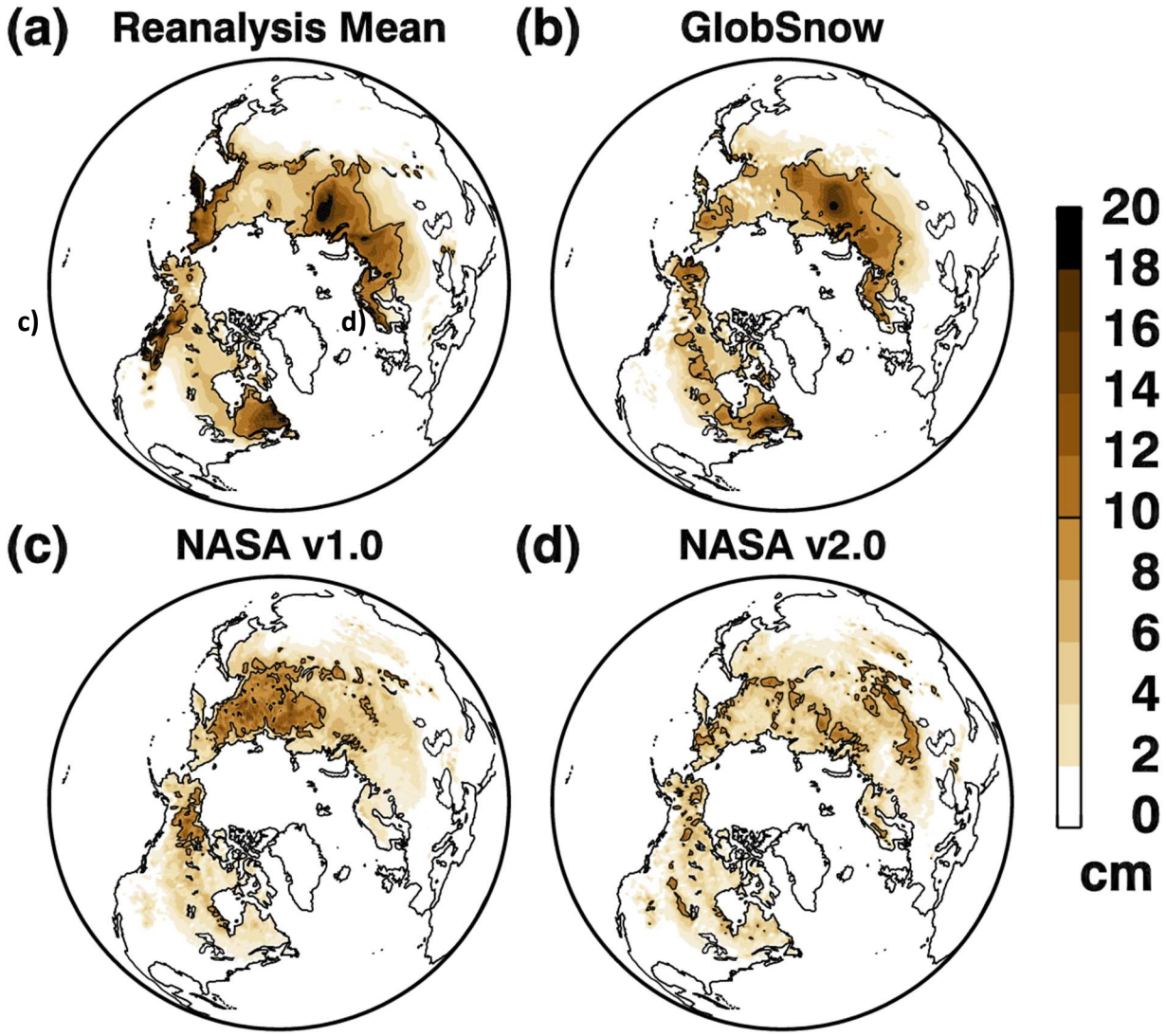

Figure 1. Mean January, February, and March (JFM) SWE over the 2003 – 2010 period for (a) four reanalysis driven products (GLDAS-2, ERA-Interim/Land, Crocus, and MERRA2); (b) GlobSnow v2.0; (c) NASA AMSR-E SWE v1.0; (d) NASA AMSR-E SWE v2.0.

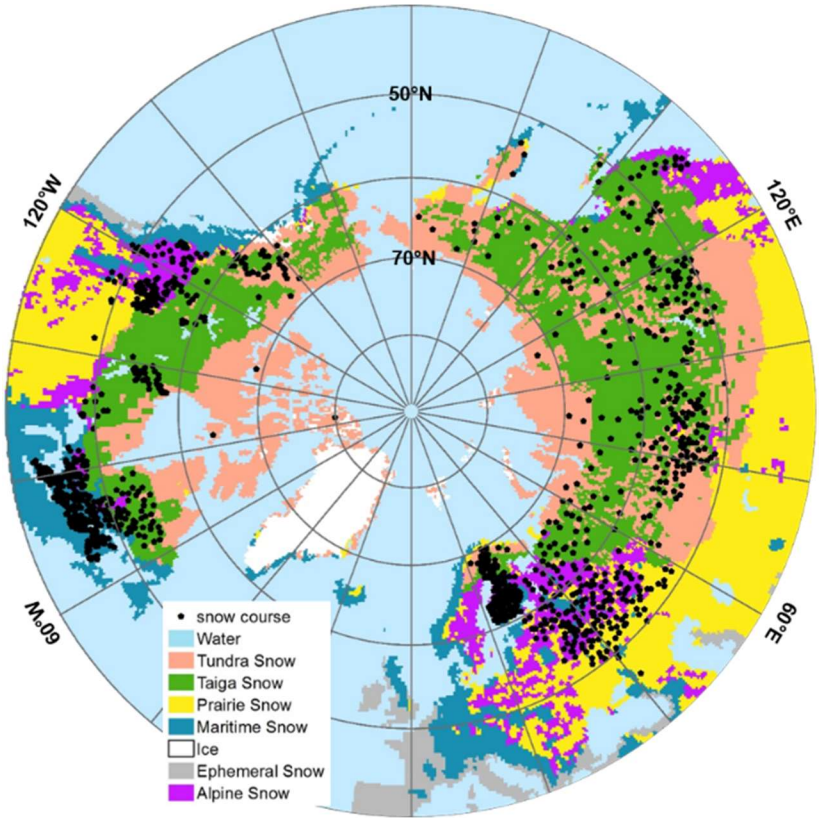

Figure 2. Centroid of 25km EASE grid cells with snow course observations used in the analysis (Sect. 2.3) overlaid on Sturm et al (1995) snow classes; snow class dataset: Sturm et al. (2009).

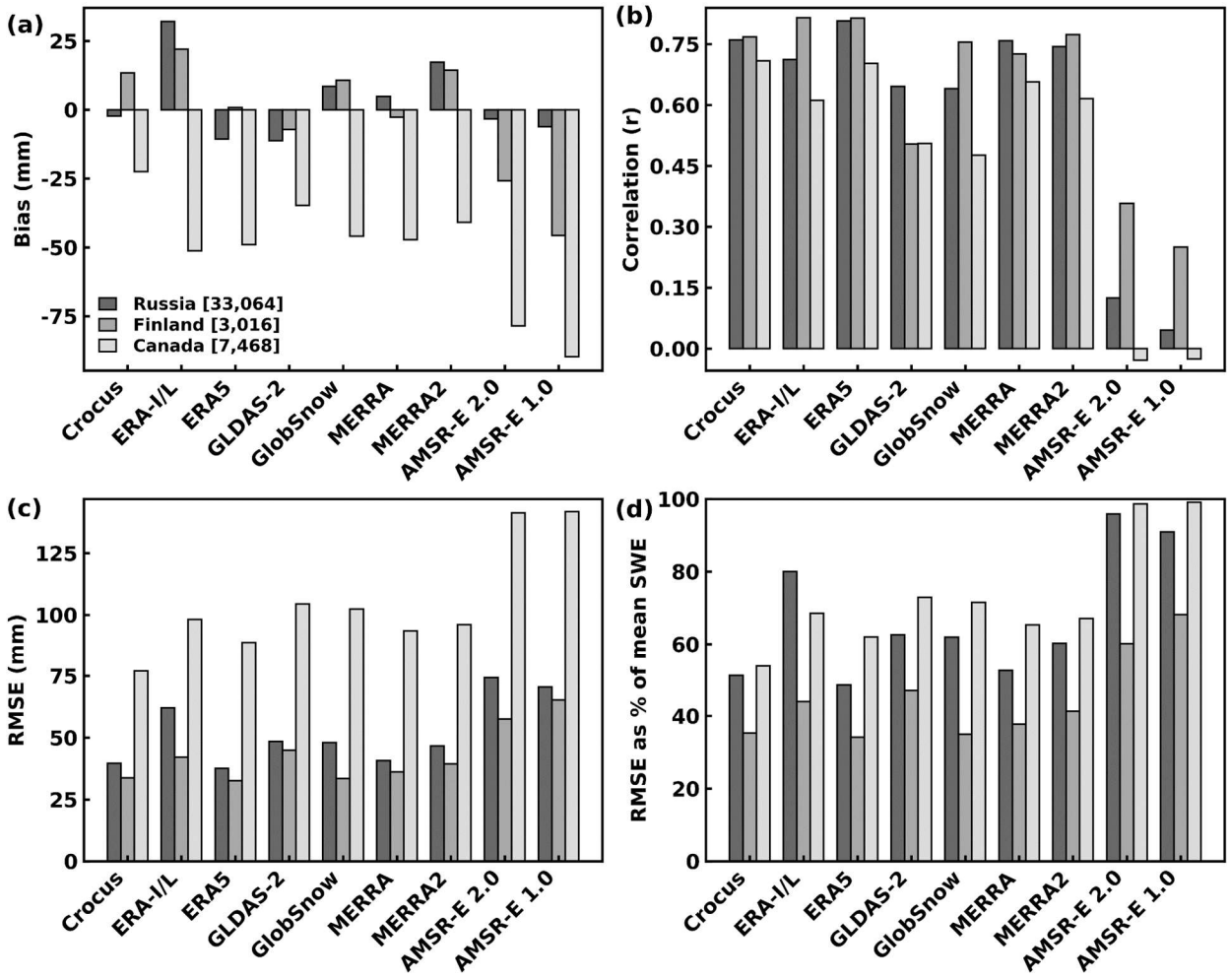

Figure 3. Validation statistics (a: bias; b: correlation; c: RMSE; d: RMSE as percentage of mean SWE) for the nine SWE products for November through April, 2002–2010 [ERA-I/L = ERA-Interim/Land; GlobSnow = GlobSnow v2.0]. Total number of grid cells with snow course measurements in square brackets in panel a.

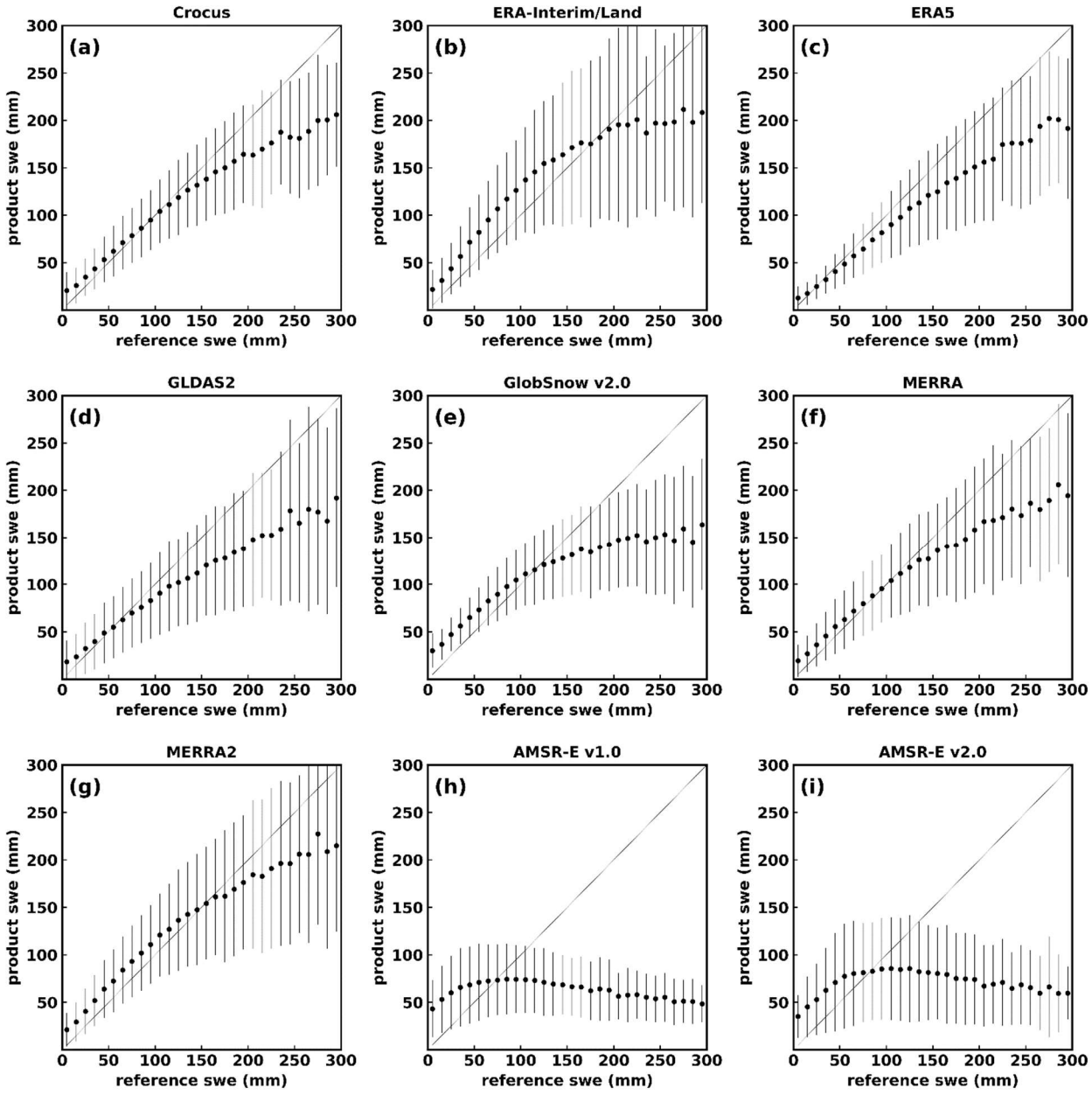

Figure 4. Performance of SWE datasets versus reference SWE ± 1 standard deviation for (a) Crocus; (b) ERA-Interim/Land; (c) ERA5; (d) GLDAS-2; (e) GlobSnow v2.0; (f) MERRA; (g) MERRA2; (h) AMSR-E v1.0; (i) AMSR-E v2.0. SWE values above 300 mm are not shown.

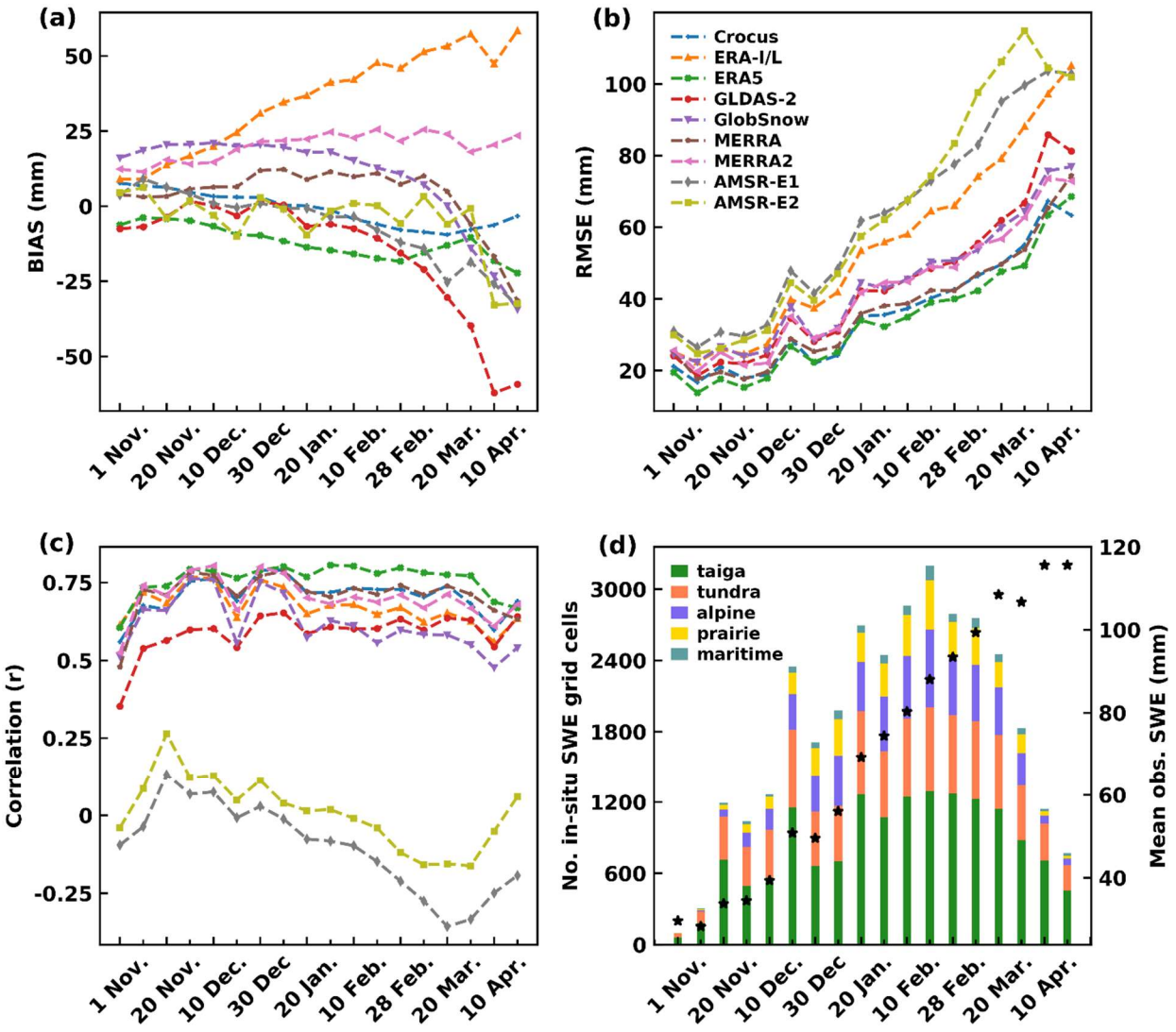

Figure 5. (a) Bias, (b) RMSE and (c) correlation coefficient relative to the Russia snow course dataset (Section 2.1) for each ten day time step over the 2002–2010 period. (d) Number of grid cells with snow course observations by Sturm snow class (bars, left-hand axis), mean observed SWE (stars, right-hand axis). [ERA-I/L = ERA-Interim/Land, GlobSnow = GlobSnow v2.0].

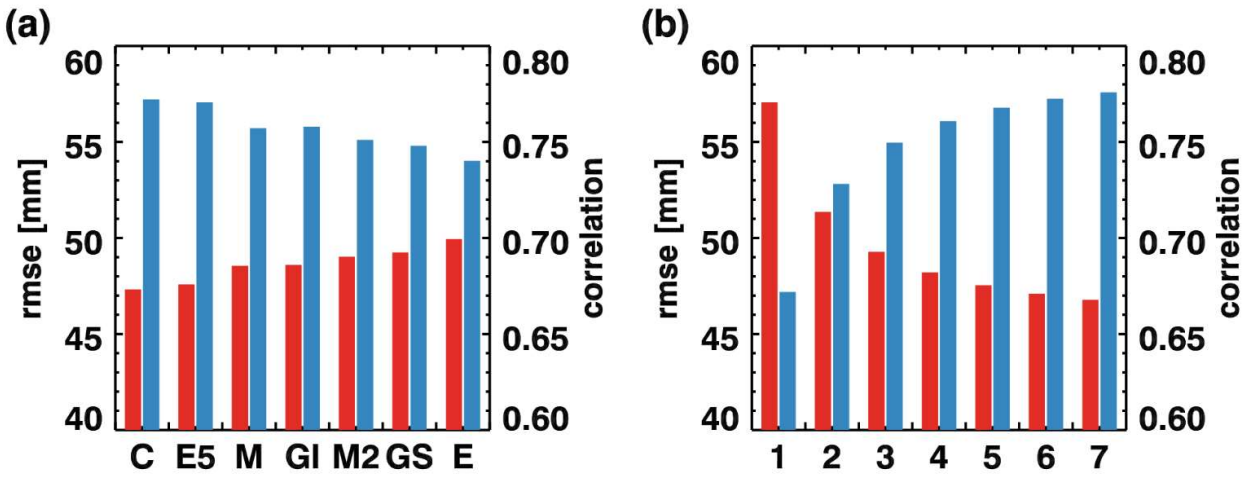

Figure 6. RMSE (red) and correlation (blue) of snow course measurements with various combinations of SWE products. (a) Average of all combinations that contain the specified individual product [C = Crocus, E5 = ERA5, M = MERRA, , Gl = GLDAS-2, M2 = MERRA2, GS = GlobSnow v2.0, E = ERA-Interim/Land] and (b) average of all combinations of N products as specified on x-axis.

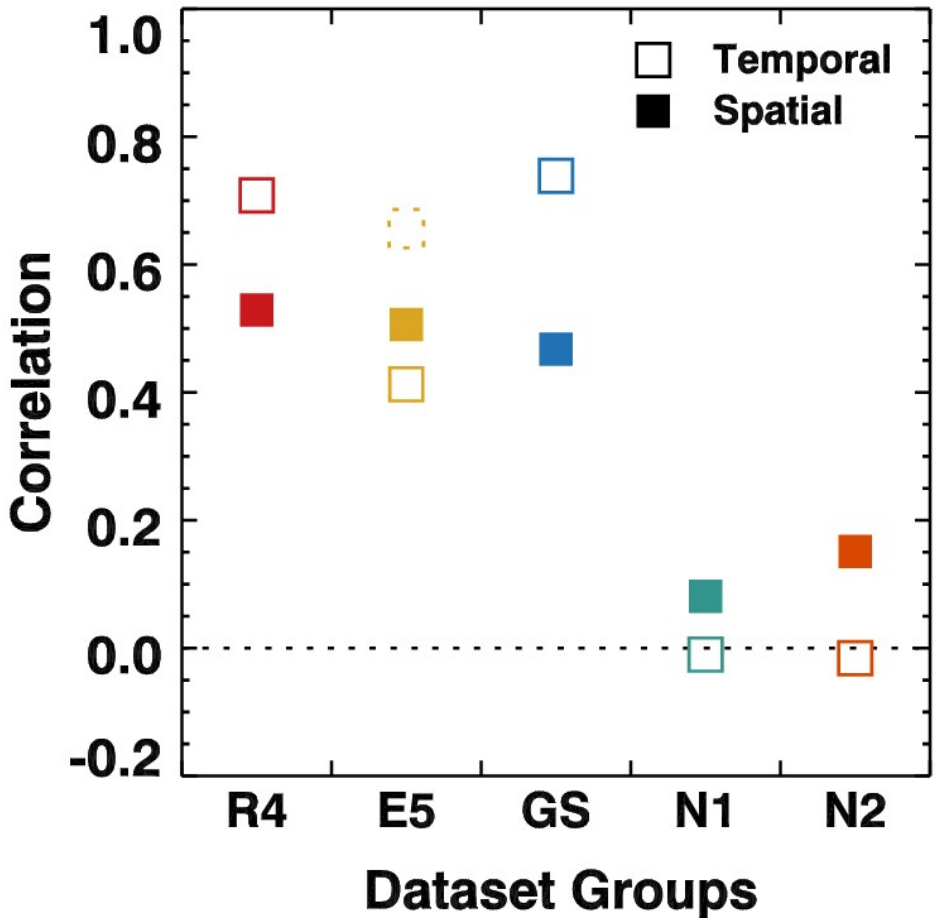

Figure 7. Temporal and spatial correlations among groups of products over the 2002–2010 time period. Temporal correlations assess the extent to which anomalous northern hemispheric snow mass jointly evolves between pairs of datasets while spatial correlations assess the pattern correlation of SWE fields for pairs of datasets; see text for details. R4 = the average of 6 pairwise correlations between Crocus, GLDAS-2, ERA-Interim/Land, and MERRA2. E5 = the average of 4 pairwise correlations between ERA5 and each R4 product. GS = the average of 4 pairwise correlations between GlobSnow v2.0 and each R4 product. N1 = the average of 4 pairwise correlations between AMSR-E v1.0 and each R4 product. N2 = the average of 4 pairwise correlations between AMSR-E v2.0 and each R4 product. The dotted square shows the impact of correcting the E5 snow mass anomalies for a discontinuity introduced in 2004.

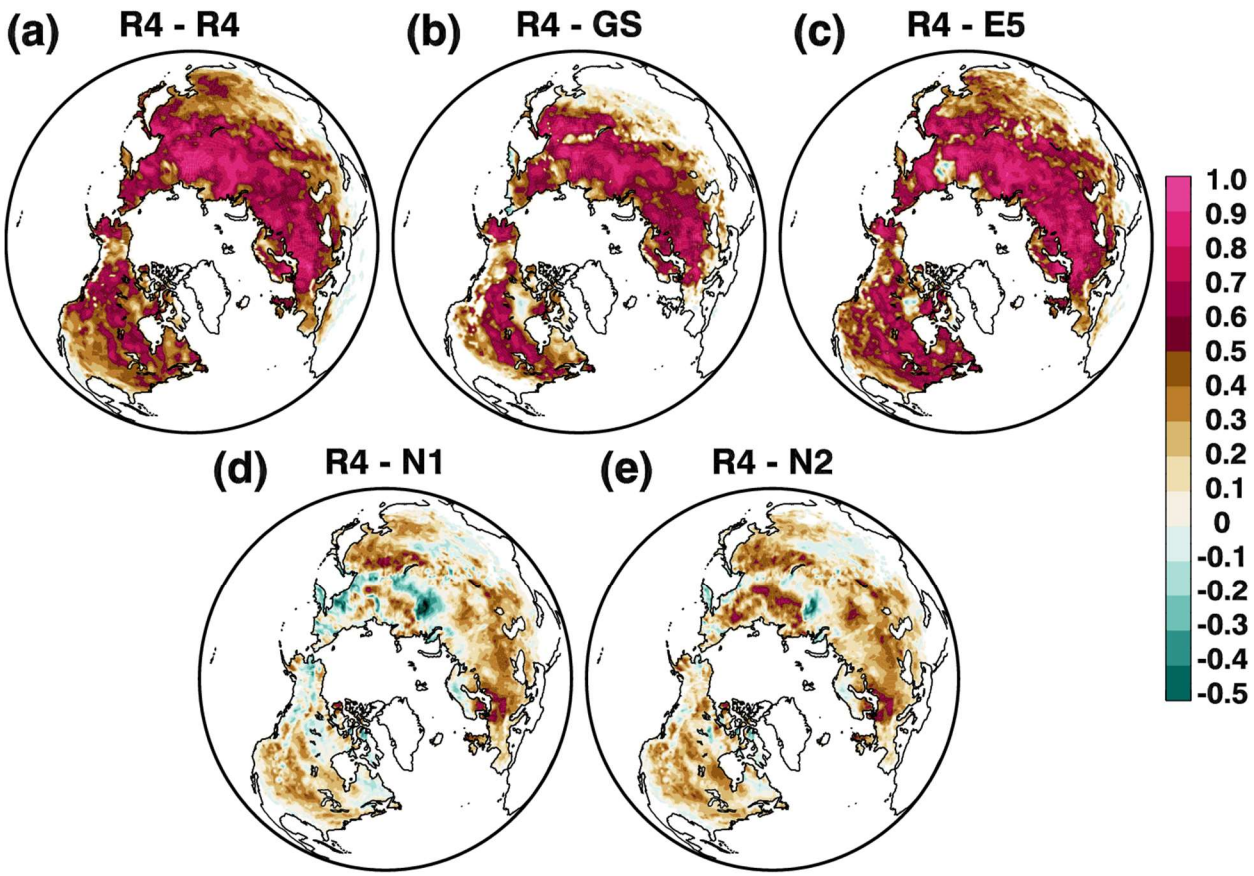

Figure 8. Correlation maps (2002–2010) for four reanalysis driven products (Crocus, GLDAS-2, ERA-Interim/Land, and MERRA2) relative to: (a) each other (mean correlation between the four reanalysis driven products); (b) GlobSnow v2.0; (c) ERA5; (d) NASA AMSR-E SWE v1.0; (e) NASA AMSR-E SWE v2.0.

Table 1. Summary of SWE products evaluated in this study.

Data Product	Method	Ancillary/ Forcing Data	Resolution	Reference/ Availability
GlobSnow v2.0	Passive microwave + in situ	Weather station snow depth measurements	25 km	Takala et al., 2011 www.globsnow.info
NASA AMSR-E v1.0	Standalone passive microwave		25 km	Kelly (2009) nsidc.org
NASA AMSR-E v2.0	Microwave + ground station climatology	Weather station snow depth climatology	25 km	Tedesco and Jeyaratnam (2016) nsidc.org†
ERA-Interim/Land	HTESSEL land surface model	ERA-interim	0.75° x 0.75°	Balsamo et al (2015) www.ecmwf.int
ERA5	HTESSEL land surface model	ERA5	0.25° x 0.25°	Hersbach et al. (2019) C3S (2017)
MERRA	Catchment land surface model	MERRA	0.5° x 0.67°	Rienecker et al (2011) GMAO (2017a)
MERRA2	Catchment land surface model	MERRA2	0.5° x 0.625°	Gelaro et al. (2017) GMAO (2017b)
Crocus	ISBA land surface + Crocus snow model	ERA-interim	1° x 1°	Brun et al (2013) ‡
GLDAS-2	Noah 3.3 land surface model	Princeton Met.	1° x 1°	Rodell et al (2004) disc.gsfc.nasa.gov

† The v2 product is not available via NSIDC over the 2002–2010 period, however data using the same algorithm is available from July 2012–present. Contact authors for availability.
‡ Contact authors for availability.

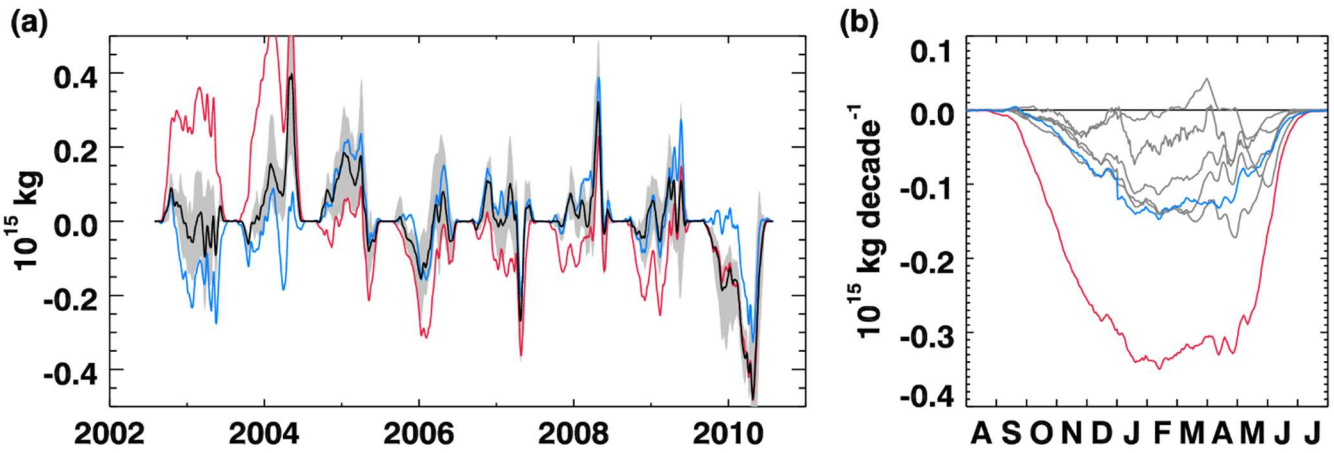

Figure S1. (a) Average NH snow mass anomalies (black) and spread (shading) calculated from five component products: MERRA2, Crocus, GlobSnow, GLDAS and ERA-Interim/Land along with snow mass anomalies from raw (red) and corrected (blue) ERA5 values. (b) Trends (1981-2010) from the five component time series used for the average in panel a (grey) along with trends from the raw (red) and corrected (blue) ERA5 time series. The ERA5 discontinuity occurs in mid-2004.

Evaluation of long term Northern Hemisphere snow water equivalent products

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Abstract. ~~Seven~~Nine gridded northern hemisphere snow water equivalent (SWE) products were evaluated as part of the European Space Agency (ESA) Satellite Snow Product ~~Inter-comparison~~Intercomparison and Evaluation Exercise (SnowPEx). Three categories of datasets were assessed: (1) those utilizing some form of reanalysis (the NASA Global Land Data Assimilation System version 2 ~~–~~ GLDAS-2; the European Centre for Medium-Range Weather Forecasts (ECMWF) interim land surface reanalysis – ERA-~~land~~Interim/Land and ERA5; the NASA Modern-Era Retrospective Analysis for Research and Applications ~~–~~version 1 (MERRA~~;~~) and version 2 (MERRA2); the Crocus snow model driven by ERA-Interim meteorology – Crocus); (2) passive microwave remote sensing combined with daily surface snow depth observations (ESA GlobSnow v2.0); and (3) standalone passive microwave retrievals (NASA AMSR-E ~~historical~~SWE versions 1.0 and ~~operational algorithms)~~2.0 which do not utilize surface snow observations. Evaluation included ~~comparisons~~validation against independent ~~surface observations~~snow course measurements from Russia, Finland, and Canada, and product intercomparison through the calculation of spatial and temporal correlations in SWE anomalies. The standalone passive microwave SWE products (AMSR-E ~~historical~~v1.0 and ~~operational~~v2.0 SWE ~~algorithms~~) exhibit low spatial and temporal correlations to other products, and RMSE nearly double the best performing product. Constraining passive microwave retrievals with surface observations (GlobSnow) provides comparable performance to the reanalysis-based products; ~~RMSEs~~RMSE over Finland and Russia for all but the AMSR-E products is ~50 mm or less~~.~~, with the exception of ERA-Interim/Land over Russia. Using a ~~four~~seven-dataset ensemble that excluded the standalone passive microwave products reduced the RMSE by 10 mm (20%) and increased the correlation ~~by~~from 0.~~1; ensembles that contain Crocus and/or MERRA perform better than those that do not.~~67 to 0.78 compared to any individual product. The ~~observed RMSE~~overall performance of the best ~~performing datasets~~multi-product combinations is still at the margins of acceptable uncertainty for scientific and operational requirements; only through combined and integrated improvements in remote sensing, modeling, and observations will real progress in SWE product development be achieved.

1 Introduction

Temporally (~20–30 years) and spatially (~10–20 km) consistent estimates of daily SWE over seasonal snow covered land are required for many applications including climate model evaluation (Mudryk et al., 2018a), verification of seasonal forecasts (Sospedra-Alfonso et al., 2016), annual updates to climate assessments (e.g. Mudryk et al., 2018b; 2019), and determination of freshwater availability (Barnett et al. 2005; Clark et al. 2011). There ~~are~~is a growing number of gridded SWE datasets available to the snow community, but these are typically affected by one or more critical shortcomings related to:

1. Challenges in using point measurements: Meaningful spatially continuous information can be derived from surface observations for regions and time periods with a sufficiently dense observing network (Dyer and Mote, 2006; Brown and Derksen, 2013); as an alternative to snow depth, ~~surface~~ snowfall measurements can also be integrated (Broxton et al., 2016). However, both snow depth and snowfall measurements from single point locations are intrinsically limited by a lack of confidence in how they capture the landscape mean across coarse grid cells ~~and surrounding areas that are not sampled.~~(Meromy et al., 2013), which is particularly problematic in areas of mixed forest vegetation, open areas prone to wind redistribution, and complex topography (most snow covered regions fall into at least one of these categories). Furthermore, there remain expansive alpine and northern regions with insufficient coverage by conventional observing networks (Brown et al., 2019).

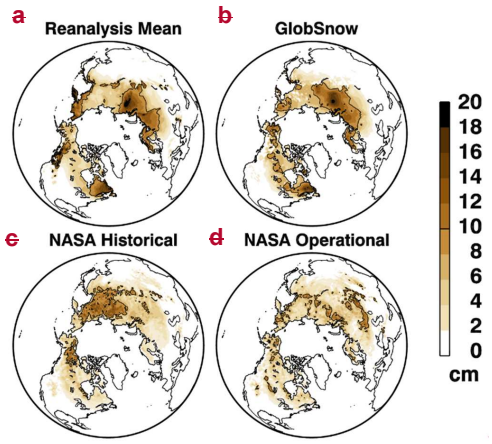
2. Reliance on models driven by atmospheric reanalysis: Most modern reanalysis products include output of land surface variables such as SWE (Balsamo et al., 2015; Gelaro et al., 2017); alternatively the meteorology from these datasets can be used to force snow models (Brown et al., 2003; Brun et al., 2013). While these snow schemes are of varying complexity, they typically do not account for important processes such as snow-vegetation interactions and redistribution by blowing snow. In addition, the spread in SWE estimates among differing reanalyses is large: not only do differences between snow models introduce uncertainties (Mudryk et al., 2015), but model-based approaches are also sensitive to the precipitation forcing, which itself is challenging to validate in complex terrain and observation sparse regions (Lundquist et al., 2015; Henn et al., 2018). There may also be temporal inconsistencies in the forcing data related to changes in the observational streams assimilated in the reanalyses~~.~~ (Robertson et al., 2011).

3. Coarse spatial resolution: Whether derived from passive microwave satellite measurements or some form of model reanalysis, the typical resolution of existing gridded SWE datasets is 25 to 100 km. While synoptic scale patterns can be resolved at this resolution, spatial variability in SWE due to topographic and land cover heterogeneity is not adequately captured. Coarse resolution is a particularly critical limitation in alpine regions, which are masked out completely in some products (e.g. Takala et al., 2011). While this is a reasonable decision for some coarse resolution products, it nevertheless is a

source of frustration for users. Coarse resolution also makes validation of SWE products challenging: the validation of large grid cells with single point measurements is conceptually unsatisfying and statistically non-robust. Regional climate models can provide higher resolution SWE information, but the computational cost related to complex atmospheric physics schemes is, at least at present, a limiting factor in producing long time series (Wrzesien et al., 2018). ~~Coarse resolution also makes validation of SWE products challenging: the validation of large grid cells with single point measurements is conceptually unsatisfying and statistically non-robust.~~There may be potential for cross-polarized C-band SAR to provide high spatial resolution snow depth information in mountain areas (Lievens et al., 2019), but these estimates currently lack a physical explanation. Since cross- polarized C-band SAR data are only available since the launch of Sentinel-1A in 2014, there is limited potential to provide climate-relevant time series.

4. Inability of remote sensing data to constrain uncertainty: The number of purely satellite derived SWE datasets is limited, and uncertainty in standalone passive microwave retrievals can be high (Kelly et al., 2003). The combination of passive microwave and surface snow depth measurements (within the GlobSnow product; Takala et al., 2011) was shown to yield performance similar to snow models driven by atmospheric reanalysis (Mudryk et al., 2015), but it relies heavily on background fields and constraints generated from re-gridded surface snow depth observations (Pulliainen, 2006). The microwave remote sensing community has made great progress in understanding and quantifying error sources (snow microstructure, deep snow, wet snow, vegetation, lake ice), all of which are exacerbated by the coarse resolution of passive microwave measurements (Foster et al., 2005; Durand et al., 2011; Lemmetyinen et al., 2011; Durand and Liu, 2012).

Previous studies have demonstrated the potential for using multi-product SWE ensembles in order to improve estimates of observed snow-related quantities (e.g. SWE and snow cover fraction ~~fields~~, integrated snow mass, snow cover extent and trends in these quantities) and to constrain uncertainty (Mudryk et al., 2015, 2017, 2018a; Krinner et al., 2018). The intent in such a strategy is that uncorrelated errors between products of the same type ~~would~~ average out, so the limitations and shortcomings of a given class of products ~~would~~ offset one another. Ideally such ensembles would draw from as many types of products as possible and use multiple versions of each type of product. To date, these ensembles have relied heavily on models driven by atmospheric analysis and include only a single dataset (GlobSnow) which utilizes remote sensing. While SWE or snow depth products can be derived using InSAR techniques (Deeb et al., 2011) and airborne LiDAR data (Painter et al., 2016), such products are only available for regionally and temporal limited domains. Hence, the long time series of passive microwave measurements provide the most straightforward pathway to increase the use of satellite data within observational SWE ensembles. Before existing passive microwave derived SWE products can be included, however, an assessment is needed because of markedly different climatological patterns (Fig. 1; discussed further in Sect. 3.1). The specific objectives of this study are to ~~evaluation~~evaluate gridded Northern Hemisphere SWE products ~~through~~by (1) ~~comparison~~*validation* with independent surface observations, and (2) *intercomparison* through calculation of the spatial and temporal correlations in SWE anomalies.


a
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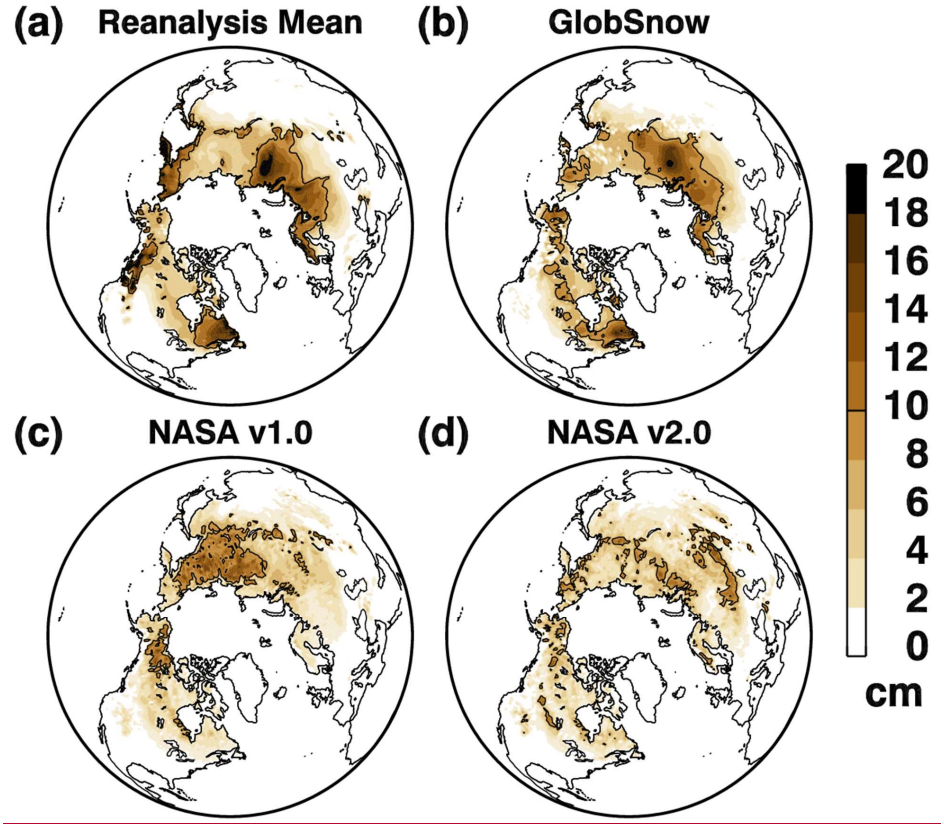

Figure 1. Mean January, February, and March (JFM) SWE over the 2003-~~–~~2010 period for (a) four reanalysis driven products (GLDAS-2, ERA-~~interim-land~~Interim/Land, Crocus, and ~~MERRA~~MERRA2); (b) GlobSnow v2.0; (c) ~~the historical~~ NASA AMSR-E ~~product~~SWE v1.0; (d) ~~the current operational~~ NASA ~~AMSRE~~AMSR-E ~~algorithm~~SWE v2.0.

2 Datasets and methods

2.1 Gridded SWE products

We evaluate three categories of northern hemisphere gridded SWE products: (1) standalone passive microwave retrievals (AMSR-E ~~historical~~SWE v1.0 and ~~operational algorithms~~v2.0); (2) passive microwave estimates combined with surface snow depth observations (GlobSnow v2.0), and (3); products which utilize some form of reanalysis (Crocus, ~~ERA-land,~~ GLDAS-2,

ERA-Interim/Land, ERA5, MERRA, MERRA2). A summary of these nine SWE datasets is provided in Table 1. All the products provide SWE directly and are available at daily or sub-daily frequency. For the four products available at sub-daily frequency, we either obtained daily mean versions directly from the product's distribution site (MERRA~~).~~, MERRA2) or sampled a consistent sub-daily snapshot for each calendar day (ERA-Interim/Land, ERA-5) which we consider to be representative of the daily mean value. The analyses described subsequently in Section 2.3 were conducted for the period 2002 –2010 to maximize temporal overlap between products.

1. *Standalone passive microwave*: The NASA ~~historical~~ AMSR-E SWE v1.0 product (https://nsidc.org/data/AE_DySno/versions/2, Tedesco et al~~.~~., 2004) is described in Kelly (2009) and evaluated in Tedesco and Narvekar (2010). Brightness temperature thresholds are utilized to identify shallow and non-shallow dry snow areas, with the depth of shallow snow set to 5 cm (Kelly et al., 2003). SWE is retrieved based on a brightness temperature difference approach (37-19 GHz; based on the original formulation of Chang et al. (1990)) with enhancements to account for the influence of vegetation, address deeper snowpacks (through the use of 10 GHz measurements), and consider the dynamic influence of snow grain size (based on the assumption that as snow depth increases, the depth average grain size increases). Snow depth is converted to SWE using the snow climate classification of Sturm et al. (1995) and snow density climatologies from Brown and Braaten (1998) and Krenke (2004). Building on the ~~historical~~v1.0 AMSR-E SWE product, NASA's current ~~'operational'~~v2.0 AMSR-E SWE algorithm utilizes an artificial neural network ~~(ANN),~~ snow emission modelling, and climatological snow depth data for the estimation of snow depth, and the detection of dry versus wet snow conditions (Tedesco and Jeyaratnam 2016). Snow density maps based on Sturm et al. (2010) are employed for conversion of retrieved snow depth to SWE. Unlike the GlobSnow approach described next, both ~~the operational and historical~~NASA AMSR-E SWE algorithms are self-contained and do not rely on any external temporally variable snow measurements.
2. *Synergistic passive microwave + in situ:* The European Space Agency GlobSnow v2.0 SWE product (data available at www.globsnow.info) is based on a retrieval method first described in Pulliainen (2006). The approach evolved from standalone passive microwave algorithms ~~in that (~~it also relies on ~~the channel difference between~~ 19 and 37 GHz measurements~~;~~), but the retrieval also integrates daily surface snow depth measurements. First, daily climate station snow depth observations are kriged to form a continuous background field independent of passive microwave retrievals. This first guess snow depth field is used as input to two iterations of forward microwave emission model simulations, one to estimate grain size, the second to estimate snow depth (Takala et al., 2011). A temporally and spatially fixed snow density value of 0.24 g cm^{-3} is applied to convert snow depth to SWE. Alpine areas are excluded due to the known ~~limitation~~limitations of this technique in regions with complex sub-grid topographical heterogeneity (Takala et al., 2011).
3. ~~*Land surface models and reanalysis*: Four~~Six SWE datasets derived from combinations of ~~land surface~~ models driven by reanalysis meteorology were used for comparison with the passive microwave products: the NASA Global Land

Data Assimilation System version 2 ~~–~~ GLDAS-2; the European Centre for Medium-Range Weather Forecasts (ECMWF) interim land surface reanalysis – ERA-~~land~~Interim/Land; and ECMWF ReAnalysis version 5 - ERA5; the NASA Modern-Era Retrospective Analysis for Research and Applications ~~–~~, version1 – MERRA, and version2 - MERRA2; the Crocus snow model driven by ERA-~~interim~~Interim meteorology – Crocus. ~~A full description of the derivation of SWE from these products~~We refer to these datasets as *snow analyses*. It is ~~provided~~important to note that spread among the snow analyses does not only depend on differences in ~~Mudryk et al. (2015). Differences in both~~ the forcing data ~~and the~~; in fact, a substantial portion of the spread stems from differences in the complexity and parametrizations of their respective snow schemes (~~which are of varying complexity) within the land surface models account for spread between these products (~~see Mudryk et al., 2015). For example, both Crocus and ERA-~~land~~Interim/Land use the same forcing data but employ different land models with different snow schemes~~. Henceforth, we refer to these datasets as *snow analyses*.~~

~~4. A summary of the seven~~ which yield significantly different validation results (Section 3.2). The impact of snow depth observations also differs between reanalysis products. Snow depth observations are directly assimilated into ERA5. For ERA-Interim/Land, however, only the forcing meteorology includes explicit assimilation of point snow depth measurements (the SWE produced by ERA-Land does not). Therefore, for ERA-Interim/Land, the use of snow depth information is one step removed from the final SWE ~~datasets used in this study is provided in Table 1. All datasets were interpolated to a regular 1° x 1° longitude–latitude grid. Before interpolation, snow over glaciers and large lakes was excluded based on the MERRA land fraction mask (consistent with Mudryk et al., 2015).~~estimates compared to ERA5, although the assimilation of snow information impacts variables such as lower tropospheric temperatures which obviously have an indirect impact on snow.

Table 1. Summary of SWE products evaluated in this study.

~~Dataset~~Data Product	Method	Ancillary/ Forcing Data	Resolution	~~Time Series~~	Reference/ Availability
GlobSnow v2.0	Passive microwave + in situ	Weather station snow depth measurements	25 km	~~1979-2015~~	Takala et al (., 2011~~)~~ www.globsnow.info
NASA AMSR-E ~~historical~~v1.0	Standalone passive microwave		25 km	~~2002-2011~~	Kelly (2009) nsidc.org

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DatasetData Product	Method	Ancillary/ Forcing Data	Resolution	Time Series	Reference/ Availability
NASA AMSR-E operationalv2.0	Microwave + ground station climatology	Weather station snow depth climatology	25 km	2002-2011	Tedesco and Jeyaratnam (2016) nsidc.org†
ERA-landInterim/Land	HTESSEL land surface model	ERA-interim	0.75° x 0.75°	1981-2010	Balsamo et al (2013)2015) www.ecmwf.int
ERA5	HTESSEL land surface model	ERA5	0.25° x 0.25°		Hersbach et al. (2019) C3S (2017)
MERRA	Catchment land surface model	MERRA	0.5° x 0.67°	1981-2010	Rienecker et al (2011) GMAO (2017a)
MERRA2	Catchment land surface model	MERRA2	0.5° x 0.625°		Gelaro et al. (2017) GMAO (2017b)
Crocus	ISBA land surface + Crocus snow model	ERA-interim	1° x 1°	1981-2010	Brun et al (2013) ‡
GLDAS-2	Noah 3.3 land surface model	Princeton Met.	1° x 1°	1981-2010	Rodell et al (2004) disc.gsfc.nasa.gov

† The v2 product is not available via NSIDC over the 2002–2010 period, however data using the same algorithm is available from July 2012–present. Contact authors for availability.
‡ Contact authors for availability.

2.12 Snow course data

Snow course data (which are fully independent of the point snow depth measurements assimilated into GlobSnow) were acquired for evaluation of the gridded SWE products. While more limited in number than snow depth observations, these

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~~transect measurements provide better consideration of sub-grid scale variability not available from operational snow depth networks which provide only single point measurements of snow depth.~~

The suite of gridded SWE products described in Section 2.1 are validated with a network of in situ snow course measurements from multiple national and regional agencies. These data consist of manual gravimetric snow measurements made at multiple locations along a pre-defined transect that are averaged to obtain a single SWE value for a given snow course on a given day. Measurements are collected along the same transect multiple times each snow season. By averaging multiple samples along a transect, the resulting SWE measurement provides better representation of sub-grid scale variability than a single point measurement and so is more suitable for evaluation of SWE at the scale of the gridded products. These snow course data are fully independent of the point snow depth measurements assimilated into GlobSnow and ERA5. Transect length, number of samples collected along each transect, and sample aggregation methods differ among reporting agencies as described below.

Russia has a long-term snow course network located near 517 meteorological stations (Bulygina et al., 2011). The snow survey transects extend for 1 to 2 km in open areas, and 500 m at forested sites. Measurements are made every ten days when at least half of the visible area around a station is snow-covered, except at forested sites where measurements are made once per month prior to 20 January. Sampling frequency is increased to five days during the spring snow melt season. The Finnish snow course network, maintained by the Finnish Environment Institute (SYKE), consists of approximately 200 transects distributed across the country. Measurements are conducted monthly around the 15th of each month, with a subset of snow courses also measured at the end of each month. Each snow course is 2 to 4 km long~~,~~ and extends through variable land cover consistent with the surrounding landscape~~.~~ (Haberkorn, 2019).

The Canadian snow course data ~~were acquired from~~are a recently updated collection pooled from a series of national and regional networks described in Brown et al. (2019). There is no comprehensive national strategy in Canada to obtain a spatially representative collection of snow course measurements. Snow courses are maintained by various jurisdictions resulting in a spatially heterogeneous sample distribution heavily biased towards population centres. For 2002 through 2010, there were ~~>~~more than 1000 ~~different~~unique snow course locations across Canada with varying sampling frequency. Measurements are typically made around the 1st and 15th of each month during the snow season (November to April). Snow courses are roughly 150 to 300 m long consisting of five to ten sampling locations (Brown et al., 2019). While the network density is ~~very~~ sparse across Canada~~,~~ and the transects are ~~much~~ shorter in length than the Russian and Finnish data, previous analysis suggests the measurements still capture reasonable landscape mean values (Neumann et al., 2006).

~~The~~ Because snow course measurements are only acquired during the snow season and zero SWE values are not reported in a consistent manner across all jurisdictions, zero SWE is not a reliable measure of snow-free conditions. All zero snow course observations were ~~converted into bi-weekly~~therefore removed prior to spatiotemporal aggregation (Sect. 2.3); SWE product zero values were also excluded. Finally, it is difficult to attach specific uncertainty values to the snow survey measurements because non-standard sampling tools are used between snow courses (e.g. no consistent snow corer diameter). Full discussion

of snow course measurement protocols and instruments is available elsewhere (Goodison et al., 1981; Brown et al., 2019; Haberkorn et al., 2019), but there is no doubt that uncertainty associated with the individual measurements (± approximately 5%; Brown et al., 2019) is overwhelmed by uncertainty in how the snow course measurements represent the landscape mean at the scale of the gridded ~~datasets. Observations were~~SWE products.

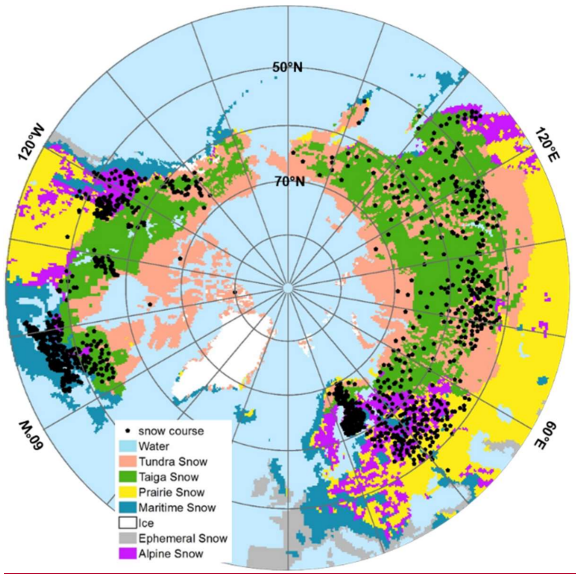


Figure 2. Centroid of 25km EASE grid cells with snow course observations used in the analysis (Sect. 2.3) overlaid on Sturm et al (1995) snow classes; snow class dataset: Sturm et al. (2009).

2.3 Validation and intercomparison methods

We assess the gridded products in two separate analyses conducted for the snow season (defined here as November – April (NDJFMA)) from November 2002 – April 2010. The first assessment is termed a *validation* because it evaluates each gridded product using the snow course data as a measure of ground truth. While the relative sparseness of the snow course measurements limits the assessment's spatial and temporal completeness, it nonetheless considers a broad range of snow classes covering both Northern Hemisphere continents (Fig. 2) and considers seasonal variability from November through April over eight years of interannual variability. We are unaware of any other studies that have evaluated the breadth of products examined here with similarly representative data and with comparable spatial and temporal coverage. The second assessment is termed an *intercomparison* and is similar to the analysis performed in Mudryk et al. (2015). This second type of

analysis is spatially and temporally complete (across the seasons and period considered). We use this analysis as it provides a more complete measure of differences among the products and is able to more readily discern differences and discontinuities between products than the validation analysis (see results regarding ERA5 in Sect. 3.3).

For the *validation* analysis, SWE product grid cells must be matched in both space and time with the snow course measurements. To achieve this, snow course observations from Canada and Finland were first grouped into bi-weekly periods using a 16 day window centred on the 1st or 15th of each month. ~~Over~~Likewise, over Russia, observations were grouped into ten-~~-~~day periods ~~corresponding to~~centred on the typical measurement dates (10th, 20th, 30th of each month). ~~For each time step, the average of all snow course measurements within a 25 x 25 km EASE2 grid cell was obtained.~~For each temporal grouping, snow course measurements falling within a given 25 x 25 km EASE grid cell (Brodzik et al., 2012) were averaged together, thereby forming a gridded snow course field (Fig. 2). Roughly 30% of these snow course grid cells had two or more separate snow courses which were averaged together while the remaining 70% had only one snow course observation. Grouping the snow course data had the largest impact over Canada and Russia where 35% and 20% of grid cells, respectively, had multiple snow courses. Although Finland's snow course network is representative of the landscape's different snow-climate classes (Sturm et al., 1995), in Canada, and to a lesser extent over Russia, tundra environments which are often remote, are under-sampled while maritime and alpine snow types are oversampled (Fig. 2).

For the validation analysis, we included all nine products in Table 1, to consider the range of available products and show the difference in performance between subsequent product generations (e.g. MERRA to MERRA2). For a given measurement date, each EASE grid cell with snow course data was paired with corresponding SWE values from each of the nine gridded products. The paired SWE values correspond to the grid cell at each product's native resolution that intersects with the centroid of the snow course EASE grid cell. In order to fairly compare how the gridded products perform against one another, only snow course data from EASE grid cells with corresponding paired values from all nine of the SWE products were analysed. This means that regions of complex topography are implicitly excluded from the validation analysis because they are masked in GlobSnow. Analyses were conducted for the snow season only (November – April). Bias and root mean squared error (RMSE) were calculated for each product-snow course pair and then averaged over the full November 2002 – April 2010 time period; correlation was calculated from all data pairs for the November 2002 – April 2010 period. To understand the influence of seasonality on product performance, bias, RMSE and correlation were also computed across all years for each biweekly period (10 day period for Russia). Validation statistics ~~in Sect. 3.2 are reported for this gridded dataset~~were calculated separately for each national snow course dataset in order to separate any sensitivity to differences in snow course measurement protocol and sample distribution. Finally, to determine the influence of SWE magnitude on product performance, all snow course-product SWE pairs were binned into 10 mm increments according to the snow course SWE. For each 10 mm increment the average product SWE was plotted against the bin midpoint.

The *intercomparison* analysis does not consider the snow course measurements, only the nine gridded SWE products. For this analysis, daily SWE from each product was interpolated to a regular 1° x 1° longitude–latitude grid. SWE values over glaciers and large lakes were excluded based on the MERRA land fraction mask (consistent with Mudryk et al., 2015). To determine the strength of agreement among datasets we use three metrics, all applied to SWE or snow mass anomalies (i.e. with the seasonal cycle removed). We only consider anomalies due to the results from Mudryk et al. (2015), which demonstrated that while different snow products can have substantial spread in their climatological snow estimates, one can and should expect a reasonable degree of agreement in their interannual and intraseasonal variability. First, we considered the correlation between each product's time series of daily Northern Hemisphere snow mass anomalies (SWE integrated over the entire Northern Hemisphere land area). Each product's time series was calculated using its respective climatology (determined for the snow season over the November 2002–April 2010 period). A correlation coefficient was calculated for each pair of datasets by correlating the two snow mass anomaly time series cropped to the snow season (November–April) over the April 2002 – November 2010 period. Secondly, we considered correlations between the patterns of anomalous SWE fields. Daily SWE anomalies were calculated for each product using its respective climatology. For each dataset pair, we calculated the daily pattern correlation between the two anomalous SWE fields and averaged the sequence of correlation values over the snow season for the 2002–2010 period. These first two metrics are bulk measures of agreement, specifically in their estimates of Northern Hemisphere snow mass anomalies and the average agreement of their pattern correlations. Finally, we also considered 'local' correlation maps of anomalous SWE. As above, we calculated daily anomalous SWE fields. Then for each dataset pair, we calculated the correlation coefficient between the daily time series of anomalous SWE at each location on the 1° x 1° grid. The correlation calculation only considers the snow season (November – April) over the November 2002 – April 2010 period. This third metric allows us to consider which regions agree more and less among the various products.

3 Results

3.1 Climatology

There is notable disagreement in the climatological SWE distribution over the ~~northern hemisphere~~Northern Hemisphere land area between standalone passive microwave products and the other data sources (Fig. 1). The pattern of high and low SWE between western and eastern Siberia is reversed for the ~~four~~ snow analyses and GlobSnow versus the two AMSR-E algorithms. This inconsistency across Eurasia was also ~~evident~~identified in analysis of older versions of passive microwave derived SWE data (e.g. Rawlins et al., 2007), reanalysis, and climate model simulations (see Fig. 2 in Clifford et al., 2010). The AMSR-E products also fail to capture a pronounced region of high SWE in eastern Canada present in the other datasets. The GlobSnow climatology is in close agreement with the snow analyses, particularly over Eurasia. The ~~four~~ snow analyses and GlobSnow also agree with other SWE climatologies derived from other sources covering different time periods and thus not included in this study (see Brown and Mote, 2009; Liston and Hiemstra, 2011).

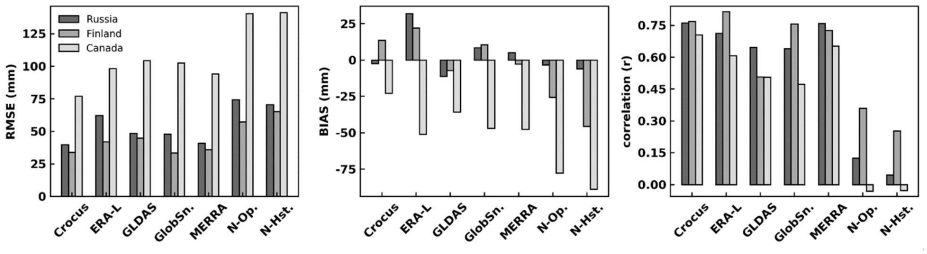
The difference in climatological SWE patterns is not solely due to the well-documented systematic underestimation in passive microwave retrievals when SWE exceeds 150 mm (Markus et al., 2006). Eastern Siberia is a low winter-season precipitation environment with very cold surface temperatures. These are ideal conditions for a thin, low density snowpack (see Liston and Hiemstra, 2011), likely composed primarily of faceted snow grains due to kinetic metamorphism, as seen in the Canadian Arctic (Derksen et al., 2014) and Alaskan North Slope (Hall, 1987). Thin snow composed of large faceted grains results in exaggerated scattering relative to the amount of SWE (Hall et al., 1991), hence the comparatively large SWE estimates for the standalone passive microwave products.

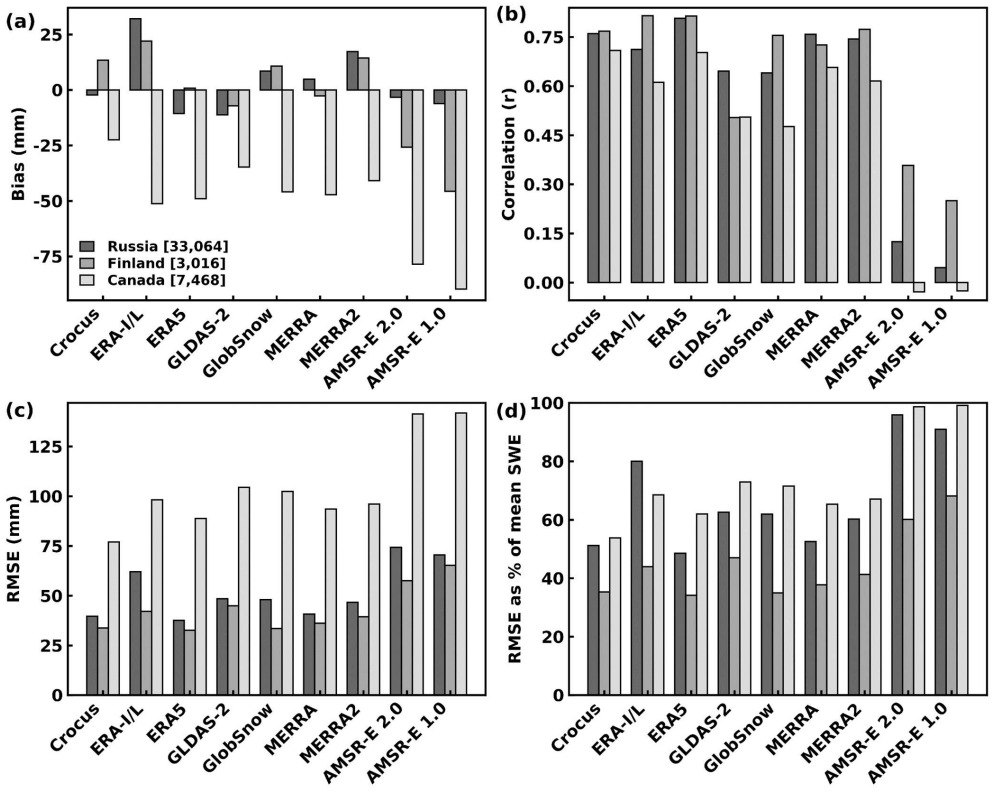
The ~~source of inability of~~reason the standalone passive microwave products fail to capture higher SWE in western Siberia, Russia, northern Europe, and eastern Canada is less clear, but may be related to weaker scattering signatures from smaller grained and deeper snow, which is further masked by microwave emission from forest cover. The ability of GlobSnow to retain sensitivity to deeper snow than the AMSR-E products is due to the assimilation of daily surface snow depth observations which work to 'nudge' the retrievals to higher values (Pulliainen, 2006). In observation-~~,~~sparse regions such as northern Quebec, the GlobSnow retrieval ~~must rely~~is more ~~on~~heavily weighted to the passive microwave retrievals, which increases uncertainty in these areas (Larue et al., 2017; Brown et al., 2018) compared to forested, deep snow regions with a dense observation network such as Finland (Takala et al., 2011).

3.2 Comparison with ~~Surface Measurements~~surface measurements

The ~~seven~~nine gridded SWE datasets were compared to Canadian, Finnish, and Russian snow course measurements for all snow seasons (November–April) over the November 2002 ~~to April 2010 period. The results are summarized by each national snow course dataset in order to separate any sensitivity to differences in snow course measurement protocol and sample distribution. Statistics were computed for SWE product grid cells matched up in space and time with the gridded snow course measurements (Sect. 2.1). To permit comparison between products, only grid cells with coincident values from all seven SWE products were retained. Mountain areas were excluded from the analysis because they are masked in GlobSnow. A summary of the validation results is provided in Fig. 2~~– April 2010 period. A summary of the validation results is provided in Fig. 3.

~~a~~ ~~b~~ ~~c~~


Russia
Finland
Canada
RMSE (mm)
BIAS (mm)
correlation (r)
Crocus
ERA-L
GLDAS
GlobSn.
MERRA
N-Op.
N-Hst.



305 **Figure 23.** Validation statistics (a: ~~RMSE~~bias; b: ~~Bias; c:~~ correlation; c: RMSE; d: RMSE as percentage of mean SWE) for the ~~seven~~nine SWE products for November through April, 2002–2010. ~~N-Op. and N-Hist. refer to the AMSR-E operational and historical products, respectively.~~ [ERA-I/L = ERA-Interim/Land; GlobSnow = GlobSnow v2.0]. Total number of grid cells with snow course measurements in square brackets in panel a.

310 All products exhibit weaker skill over Canada, where the RMSE for all products is roughly twice that of Finland and Russia. Larger absolute bias and RMSE over Canada may be attributed, in part, to a higher average SWE ~~(mean of all snow course observations > 140 mm compared to < 100 mm for both Finland and Russia).~~since the mean SWE of all snow course grid cells used for validation (Sect. 2.3) is 143 mm in Canada compared to 96 mm in Finland and 76 mm in Russia. However, the RMSE, expressed as a percentage of the mean observed SWE (of grid cells used in the analysis) is still higher over Canada for almost

all products, indicative of poorer relative performance. The exception is ERA-Interim/Land which has poorer relative performance over Russia than over either Finland or Canada, consistent with product intercomparisons from Mudryk et al. (2015).

Crocus had the smallest bias over both Canada (-22 mm) and Russia (-2.3 mm); Crocus and ERA5 had the strongest correlations over Canada (~0.7). ERA5 had the lowest RMSE and strongest correlation over Finland (33 mm, 0.8;tied with ERA-Interim/Land) and Russia (38 mm, 0.8), and the lowest bias over Finland (0.8 mm). Performance of the standalone passive microwave products (AMSR-E) is noticeably weaker for all regions and validation statistics ~~with the exception of bias over Russia. Crocus had the smallest RMSE and bias and strongest correlation over both Canada and Russia. Over Finland and Russia, all except the AMSR-E products have RMSE values of approximately 50 mm or less, with the exception of ERA-land over Russia.~~(with the exception of bias over Russia). RMSE for the standalone passive microwave products is nearly double that of the best performing product for both Finland and Canada, with slightly better results over Russia. For Finland and Russia, bias ranged between ±15 mm for all datasets except ERA-~~land~~Interim/Land (> +20 mm) and the standalone passive microwave products~~.~~ and MERRA2 over Russia (+17 mm). Over Canada, bias ranged from -23 to -51 mm for all but the AMSR-E products ~~(~~(bias of -78 to -~~89~~90 mm). ~~Correlation~~For all regions, correlation coefficients for all but the standalone passive microwave products ~~was~~were ~0.5 and greater. The AMSR-E products exhibited lower or even negative correlations with snow course measurements for all three reference datasets.

We find that among GlobSnow, Crocus, ERA-~~land~~Interim/Land, ERA5, GLDAS~~, and~~-2, MERRA and MERRA2 no individual product consistently performs best with respect to the RMSE, bias, and correlation statistics *across all regions*. This is an important finding, as it shows no clear advantage to using a single type of snow analysis, whether it is remote sensing combined with surface observations, an external snow model driven by reanalysis meteorology, or the land surface schemes within reanalyses. With higher RMSEs, greater bias, and weaker correlations relative to the other ~~five~~seven datasets, this assessment ~~raises concerns about~~shows the ~~ability of current~~ standalone passive microwave algorithms ~~to~~do not perform in a comparable fashion to the other products. ~~It is important to note that the RMSE of the best performing products is at the margins of acceptable uncertainty for operational and scientific requirements (Rott et al., 2010; Larue et al. 2017; Derksen and Nagler, 2019).~~

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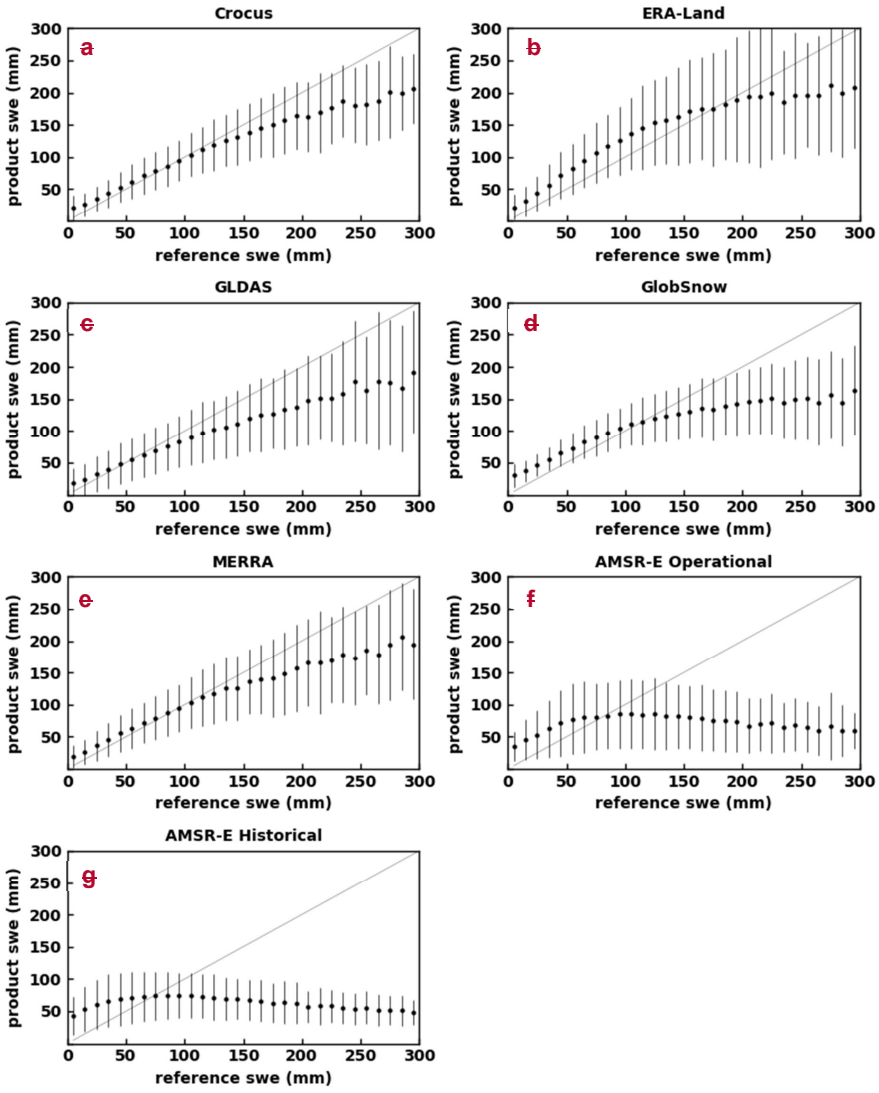
To determine the influence of SWE magnitude on product performance, all three reference snow course datasets were binned into 10 mm increments for comparison with the gridded SWE estimates (Sect. 2.3, Fig. ~~3~~4). Crocus and MERRA perform ~~in a similar fashion,~~ similarly, with reasonable agreement up to about 150 mm of SWE and a tendency to ~~under (over) estimate~~underestimate SWE for deeper ~~(shallow)~~ snow~~.~~ and overestimate SWE for shallow snow. MERRA2 behaves in a similar fashion, but slightly overestimates SWE below ~150 mm. The performance of GLDAS-2 and ~~GlobSnow~~ERA5 is similar to Crocus and MERRA~~,~~ except that ~~GLDAS underestimates~~ they both underestimate SWE across a larger range of reference values ~~(above ~~(≥100 mm), consistent with the negative bias in Fig. ~~2b, while~~ 3b (with the exception of ERA5 over Finland). GlobSnow overestimates SWE up to ~100 mm~~.~~ and underestimates above ~130 mm while ERA-~~land~~Interim/Land

overestimates SWE up to ~180 mm, consistent with the positive bias over Russia and Finland (Fig. ~~2b).~~3b) The ~~historical~~ AMSR-E v1.0 product exhibits low sensitivity to SWE, especially for values >~~60~~70 mm and overestimates low SWE values. Better results were found for the newer AMSR-E ~~operational algorithm~~v2.0 product, although the retrievals plateau at about 100 mm, and show no sensitivity to further SWE increases.


Crocus
a
ERA-Land
b
GLDAS
c
GlobSnow
d
MERRA
e
AMSR-E Operational
f
AMSR-E Historical
g
product swe (mm)
reference swe (mm)
0
50
100
150
200
250
300

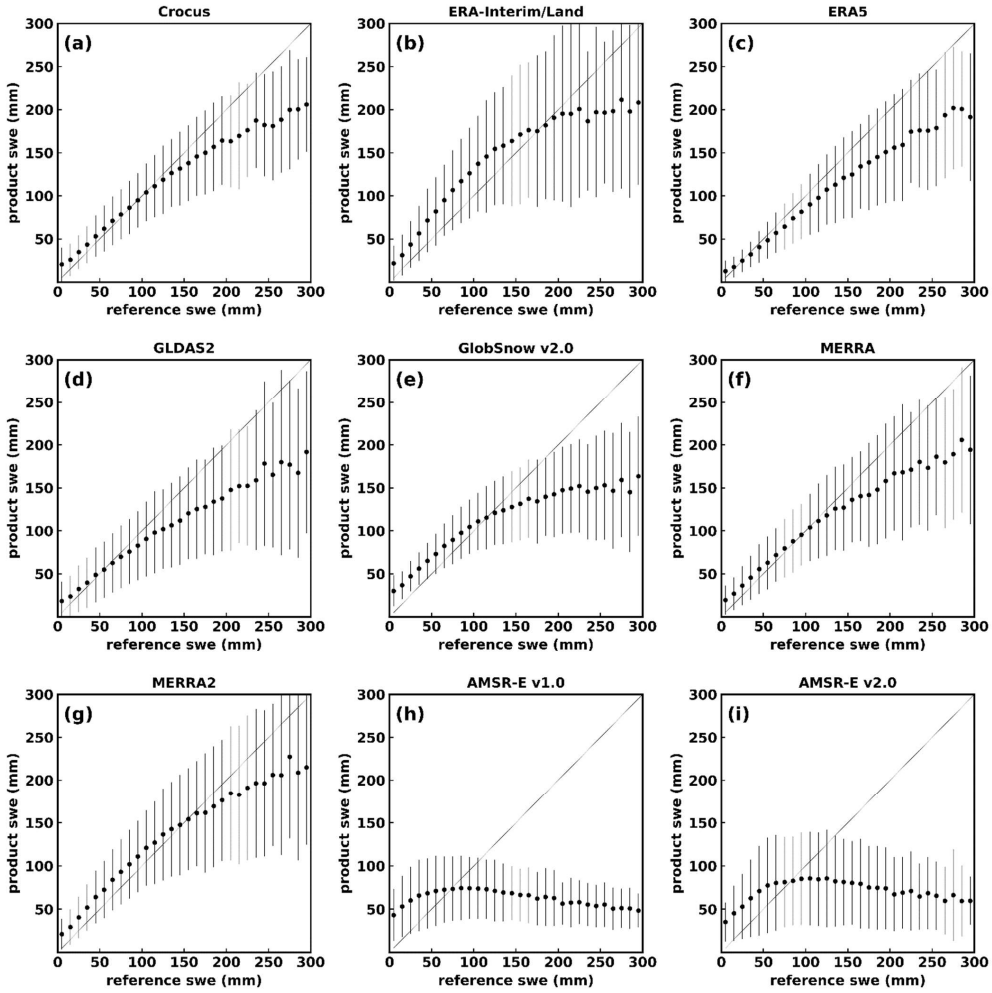


Figure ~~3. Retrieval performance~~4. Performance of SWE datasets versus reference SWE ± 1 standard deviation for (a) ~~GlobSnow; (b)~~ Crocus; (~~c) GLDAS~~b) ERA-Interim/Land; (c) ERA5; (d) ~~MERRA~~GLDAS-2; (e) ~~ERA-land~~GlobSnow v2.0; (f) MERRA; (g) MERRA2; (h) AMSR-E ~~historical; (g~~v1.0; (i) AMSR-E ~~operational~~v2.0. SWE values above 300 mm are not shown.

To quantify the influence of seasonality on product performance, validation statistics (RMSE, bias, correlation) were computed at a bi-weekly time step (10 days for Russia) for 2002 through 2010. (Sect. 2.3). Figure 45 shows the monthly evolution from

November through April over Russia and provides insight into both the seasonal evolution of product-specific uncertainty~~,~~ and the spread in uncertainty between products. In general, RMSE and bias magnitude both increase over the course of the snow season. Early in the snow season, the RMSE and bias magnitudes are low because snow is shallow, although even small errors can produce high relative RMSE. As SWE increases through the snow accumulation season, the RMSE ~~magnitude~~ and the spread in RMSE between products increases. ~~Bias becomes~~While not true for every product, bias also tends to become increasingly negative over the course of the snow season ~~with the notable exception of ERA-land (over Russia) which trends towards larger positive values. This is consistent with anomalously high SWE in ERA-land over Eurasia reported elsewhere (Mudryk et al., 2015). Toward~~. By the end of the snow season, inter-product spread in ~~the error statistics~~RMSE and bias are at a maximum. Peak uncertainty late in the season is driven by cumulative errors over the entire season, differences in the timing of snow melt onset, and different melt rates. Whereas the RMSE and bias evolve over the course of the snow season, the magnitude of correlation for all but the AMSR-E products is stable. This is an encouraging result as it indicates that SWE anomalies should be reasonably realistic throughout the season, even if climatological amounts of SWE differ strongly between analyses. A similar seasonal evolution of product specific uncertainties is observed for both Finland and Canada (not shown).

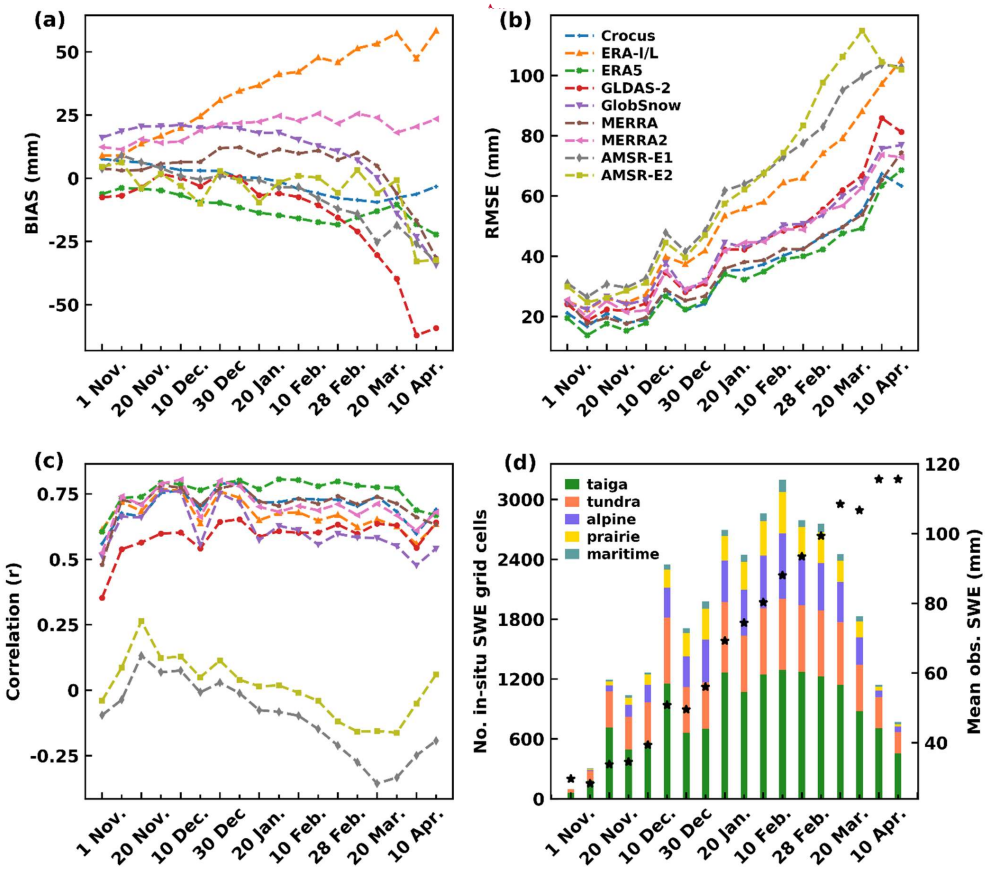


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Figure 5. (a) Bias, (b) RMSE and (c) correlation coefficient relative to the Russia snow course dataset (Section 2.1) for each ten day time step over the 2002–2010 period. (d) Number of grid cells with ~~the bulk comparison to the snow course measurements~~snow course observations by Sturm snow class (bars, left-hand axis), mean observed SWE (stars, right-hand axis). [ERA-I/L = ERA-Interim/Land, GlobSnow = GlobSnow v2.0].

380 The previous analyses summarized in ~~Fig. 2, and the summaries of product performance versus SWE magnitude in Fig. 3,~~ Figures 2–4 indicate that Crocus ~~and~~, MERRA ~~appear to~~and ERA5 perform slightly better than the other reanalysis-based products and GlobSnow, while the two AMSR-E products ~~exhibit a greater degree of uncertainty. Crocus tends~~

~~to have biases near zero and a low RMSEs for most regions and time steps~~ perform substantially worse. To what extent do these conclusions suggest that one should choose a single gridded SWE product as ~~does MERRA, except late in~~ the 'best' dataset? We address this question by analyzing how the error statistics (RMSE and correlation) of multiple-product combinations compare to those of individual products. Such multi-product SWE ensembles have previously been employed to charaterize uncertainty (e.g. Mudryk et al., 2015, 2017, 2018a; Krinner et al., 2018). Here we demonstrate that such ensembles also tend to improve overall accuracy. The two AMSR-E products were excluded from this analysis because of the low correlation with snow course measurements as illustrated in Figs. 3c, 4h, 4i, and 5c. Further, for this analysis, we did not separate error statistics by country (Russia, Finland and Canada are considered on aggreate). Figure 6a confirms the conclusion that Crocus, MERRA and ERA5 perform slightly better than the other products since the average of all product combinations that involve those particular snow analyses have lower RMSE and higher correlation than averages involving the remaining products. However, we find that combinations of products often have a lower RMSE and higher correlation than individual products. For example, *any* possible combination of two or more products has improved RMSE and correlation compared to GLDAS-2, GlobSnow or ERA-Interim/Land considered individually (not shown explicitly). For MERRA and MERRA2, more than 90% of all possible combinations of two or more products have improved RMSE and correlation compared to the single product. For Crocus, approximately 40% of product combinations have improved RMSE and correlation [than the single product] while for ERA5, 70% of all possible product combinations have lower RMSE and 35% have higher correlation. This tendency for multi-product combinations to have improved accuracy is demonstrated generally in Figure 6b. As the number of products included in a multi-product combination increases, the correlation improves and the RMSE decreases with the lowest RMSE and highest correlation attained when all seven products are combined. This improvement in accuracy suggests that, to some extent, each product has randomized errors which are averaged out by considering multiple products. Because the RMSE of even the best performing products is at the margins of acceptable uncertainty for operational (<15%; Rott et al., 2010; Larue et al. ~~snow season.~~2017) and scientific (10-25%; Derksen and Nagler, 2019) requirements, the increase in accuracy represents a simple method to yield performance gains.

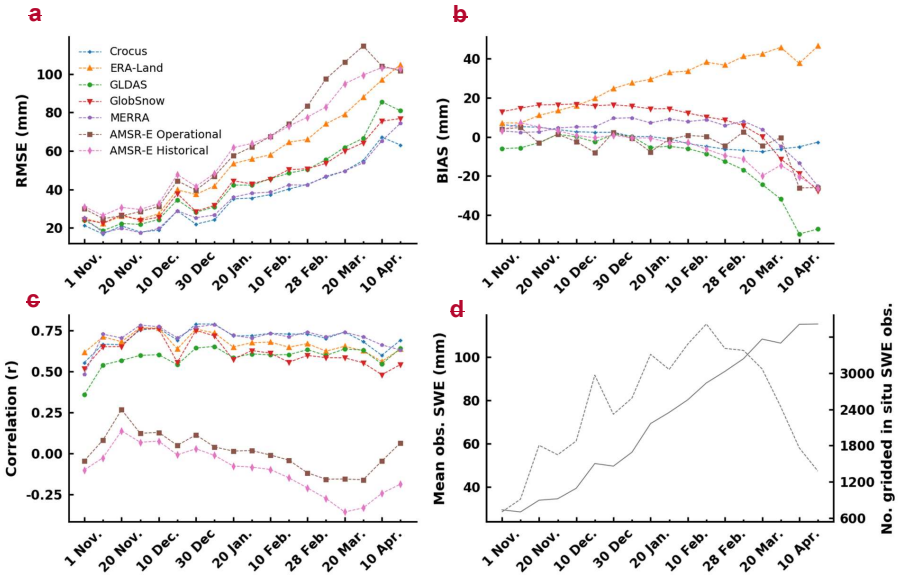

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Figure 4. (a) RMSE, (b) bias and (c) correlation coefficient relative to the Russia snow course dataset (Sect. 2.1) for each tenday time step over the 2002-2010 period. (d) Solid line: mean SWE value over all Russian snow course measurements for each time step; dashed line: number of Russian gridded snow course observations.

Given that no one product is always the best performer with respect to error statistics and regions analysed, we investigated the effect of using multi-product SWE ensembles to minimize uncertainty (e.g.

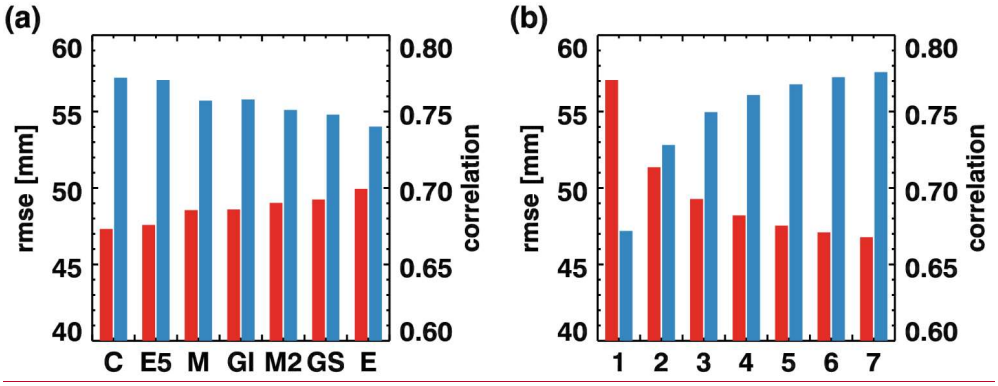
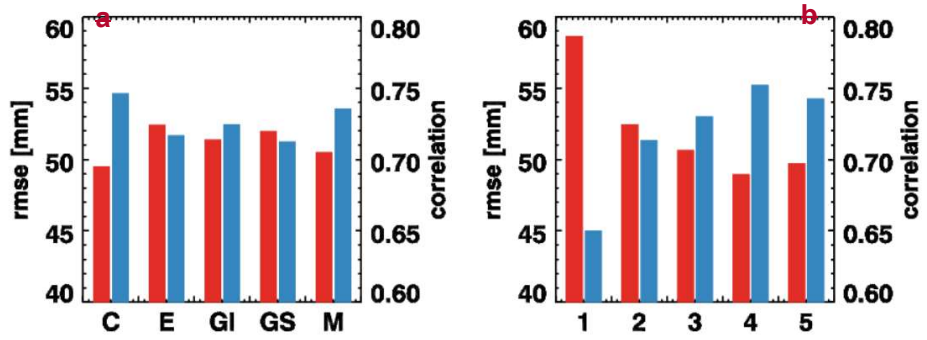


Figure 6. Mudryk et al., 2015, 2017, 2018a; Krinner et al., 2018). The two AMSR-E products were excluded from this comparison because of the low correlation with snow course measurements as illustrated in Figs. 2c, 3f, 3g, and 4c. As the number of products included in a given inter-product ensemble increases, the correlation improves and the RMSE decreases (Fig. 5b). The level of improvement, however, saturates when four products are included in the ensemble. In addition, ensembles that contain contain Crocus and/or MERRA perform better than those that do not (Fig. 5a). This suggests that although there is no single best product, there are some products (Crocus and MERRA) that should be included in any multi-product mean. Importantly, four- and five- product ensembles that include Crocus and MERRA have higher (lower) correlation (RMSE) with snow course measurements compared to that of any individual product.



~~Figure 5.~~ RMSE (red) and correlation (blue) of snow course measurements with various combinations of SWE products. (a) Average of all combinations that contain the specified individual product [C = Crocus, ~~E = ERA-Land~~E5 = ERA5, M = MERRA, , Gl = GLDAS-2, M2 = MERRA2, GS = GlobSnow, ~~M = MERRA~~ v2.0, E = ERA-Interim/Land] and (b) average of all combinations of N products as specified on x-axis.

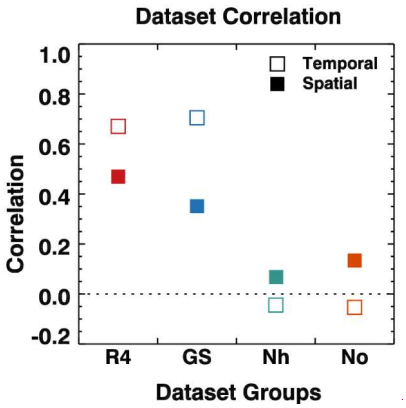
3.3 Correlation Analysis

~~To determine the strength of agreement among datasets, two types of pairwise correlations were calculated. Temporal correlations were calculated for time series of daily northern hemisphere snow mass (SWE integrated over the land area). A value was determined for each pair of datasets by correlating the two snow mass anomaly time series for all winter days (November–April (NDJFMA)) over the 2003–2010 period. Spatial correlations were calculated for a given dataset pair by averaging the sequence of pattern correlations of anomalous daily SWE calculated for all winter days (NDJFMA) over 2003–2010. Both anomalous SWE fields and anomalous snow mass were calculated for each dataset using its respective 2003–2010 climatology. Calculated as such, these correlations reflect both intra-seasonal and inter-annual covariance.~~

~~In all cases~~To determine the strength of agreement among datasets, temporal and spatial correlation analysis was performed as described in Section 2.3. In preparing the datasets for intercomparison, a very strong negative trend since 1980 was found for ERA5 snow mass. This is driven by a stepwise discontinuity introduced by the assimilation of satellite derived binary snow/no-snow estimates starting in 2004 (Patricia de Rosnay, personal communication; see supplementary Fig. 1). While this change addressed a positive snow extent bias during the melt season (e.g. Orsolini et al., 2019), it renders the raw ERA5 snow mass time series is unsuitable for climate analysis. We therefore considered ERA5 separately from the other snow analyses (Crocus, GLDAS-2, MERRA2, ERA-Interim/Land) for the intercomparison analysis. Results obtained substituting MERRA with MERRA2 were similar so only those including MERRA2 are presented. In the subsequent analysis R4 refers to a suite of four products (Crocus, GLDAS-2, MERRA2 and ERA-Interim/Land) that rely on reanalysis in some way.

Each of the products in the R4 suite exhibit moderately strong spatial and temporal correlations with each other (Fig. 7). The correlations, ranging between 0.5 and 0.7, represent the average of the six pairwise combinations of these four products. The agreement among these four datasets is consistent with the expected coherence of their forcing meteorologies and the relative influence of land model and meteorological forcing on hemispheric scale snow mass previously established by Mudryk et al. (2015). While Figure 7 illustrates that the spatial patterns of ERA5 snow mass anomalies are comparable those of GlobSnow and the R4 products, the stepwise discontinuity in its climatology lowers the correlation of its snow mass time series. It is possible to correct for this discontinuity in an *ad hoc* manner by adjusting the snow mass starting in the fall of 2004 by the difference in the climatology before and after the discontinuity. Applying this correction yields correlation values more in line with those seen among the R4 products and GlobSnow. For the snow analyses and GlobSnow, the mean pattern correlation is lower than the corresponding temporal correlation of total snow mass (Fig. ~~6~~7). This ~~result~~ may be due to the presence of opposite-signed spatial biases that cancel when spatially aggregated into a snow mass time series. ~~The four datasets which rely on reanalysis in some way (Crocus, GLDAS, MERRA, ERA-land) exhibit a moderately strong spatial and temporal correlation~~

~~with each other. These correlations range between 0.5 and 0.7 (illustrated in the R4 symbols in Fig. 6), and represent the~~
460 ~~average of the six pairwise combinations of these four products. The agreement among these four datasets is expected since ERA-land and Crocus both use the same forcing meteorology (Table 1), and the ERA meteorology is itself well correlated with that of MERRA and GLDAS. GlobSnow, which is completely independent from the products using reanalysis, is reasonably well correlated (especially the temporal correlations) with the R4 products (illustrated in the GS symbols in Fig. 6). There~~In contrast to the snow analyses and Globsnow, there is a lack of temporal and spatial correlation between the AMSR-
465 E products and the R4 datasets. Spatially, this is an expected result given the differences in climatological SWE patterns shown in Fig. 1. The weak temporal correlation means the ~~SWE~~snow mass anomalies do not evolve in-phase with the other products as the snow season evolves.



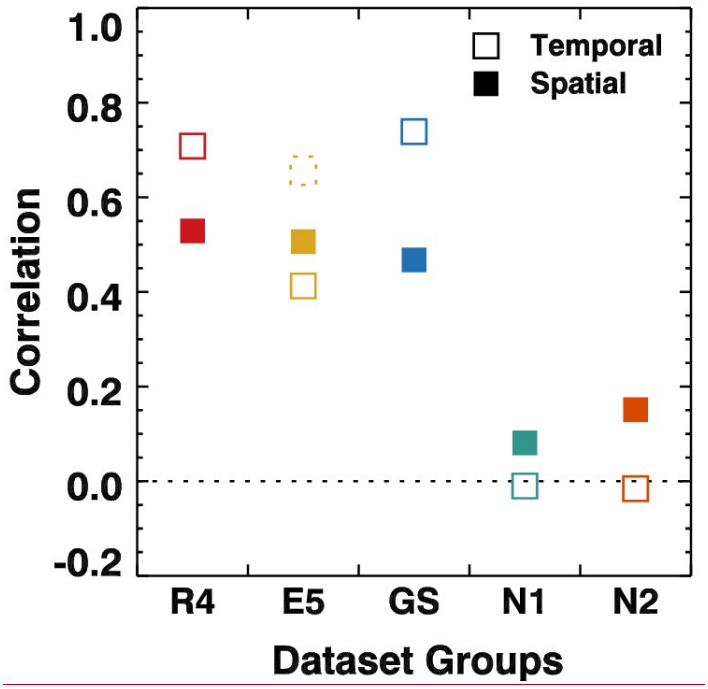
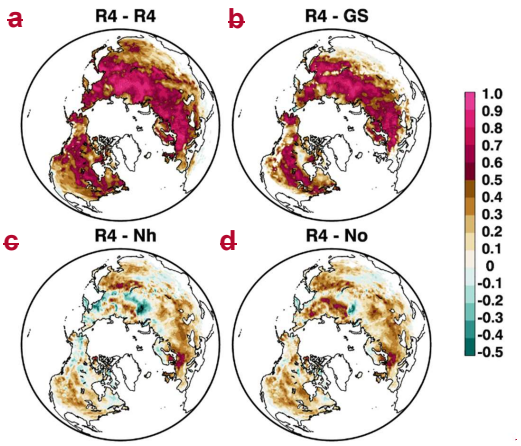


Figure ~~6. Representative values for temporal~~ 7. Temporal and spatial correlations among groups of products over the ~~2003~~2002–2010 time period. ~~(~~Temporal correlations assess the extent to which ~~total~~anomalous northern hemispheric snow mass jointly evolves between pairs of datasets~~;~~ while spatial correlations assess the pattern correlation of SWE fields for pairs of datasets~~.) See;~~ see text for details. R4 = the average of 6 pairwise correlations between Crocus, GLDAS-2, ERA-~~land~~Interim/Land, and ~~MERRA.~~ MERRA2. E5 = the average of 4 pairwise correlations between ERA5 and each R4 product. GS = the average of 4 pairwise correlations between GlobSnow v2.0 and each R4 product. ~~Nh~~N1 = the average of 4 pairwise correlations between AMSR-E ~~historical~~v1.0 and each R4 product. ~~No~~N2 = the average of 4 pairwise correlations between AMSR-E ~~operational and each R4 product~~v2.0 and each R4 product. The dotted square shows the impact of correcting the E5 snow mass anomalies for a discontinuity introduced in 2004.

Further insight is gained through the calculation of correlation maps among groups of datasets (Fig. ~~7~~8), where temporal correlations of daily SWE are calculated ~~as above~~analogous to Northern Hemisphere snow mass but for each grid cell. As expected, the ~~modern era~~ reanalysis datasets are strongly correlated to each other (R4-R4 and R4-E5 in Fig. ~~7~~8). Correlations between GlobSnow and the R4 products are strong across most snow covered regions of the ~~northern hemisphere~~Northern Hemisphere (GS-R4), with the exception of parts of Arctic Canada and the ephemeral snow zones of both North America and Eurasia (note that alpine areas are masked in the GlobSnow product). ~~–~~As noted earlier, the performance of GlobSnow is

closely tied to the density of snow depth data used as inputs to the retrievals (Larue et al., 2017; Brown et al., 2018) which likely contributes to the low correlations in parts of Arctic Canada where there are relatively few snow depth observations. The NASA AMSR-E ~~historical~~v1.0 dataset exhibits very weak anomaly correlations with the R4 datasets (~~Nh~~N1-R4), and even negative correlations over the boreal forest of North America and parts of central and eastern Siberia. The AMSR-E ~~operational~~v2.0 algorithm shows improved anomaly correlations over eastern Siberia (~~No~~N2-R4; likely by better accounting for the combination of shallow snow and large snow grains found in this region (Tedesco and Jeyaratnam, 2016)) and the boreal forest of North America, although correlations remain weak over the remainder of the snow-covered northern hemisphere.



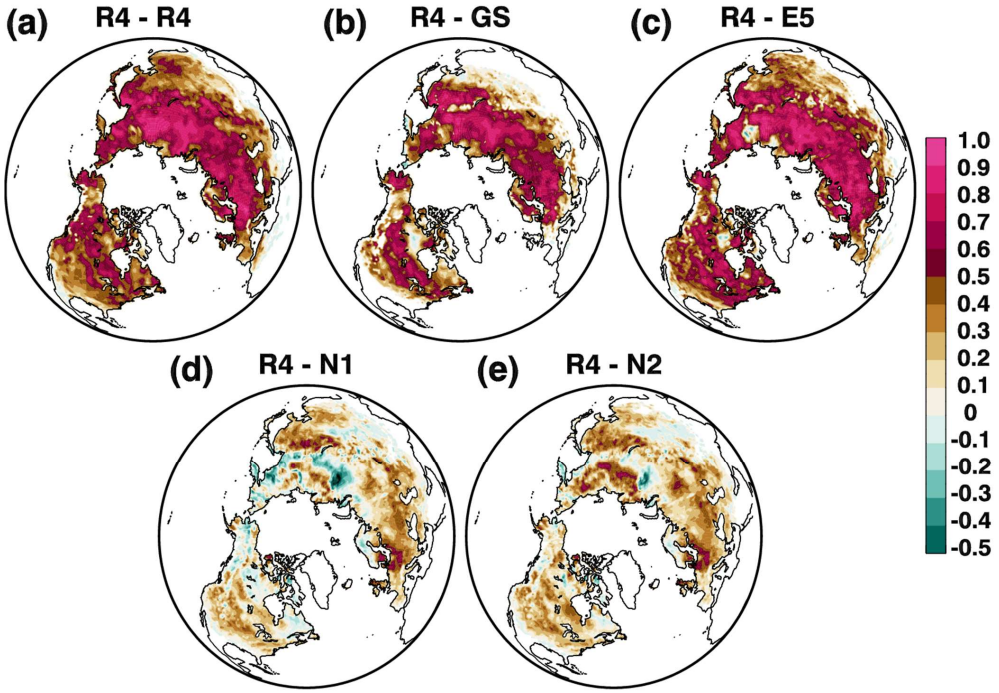


Figure ~~7~~8. Correlation maps (2002–2010) for four reanalysis driven products (Crocus, GLDAS-2, ERA-~~land~~Interim/Land, and ~~MERRA~~MERRA2) relative to: (a) ~~each~~ each other (mean correlation between the four reanalysis driven products); (b) GlobSnow v2.0; (c) ~~the~~ERA5; (d) NASA AMSR-E ~~historical product; (d) the operational~~SWE v1.0; (e) NASA AMSR-E ~~algorithm~~SWE v2.0.

4. Conclusions and Discussion

In this study, we compared three types of northern hemisphere gridded SWE products: (1) those utilizing some form of reanalysis (Crocus, ERA-~~land~~Interim/Land, ERA5, GLDAS-2, MERRA, MERRA2); (2) passive microwave remote sensing combined with surface observations (GlobSnow v2.0); and (3) standalone passive microwave retrievals (AMSR-E ~~historical product~~v1.0 and ~~operational algorithm~~v2.0). There is past evidence of acceptable algorithm performance for standalone passive microwave products, particularly in open environments with relatively shallow snow (Derksen et al., 2004; Vuyovich et al., 2014), or when SWE retrievals are converted to snow cover extent (Brown et al., 2010). At the continental scale however, the standalone AMSR-E SWE products have stark differences in climatological SWE patterns compared to other available products (see Fig. 1).

Evaluation against snow course measurements from Russia, Finland, and Canada~~,~~ show higher RMSE and bias, and lower correlation for standalone passive microwave products compared to the ~~five~~seven other datasets (Fig. 2~~3~~). While uncertainty for all products tends to increase with deeper snow, this is a critical issue for the AMSR-E products because of pronounced negative bias even at relatively low SWE values (<100 mm; Fig. 3~~4~~ and 4~~5~~). Although there is no single ~~best~~ product that consistently performs best over all regions with respect to bias, RMSE and correlation, ~~there are some products, namely~~ Crocus and ~~MERRA, that should be included in any multi-~~ERA5 do perform best across the range of snow conditions captured by the validation dataset. However, while a particular product ~~mean~~may outperform others over some regions, this is no guarantee that it will do so everywhere, so we are not recommending any one product. Furthermore, we have demonstrated that averaging multiple products together tends to lead to additional accuracy improvements (Fig. ~~5).~~ 6), while as exemplified by ERA5, a single product may have properties which lend itself to one type of analysis but make it unsuitable for others.

Correlation analysis performed with respect to both space and time shows consistent behaviour with strong statistical agreement among the ~~four~~six reanalysis-based products and GlobSnow (consistent with Mudryk et al., 2015), which clearly benefits from the ingestion of daily surface snow depth data into the retrievals~~.~~ compared to the standalone passive microwave datasets. ERA5 also assimilates point snow depth observations into a state-of-the-art assimilation system and yields excellent validation results. The slightly stronger validation for ERA5 compared to GlobSnow suggests the impact of the ERA5 assimilation system, which ingests multiple data streams, improves the SWE estimates more than the impact of passive microwave remote sensing on the GlobSnow retrievals (which also assimilates point snow depth observations). However, it is important to highlight that the validation results do not convey that the raw ERA5 snow mass time series contains a significant discontinuity in 2004, caused by an abrupt change to assimilate satellite derived snow extent information. So, while ERA5 may provide one of the better SWE estimates for instantaneous applications like numerical weather prediction, the data are unsuitable (at least in an uncorrected form) for climate analysis.

As with any continental-scale evaluation, our results may (or may not) apply to small regions or local domains, and the validation results do not apply to alpine areas which contribute a large proportion (~30%) (Wrzesien et al., 2019) to the total northern hemispheric SWE. In areas of complex terrain, uncertainty in meteorological forcing within reanalyses, particularly precipitation amount and phase (Lundquist et al., 2019) must also be considered. Further, in alpine regions the coarse resolution of the gridded SWE products (25 km or more) does not lend itself to comparison with snow course observations because of limited representativeness of surface observations in complex terrain and across elevation gradients; a different validation approach is likely needed for mountain areas.

The AMSR-E products exhibit weak spatial agreement and negative temporal anomaly correlations with the other datasets (Fig. 6~~7~~ and ~~7).~~

8). The retrieval of SWE solely from passive microwave measurements is a difficult challenge, and despite the best efforts of many research groups over many decades, passive microwave ~~- -~~based standalone algorithms do not perform as well as other methods that make use of ancillary snow depth measurements or snow models. Although there are many attractive attributes (wide swath, all-weather imaging, long legacy time series, and theoretical sensitivity to SWE under simplified assumptions) passive microwave data has always been a measurement of opportunity for snow applications, not an ~~idealized~~ideal measurement system. This introduces intrinsic biases and errors into the standalone retrieval scheme because of the non ~~"optimal"~~'optimal' nature of these measurements for snow applications.

Despite these challenges, there are opportunities to utilize satellite passive microwave measurement as a component of SWE product development moving forward. Machine learning operators show great potential for the radiance-based assimilation of brightness temperatures (e.g. Forman and Reichle 2014) analogous to how L-band brightness temperatures are assimilated for improved soil moisture analyses. Assimilation approaches also show potential for addressing challenges posed by stratigraphy (Durand et al., 2011; Andreadis and Lettenmaier, 2012) and deep snow (Li et al., 2012). While coarse resolution is an inherent challenge with satellite passive microwave measurements, enhanced resolution products spanning multiple decades are now available (~~Takala et al., 2017;~~ Long and Brodzik, 2016; Takala et al., 2017).

The combination of brightness temperature measurements, surface snow depth observations, and forward radiometric modeling are able to produce skillful SWE products. This approach was already used successfully within the ESA GlobSnow project, and ~~it~~ will be further enhanced within the ESA Climate Change Initiative (CCI) snow project. It is important to note that the brightness temperature component of the GlobSnow/Snow CCI retrieval has direct heritage to standalone passive microwave retrieval approaches which date back to the first generation of passive microwave imagers launched in the 1970s. This also suggests that research focusing on passive microwave interactions with snow parameters should not be neglected as, ultimately, better understanding of the underlying physics is a ~~necessary~~positive step for algorithm improvement.

While the continued development of a remote sensing ~~capability~~capabilities for SWE represents an important observational capability, it is necessary to also appreciate the quality of the large scale model derived SWE products. The combination of reanalysis meteorology and snow models yields very useful snow information, which can be refined as forcing data (particularly precipitation) and snow models continue to improve. Only through combined and integrated improvements in remote sensing, modeling, and observations will real progress in SWE product development be achieved and sustained.

Data availability. ~~Eric Brun~~Vincent Vionnet and Bertrand Decharme both provided data from the Crocus snowpack model; the NASA AMSR-E ~~operational~~SWE v1.0 dataset and is available from the paper's authors upon request as is the NASA AMSR-E ~~operational~~SWE v2.0 dataset. The remaining datasets are available for download via the links and references provided in Sect. 2.

Competing interests. The authors declare that they have no conflicts of interest.

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