Using CloudSat-CPR Retrievals to Estimate Snow Accumulation in the Canadian Arctic

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Abstract  Snow is a critical contributor to our global water and energy budget, with profound impacts for resource water availability and flooding in cold regions. The vast size and remote nature of the Arctic present serious logistical and financial challenges to measuring snow over extended time periods. Satellite observations provided by the Cloud Profiling Radar instrument—installed on the National Aeronautics and Space Administration satellite CloudSat—allow the retrieval of snowfall rates in high-latitude regions, which have been used to estimate surface snow accumulation. In this study, a validation of CloudSat-derived terrestrial snow estimates is presented at four Environment and Climate Change Canada weather stations situated in the Arctic for the common period 2007–2015. Comparisons of monthly climatological snow accumulation show mean biases of less than 1.5-mm snow water equivalent annually. Monthly time series exhibit correlations above 0.5 and root-mean-square error below 10-mm snow water equivalent at the two highest-latitude stations (Eureka and Resolute Bay) with correlations falling below 0.5 south of 70°N. CloudSat was also found to underestimate annual mean snow accumulation at the majority of sites, suggesting a potential negative bias in CloudSat’s accumulation estimates, or underestimation related to sampling. These results imply that CloudSat can provide reliable estimates of snow accumulation across similar high-latitude regions above 70°N.

1. Introduction

Snow in the Arctic is critical to the hydrologic cycle and energy budget of the region (Bokhorst et al., 2016; Brown et al., 2003; Déry & Brown, 2007). Changes in snow accumulation impact flood frequencies and timings and water resource availability and have important consequences to regional biological activity, diversity, and ecosystem function (Cooper, 2014; Hansen et al., 2014). Understanding the impact of climate change on Arctic snow is, therefore, of critical importance and is made more urgent by observed accelerated warming in high-latitude regions in recent years (Bromwich et al., 2013; Brown & Mote, 2009; Church et al., 2013). A common method for quantifying differences in snow accumulation is to examine changes in snow water equivalent (SWE), which is the amount of water produced by a snow pack if it was instantaneously and completely melted. In situ SWE observations above 70°N are only available from approximately 21 of 1,735 weather stations across Canada (Mekis et al., 2018). These stations provide near-continuous observational records of climate parameters such as precipitation (quantity and type) and ground temperature (ECCC, 2017). Monitoring snow accumulation (along with the associated uncertainties) allows us to identify the rates at which Arctic snow is being deposited, providing new insights into potential flood hazards along with estimates of the amount of water entering the hydrologic system during springtime melt events. Station data have been used effectively to track changes in snow accumulation at other high-latitude locations in Canada as described in Derksen et al. (2003); however, it can be susceptible to issues with blowing snow and phase identification and includes uncertainty introduced from the decisions and assumptions made in the processing of instrumental observations (Mekis et al., 2018). The expensive operational and maintenance costs required to keep weather stations running across an area as large and remote as the Canadian Arctic results in sparse data coverage and poor sampling throughout the region (Derksen & Brown, 2012; Liston, 2004).

Another option for estimating snow accumulation is reanalysis systems, which comprise a numerical model constrained by available observations to provide complete spatiotemporal coverage. Some commonly used reanalysis products for snow are MERRA-2 and the Arctic System Reanalysis (ASR), which both provide estimates of SWE across the Canadian Arctic (Bromwich et al., 2016; Gelaro et al., 2017). Differences between these products relate mainly to the details of their underlying modeling systems, and it can be challenging...
to evaluate which of a collection of similar reanalyses is the “best.” For this reason, a useful approach has been to combine a series of reanalysis products together through averaging, or “blending,” in an effort to increase the signal-to-noise ratio, much like the approach used in ensemble numerical weather prediction (Molteni et al., 1996).

An example of a blended SWE product is Blended-4, which is calculated as the mean of four daily gridded SWE products across the Northern Hemisphere (Mudryk et al., 2015). These products provide estimates of SWE in high-latitude regions but are often limited by coarse spatial resolutions and relatively few available observational constraints, which contributes to considerable uncertainties associated with their estimates (Kushner et al., 2018; Lindsay et al., 2014; Mudryk et al., 2015).

Remote sensing has great potential for collecting estimates of snow accumulation across the Arctic, as it can provide excellent spatial coverage with year-round sampling. The Cloud Profiling Radar (CPR) on board the National Aeronautics and Space Administration CloudSat satellite generates vertical reflectivity profiles of a cloud’s inner structure (Stephens et al., 2002). Derived data products from CloudSat can be used in the classification of precipitation to identify areas of hydrometeor content within a cloud and provide estimates of surface snowfall rates that agree closely with in situ SWE measurements when sufficiently aggregated at high latitudes (Behrangi et al., 2016; Matrosov et al., 2008; Tanelli et al., 2008). CloudSat is especially suited for monitoring high-latitude regions at monthly timescales due to the nature of its 16-day repeating orbit which can provide up to 25 instantaneous cloud measurements per month at 80°N (Figure 1a). However, sampling can be an issue when moving to lower latitudes as orbital granule tracks become less concentrated over a region resulting in fewer total observations compared to similarly sized grid cells at higher latitudes (Hiley et al., 2010). The effect of CloudSat’s orbit on overpass quantity is highlighted by the difference in monthly overpass counts for two stations (Eureka and Cambridge Bay) over 10° latitude in Figure 1b.

We build on the work of Hiley et al. (2010) to perform a validation of CloudSat estimates against in situ snow accumulation observations with a focus on Arctic stations (spanning 63°N to 80°N) over a prolonged CloudSat data record (2007–2015). Solid precipitation is evaluated in this study instead of total precipitation as the gridded data sets we compare against here strictly provide estimates of snow on ground. We adopt the validation criteria described in Hiley et al. (2010) and Palerme et al. (2014), who found that temporal correlations above $r = 0.5$ and root-mean-square error (RMSE) below 10-mm SWE display good agreement between CloudSat estimates and in situ and reanalysis data. These criteria are important as they allow us to assess whether CloudSat is capable of capturing the general seasonality of accumulation present at each station throughout the year. Additionally, RMSE of this magnitude is a useful metric for assessing month-to-month variability in CloudSat’s estimates of SWE accumulation at each station and allows us to identify locations and periods which exhibit high uncertainty in our analysis. These comparisons are critical to evaluate whether CloudSat can be used to provide Pan-Arctic estimates of snow accumulation.

The primary goals of this work:
1. Identify the spatial and temporal scales required for obtaining a sufficiently large number of CPR samples for comparison across the Arctic
2. Compare derived CloudSat snow accumulation estimates with station data to determine whether CloudSat is a reliable source for monitoring snow across the Arctic
3. Examine the agreement between CloudSat and reanalysis system estimates of snow accumulation by investigating their correlations, RMSE, and bias.

2. Data and Methods

2.1. CloudSat Data
The CPR installed on CloudSat is a nadir-looking 94-GHz frequency (W-band) radar that measures the power backscattered from cloud particles to identify the presence of hydrometeors within a cloud (Hudak et al., 2008; Stephens et al., 2002). CloudSat’s CPR observes the lowest 30 km of the atmosphere divided into 125 layers (bins) of 240 m in depth, with a 1.7 km by 1.3-km ground footprint (Palerme et al., 2014). The lowest bins of the profile, up to an altitude of 1,440 m above the surface, are contained within a radar “blind zone” where CloudSat is unable to discern meaningful observations due to interference from terrain backscatter (Milani et al., 2018). In order to derive an estimate of surface snowfall, CloudSat makes use of a “near-surface bin” (NSB), which is the lowest precipitating layer outside of the blind zone in the vertical cloud profile (Li L. & Tanelli, 2007). The snowfall rate from this NSB is extrapolated down from the cloud to the terrain below, which is then used to provide an estimate of the surface snowfall rate at that point directly beneath the cloud (Wood & L’Ecuyer, 2013). This NSB extrapolation can be seen in a reflectivity profile (Figure 2a) retrieved from a CloudSat overpass near Eureka station, which is used in the generation of interior cloud snowfall rates (Figure 2b) and surface snowfall rates (Figure 2c).

The 2C-SNOW-PROFILE product (Version R05) provides instantaneous estimates of liquid equivalent snowfall rates within the cloud and at the surface based on retrieved radar reflectivity profiles provided by the CPR (Wood et al., 2014). This product has been examined in previous studies over Antarctica as described by Milani et al. (2018) and Palerme et al. (2014) for comparisons with reanalysis product estimates of snow. The CloudSat data record is available from February 2006 to August 2016 but contains a series of gaps due to battery failures that resulted in a break in CPR measurements during September to December 2009, January 2011, and May 2011 to April 2012. These outages reduce the total number of CloudSat observational months at each station over its full data record from 108 to 91, and the missing time periods are depicted in

![Figure 2](image-url)
the shaded regions at both of the stations shown in Figure 1b. Following the 2011 battery anomaly, CloudSat entered a Daylight Only Operations mode where CPR activity was restricted to the sunlit portions of CloudSat's orbit Nayak (2012). However, due to CloudSat's solar array angle and orbital path, the frequency of high-latitude Northern Hemisphere observations was unaffected by the activation of Daylight Only Operations mode, and monthly overpass counts remain relatively stable across the full temporal span of our study (Figure 1b).

Estimates of snowfall rate from individual profiles have been shown to include uncertainties of up to 150–250% from a combination of features of CloudSat's retrieved precipitation state, particle model parameters, fallspeed model, and assumptions about cloud particle distributions (Duffy & Bennartz, 2018; Wood & L'Ecuyer, 2013). However, previous work by Hiley et al. (2010) and Palerme et al. (2014) has shown that by aggregating a representative sample of discrete CloudSat profiles along the track into an “overpass average” snowfall rate, the uncertainty is considerably reduced, and the signal-to-noise ratio is increased. The challenge to be addressed here is to identify the number of overpasses required to constitute a representative sample, in which geographical locations such a sample can be obtained, and over what time period.

To aggregate CloudSat overpasses in the vicinity of weather stations (see section 2.2), we first define a 1° grid box around each station and extract all CloudSat profiles occurring within the box during each month. We experimented with varying grid sizes for this comparison and found that the 1° grid performed optimally with strong correlations (0.79 at 1° compared to 0.61 at 0.5° at Eureka) and low RMSE (5.2-mm SWE at 1° compared to 8.5-mm SWE at 0.5° at Eureka) between monthly CloudSat and station measurements of SWE. Each transect of CloudSat through a grid box is defined as an overpass, and each overpass typically comprises 100–200 discrete vertical profiles. The overpass average snowfall rate is calculated as the median snowfall rate from all profiles; early on we found a small number of outlier profiles reporting unfeasibly high surface snowfall rates, and so the median is more representative than the mean of the average snowfall rate across a grid box. The mean monthly snowfall rate (in mm SWE hr⁻¹) is then calculated as the mean of all overpass medians in each month. Finally, assuming a constant snowfall rate throughout the month, monthly snowfall accumulation is estimated by multiplying each mean monthly snowfall rate by the total number of hours in a given month. To compare against the land-only in situ SWE measurements and the land-only gridded SWE products, the resulting CloudSat accumulation estimate is then multiplied by the land cover fraction of the grid box around each station to derive an estimate of terrestrial SWE.

2.2. In Situ and Reanalysis Data

Reference measurements of Arctic snow, and related climate variables, for the validation are obtained from two sources. Daily historical observations of total precipitation, total rainfall, and 2-m air temperature over a 9-year time period are collected from four weather stations operated by Environment and Climate Change Canada (ECCC) as described in Table 1 and Figure 1a. These precipitation observations are recorded at each station by an automatic precipitation weighing gauge, which uses vibrating wire transducers to weigh a collection bucket each day and in turn derive an estimate of the total daily precipitation (Mekis et al., 2018). Measurements of total daily SWE are computed at each station as the difference between total precipitation and total rainfall for each day. On days when total rainfall is missing but total precipitation is available, solid and liquid precipitation are separated using a similar method to Brown et al. (2003). Any precipitation measured on days when the daily maximum temperature (T_max) is equal to or below 0 °C is classified as entirely

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**Table 1**

| Station     | Lat   | Lon   | Elevation | WMO ID | TC ID | Missing days |
|-------------|-------|-------|-----------|--------|-------|--------------|
| Eureka      | 79.99 | −85.93| 10        | 71917  | WEU   | 0            |
| Resolute Bay| 74.72 | −94.97| 67.7      | 71924  | YRB   | 37           |
| Cambridge Bay| 69.11| −105.14| 31.1      | 71925  | YCB   | 18           |
| Iqaluit     | 63.75 | −68.54| 33.5      | 71321  | XFB   | 85           |

*Note.* Longitude (Lon) is measured in degrees east, elevation is measured in meters above sea level, and TC IDs are meteorological identifiers assigned to each station by Transport Canada.
Figure 3. Estimates of monthly climatological snow accumulation at Eureka, Cambridge Bay, Resolute Bay, and Iqaluit. Red shaded regions correspond to the 95% sampling confidence intervals from CloudSat. Mean annual snow accumulation (mm/month) is displayed as colored dashed lines.

snow, and any precipitation measured when $T_{\text{max}}>5\,^\circ\text{C}$ is classified as entirely rain. For temperatures between 0 and $5\,^\circ\text{C}$, the rain fraction is given by $f_{\text{rain}}=T_{\text{max}}/5$, and the snow fraction is $f_{\text{snow}}=1-f_{\text{rain}}$.

The number of missing observations in this study is shown in Table 1 for all stations. Missing days appear sparsely distributed across all years with only 3 of the 432 total station months (108 months x 4 stations) having more than 10 total missing days. All nonmissing daily snow accumulation values are then used to derive a mean daily snow accumulation (in mm SWE) for each month at each station. Assuming a constant snowfall rate for all days in a month, the mean daily snow accumulation for each month is then multiplied by the number of days in that month to provide an estimate of total monthly snow accumulation at the station.

The second source of reference data used in this work comes from gridded reanalysis and model estimates of SWE. The Blended-4 gridded product is calculated as an unweighted average of MERRA-2, GlobSnow, CROCUS, and the Simple Snow Model produced by Ross Brown (Brown & Brasnett, 2010; Mudryk et al., 2015). Data from the Blended-4 SWE gridded product are regridded from 0.5° resolution to 1° resolution so that it aligns with the grid used for CloudSat overpass aggregation at each station. Since the Blended-4 product provides daily estimates of SWE on ground, we estimate monthly snow accumulation as the sum of all positive differences in SWE from consecutive days: $\sum_{i=1}^{n-1} d_i \quad \forall \quad d > 0$, where $i$ is the subscript for each day in a month, $n$ is the total number of days in a month, and $d$ is the difference in mm SWE computed as $d = SWE_{t+1} - SWE_t$ (Broxton et al., 2016). This method does not account for any melt or sublimation that may have occurred between two consecutive days but provides a conservative estimate of accumulation (only) that can be compared with snowfall estimates from CloudSat. A similar regridding process and accumulation calculation is also performed for the two reanalysis products to be assessed, ASRV1 and ASRV2.

3. Validation of CloudSat Snowfall Estimates at Stations in the Canadian Arctic

3.1. Climatological Mean Snow Accumulation

We first examine CloudSat’s ability to sample monthly climatological snow accumulation at each of the four ECCC stations. Figure 3 compares the seasonal cycle of monthly climatological snow accumulation observed at each station and estimated by CloudSat in a 1° grid box containing the station. The seasonal cycle of
Figure 4. Mean annual snow accumulation (mm SWE per month) calculated for each station, for CloudSat, Blended-4, ASRV1, and ASRV2. Also included are the 95% confidence intervals for each sample.

Mean annual snow accumulation at all stations shows higher values in September, October, and November, with reduced accumulation throughout December, January, and February and March, April, and May (excluding Resolute Bay), followed by low levels of accumulation during the warm season. CloudSat mostly captures the broad features of the seasonal cycle, exceeding the validation criteria of correlation >0.5 and RMSE <10 mm SWE, with only the southernmost station Iqaluit performing worse than our threshold (r = 0.28, RMSE = 4-mm SWE). In terms of mean monthly snow accumulation, all of the stations displayed similar values (less than 1.5-mm SWE difference) to that of CloudSat, excluding Iqaluit, which has a difference in mean annual snow accumulation of approximately 4 mm SWE (Figure 4). The nature of CloudSat’s orbit significantly reduces the number of overpasses above ground stations at lower latitudes (see Figure 1a). For example, using a 1° grid, Eureka (82°N) receives on average 15–25 overpasses per month, while Iqaluit (63°N) receives only 2–3. This difference in sampling results in a poorer representation of accumulation and declining agreement between CloudSat and station measurements at more southerly locations.

Additionally, based on the 95% confidence interval computed from the CloudSat sample, CloudSat’s results are consistent with the monthly mean accumulation reported at each station. However, we note a general underestimation of approximately 50% in CloudSat snow accumulation throughout December and January across all stations. A contributing factor to the underestimation noted in CloudSat’s 2C-SNOW-PROFILE snowfall has been previously attributed to the inability of the CPR to capture low cumuliform snowfall which comprise about 36% of global snowfall occurrence, within CloudSat’s blind zone in the lowest 1.5 km (Bennartz et al., 2019; Kulie & Milani, 2018). The impact of near-surface snowfall on CloudSat estimate underestimation is further noted in a study by Maahn et al. (2014), which showed (for a similar high-latitude location in Antarctica) that CloudSat underestimates total annual snowfall by approximately 10% due to shallow cumulus snowfall occurring within the radar blind zone.

Turning to a comparison of CloudSat with the gridded SWE products, the seasonal cycle of Blended-4 is similar to CloudSat at all stations with correlations of approximately 0.5, excluding Resolute Bay (r = 0.03). However, during the main accumulation season (October–May), Blended-4 and ASRV1 estimates of climatological monthly mean accumulation are systematically higher than CloudSat’s estimates at all stations. ASRV2 displays similar overestimation at all stations excluding Resolute Bay. Reanalysis system estimates have been shown in a study by Koyama and Stroeve (2019) to display similar overestimation in solid precipitation across high-latitude regions in Greenland when compared with weather station observations (see section 4). Overall, CloudSat appears to more closely capture the seasonal cycle of accumulation at each
Figure 5. Monthly snow accumulation (mm SWE) estimates from CloudSat and Blended-4 compared with ECCC measurements at Eureka and Cambridge Bay. The red shaded regions correspond to the 95% sampling confidence intervals from CloudSat.

station and provides more accurate estimates of annual mean snow accumulation than that of the gridded SWE products.

3.2. Interannual Variability

We next examine monthly mean estimates of snow accumulation over all 91 nonmissing months in the CloudSat data record (2007–2015), which allows us to compare time series from CloudSat, ECCC, and the reanalysis products. For brevity, we focus on Eureka and Cambridge Bay (Figure 5), since most of the same features are found at Resolute Bay and Iqaluit (not shown). Overall, the performance of CloudSat at Eureka is substantially better than at Cambridge Bay (correlation $r = 0.79$ vs. $r = 0.21$, respectively). Working at a monthly time scale means that fewer CloudSat overpasses are available for each month, and so the time series display higher uncertainties and larger RMSE than the results from the climatological monthly means (Table 2). However, Eureka continues to display lower RMSE when compared to ECCC (5.2-mm SWE) than Cambridge Bay (8.5-mm SWE) at these timescales.

These results suggest an approximate scaling that for 5° increase in latitude between stations, we find a corresponding positive increase in the correlation in interannual variability, with the largest increase occurring between Cambridge Bay and Resolute Bay (between 69°N and 74°N). Furthermore, these results imply that there exists an approximate southern latitude around 70°N, poleward of which CloudSat observations, based on our validation criteria, show greater reliability for estimating monthly snow accumulation at a 1° spatial resolution. To test whether computing averages over longer than 1 month could improve the sampling sufficiently to extend the region of greatest reliability further south, we also construct time series of annual mean snow accumulation at all stations. The annual mean results (not shown) display a similar latitudinal relationship to the monthly time series, with the highest correlation between CloudSat and Eureka (0.88) and the lowest at Iqaluit (−0.01). Additionally, for the stations equatorward of 70°N (Cambridge Bay and Iqaluit), moving from monthly to annual timescales still provides sample sizes that are too small to derive an estimate of snow accumulation that on a 1° spatial grid agrees well with in situ data.

A clearer picture of interstation similarities and differences is presented using scatter plots of monthly snow accumulation (Figure 6) for Eureka and Cambridge Bay for three pairs of data products: ECCC (EC) versus

| Station       | Correlation | RMSE |
|---------------|-------------|------|
|               | CS and EC   | CS and B4 | B4 and EC | CS and EC | CS and B4 | B4 and EC |
| Eureka        | 0.79        | 0.57     | 0.71      | 5.2      | 7.3       | 6.3       |
| Resolute Bay  | 0.57        | 0.14     | 0.36      | 9.4      | 12.7      | 8.3       |
| Cambridge Bay | 0.21        | 0.06     | 0.66      | 8.5      | 13.1      | 8.5       |
| Iqaluit       | 0.00        | 0.28     | 0.21      | 31.6     | 25.4      | 24.9      |
Figure 6. Scatter plots displaying interannual variability of snow accumulation (mm SWE) for both Eureka (red) and Cambridge Bay (blue), between (a) EC and CS, (b) CS and B4, and (c) EC and B4.
CloudSat (CS), CloudSat versus Blended-4 (B4), and ECCC versus Blended-4. The data are extracted from the 91 months shown in the time series in Figure 5 where the CloudSat distributions display relatively strong correlations (above 0.5) at high-latitude stations ($r = 0.79$ Eureka) with lower correlations further south ($r = 0.21$ at Cambridge Bay). We identified 33 out of 91 months at Cambridge Bay with zero snow accumulation from CloudSat when the corresponding value from ECCC is nonzero, compared to only nine of these months at Eureka. This difference is again likely related to the poor temporal sampling from CloudSat in a $1^\circ$ grid box at latitudes equatorward of $70^\circ$N. With an average of only five CloudSat overpasses per month at Cambridge Bay, this appears insufficient to accurately derive estimates of monthly snow accumulation. The suggestion is that with so few samples CloudSat is missing a significant number of snowfall events occurring near the station during each month.

The comparison between CloudSat and the Blended-4 gridded product shows a similar positive bias in snow accumulation in the Blended-4 estimates to that noted in the climatology (Figures 6b and 6c). This suggests that CloudSat’s snow accumulation estimates are closer in overall magnitude to observed measurements at the stations. However, Figure 6c displays a much stronger correlation between the Blended-4 and station data at Cambridge Bay ($r = 0.66$) compared to that of CloudSat and the station data ($r = 0.21$), which further highlights potential issues with CloudSat sampling at latitudes south of $70^\circ$N.

4. Discussion

There are several important factors contributing to uncertainty in CloudSat-based estimates of snow accumulation. First, we have shown several times above that uncertainty due to limited temporal sampling from CloudSat becomes a critical source of uncertainty equatorward of $70^\circ$N. To some extent, we have shown that the effect of sampling uncertainty can be mitigated by taking temporal averages (Hiley et al., 2010); however, this remains a problem at lower-latitude stations. Furthermore, comparing aggregate estimates of snowfall from CloudSat over a grid with a point estimate at a station, produces additional uncertainty, since observations recorded at the station could occur at a different time, and/or place, from where CloudSat is able to sample. Spatial variability of snowfall is another major challenge when comparing point station measurements to that of a large surrounding grid box since the snowfall rate and density may vary by large amounts across a grid box compared to what is observed at the station (Elder et al., 1991; Schirmer et al., 2011). In order to combat this issue, we tested four different spatial grid sizes ($0.5^\circ$, $1^\circ$, $1.5^\circ$, and $2^\circ$) to identify the optimal grid for use in our comparisons. Our findings indicated that the $1^\circ$ grid was optimal as it produced results with lower RMSE and higher correlations when compared to the station data, and this resolution was similar to other high-latitude studies using CloudSat for monitoring snow (Milani et al., 2018; Palerme et al., 2017).

Additional uncertainty also arises from any near-surface precipitation occurring within CloudSat’s radar blind zone in the lowest 1,440 m of the atmosphere, where ground interference impacts the quality of CloudSat’s retrievals. A recent comparison over Greenland displays similar findings from issues arising as a result of ground clutter over alpine regions influencing CPR retrievals of snowfall in the lowest precipitating bin (Bennartz et al., 2019). The presence of ground clutter contamination contributing to physically improbable snowfall rates is also clearly visible in the secondary reflectivity maximum (between 20 and 30 dBZ) in Figure 6a from Kulie and Bennartz (2009), as well as in the unphysically high near-surface reflectivities (nearing 30 dBZ) for multiple CloudSat overpasses across Greenland in Figure 7 from the same study.

Adding to uncertainties in the detection of snowfall, the CPR has a minimum detectable signal intensity of $\sim 29$ dBZ, which allows for the detection of light intensity precipitation but is unable to accurately record measurements of intense precipitation due to radar signal attenuation caused by the presence of excessive ice water content, cloud liquid water, and water vapor interference (Haynes et al., 2009; Hudak et al., 2008; Kulie et al., 2010). Additionally, assumptions used by CloudSat to describe snow grain shape and particle size have been shown to be dominant contributors to modeled reflectivity (up to 4 dB) and snowfall rate uncertainties (40–60%) (Wood et al., 2013).

When we consider the reference snow accumulation values from ECCC station observations, we must also consider the measurement uncertainty associated with the precipitation weighing gauges and the Data Management System used to record and process surface weather data. There are several decisions made by the Data Management System in generating data records of total precipitation and the climatic assumptions used to facilitate these decisions add additional uncertainty toward each recorded measurement (Mekis et
al., 2018). Additionally, the precipitation weighing gauges used in the collection of total precipitation data at each of the stations are required to operate under a variety of challenging environmental conditions due to their Arctic locale. These extreme conditions can lead to problems with precipitation phase identification, precipitation accumulation on the gauge opening, and snow capping over the gauge top which can block observational records for extended time periods (Colli et al., 2015).

Undercatch bias is an additional source of observational uncertainty that needs to be considered when using measurements from automatic weighing gauges. Undercatch occurs when solid precipitation falls in the presence of wind which distorts the velocity of the falling snow and results in snow particles missing the opening of the measurement gauge (Kochendorfer et al., 2017). This undercatch effect is notable in the Arctic where most snow falls when it is windy, and as a result of this, snow gauge measurements have previously been shown to underestimate snowfall by up to 50% in this region, suggesting CloudSat's estimates are potentially more negatively biased than what is described by the current in situ records as shown in Figure 3 (Liston & Sturm, 2004). Undercatch can be somewhat mitigated through the use of wind shields (e.g., Alter or Nipher), and it has been suggested by Mekis et al. (2018) that shielded weighing gauges like those used in this study provide a good estimate of precipitation throughout all seasons. Bias correcting in situ data sets can also be completed through the use of tuned transfer functions, which are derived from a combination of precipitation measurements specific to the region, and gauge and shield configurations (Kochendorfer et al., 2017; Mekis et al., 2018). However, bias correction of in situ SWE was not attempted in this study due to a lack of up-to-date gauge metadata, along with sparse ancillary regional precipitation measurements.

Uncertainties in reanalysis estimates of SWE are additional factors, which may contribute to the overestimation noted in the reanalysis comparisons with both ECC and CloudSat. A study by Koyama and Stroeve (2019) noted similar overestimation in precipitation between ASRV1 and station data at high-latitude weather stations in Greenland, due to the poorly constrained nature of the region along with the influence of local wind events and the corresponding variations in solid precipitation. Bromwich et al. (2016) note positive summertime precipitation biases across polar regions in ASRV1 that exist due to inadequacies in the convective and rational model physics used in producing estimates of precipitation in the underlying numerical model. Furthermore, Mudryk et al. (2015) highlight how differences in the assimilated observational data sets and assimilation schemes used in reanalysis products influence performance and bias, with gridded data sets varying by up to 50% throughout the Northern Hemisphere. Additionally, since our derived estimates of accumulation from the gridded SWE products do not include any losses due to melt or sublimation, CloudSat estimates may exhibit an even stronger negative bias than revealed by this comparison.

5. Conclusion

Due to the nature of CloudSat’s orbit, the Arctic receives a high frequency of overpasses, which results in an increased chance at observing synoptic snowfall events throughout the region. Using aggregated CloudSat profiles of snowfall rates, we are able to generate monthly estimates of snow accumulation from a 1° grid box over four Arctic stations. Comparing our CloudSat estimates with surface measurements from these stations allows us to identify areas of agreement, error, and uncertainty. Long-term climatological CloudSat estimates of accumulated SWE display similar seasonal cycles to what is reported by the ECC stations with strong correlations and low RMSE. Monthly CloudSat estimates at the two stations above 70° N (Eureka and Resolute Bay) performed favorably when compared with in situ data by displaying strong correlations above 0.5 and RMSE below 10-mm SWE.

As we move further south, the CloudSat overpass count begins to decline and we note decreasing correlation and increasing RMSE between monthly CloudSat estimates and station observations. When considering all four stations, we find that the highest error occurs at Iqaluit, which is located at the lowest latitude and includes the fewest total number of CloudSat overpasses. These results suggest that the latitude in which CloudSat begins to perform optimally (in terms of 1° monthly correlations with ECC station observations above 0.5 and RMSE less than 10-mm SWE), exists somewhere between Resolute Bay and Cambridge Bay where we begin to receive a minimum of approximately seven overpasses from CloudSat per month. Moving south from this location, we find the 1° grid too restrictive in terms of overpass sampling at a monthly timescale and recommend that a coarser resolution be considered to incorporate more overpasses into the aggregation process.
CloudSat also appears to underestimate snow accumulation across the Arctic with monthly and annual averages showing less accumulation compared to both the station and reanalysis. This is noted at Iqaluit, Cambridge Bay, and Resolute Bay, with only Eureka displaying a higher monthly average snow accumulation estimate from CloudSat than the station observations. The differences between Eureka and the other stations may be related to the decreasing sample size as we move south, or the extreme dry conditions at Eureka combined with the fact that CloudSat has been shown to have difficulty differentiating between solid and liquid precipitation when temperatures are fluctuating near 0 °C and potentially incorrectly classifying the precipitation being recorded by the ground station (Liu, 2008).

Our findings here suggest that CloudSat-CPR estimates can be used as an effective perspective toward generating monthly 1° snow accumulation estimates throughout regions above 70°N. This aggregation method could therefore be generalized to a grid outside of the four stations examined in this work, to provide new insights into snow accumulation throughout other Arctic regions.

References
Behrangi, A., Christensen, M., Richardson, M., Lebsock, M., Stephens, G., Huffman, G. J., et al. (2016). Status of high-latitude precipitation estimates from observations and reanalyses. Journal of Geophysical Research: Atmospheres, 121, 4468–4488. https://doi.org/10.1002/2015JD024546

Bennartz, R., Fett, F., Pettersen, C., Shupe, M. D., & Schuettemeyer, D. (2019). Spatial and temporal variability of snowfall over Greenland from CloudSat observations. Atmospheric Chemistry and Physics Discussions, 19, 8101–8121.

Bokhorst, S., Pedersen, S. H., Brucker, L., Anisimov, O., Bjerke, J. W., Brown, R. D., et al. (2016). Changing Arctic snow cover: A review of recent developments and assessment of future needs for observations, modelling, and impacts. Ambio, 45(5), 516–537.

Bromwich, D. H., Nicolas, J. P., Monaghan, A. J., Lazzara, M. A., Keller, L. M., Weidner, G. A., & Wilson, A. B. (2013). Central West Antarctica among the most rapidly warming regions on Earth. Nature Geoscience, 6(2), 139–145.

Bromwich, D. H., Wilson, A. B., Bai, L.-S., Moore, G. W. K., & Bauer, P. (2016). A comparison of the regional Arctic System Reanalysis and the global ERA-Interim Reanalysis for the Arctic. Quarterly Journal of the Royal Meteorological Society, 142(695), 644–658.

Brown, R., & Brasnett, B. (2010). Canadian Meteorological and Oceanic Centre (CMOC) daily snow depth analysis data, version 1. NASA National Snow and Ice Data Center Distributed Active Archive Center, https://nsidc.org/data/NSIDC-0447/versions/1/.

Brown, R. D., Brasnett, B., & Robinson, D. (2003). Gridded North American monthly snow depth and snow water equivalent for GCM evaluation. Atmosphere–Ocean, 41(1), 1–14.

Brown, R. D., & Mote, P. W. (2009). The response of Northern Hemisphere Snow Cover to a changing climate. Journal of Climate, 22(8), 2124–2145.

Broxton, P. D., Dawson, N., & Zeng, X. (2016). Linking snowfall and snow accumulation to generate spatial maps of SWE and snow depth. Earth and Space Science, 3(6), 246–256.

Church, J. A., Clark, P. U., Cazenave, A., Gregory, J. M., Jevrejeva, S., Levermann, A., et al. (2013). Sea level change. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Colli, M., Rasmussen, R., Thériault, J. M., Lanza, L. G., Baker, C. B., & Kochendorfer, J. (2015). An improved trajectory model to evaluate the collection performance of snow gauges. Journal of Applied Meteorology and Climatology, 54(8), 1826–1836.

Cooper, E. J. (2014). Warmer shorter winters disrupt Arctic terrestrial ecosystems. Annual Review of Ecology, Evolution, and Systematics, 45(1), 271–295.

Derksen, C., & Brown, R. (2012). Spring snow cover extent reductions in the 2008–2012 period exceeding climate model projections. Geophysical Research Letters, 39, L19504. https://doi.org/10.1029/2011GL053387

Derksen, C., Walker, A., & Goodison, B. (2003). A comparison of 18 winter seasons of in situ and passive microwave-derived snow water equivalent estimates in Western Canada. Remote Sensing of Environment, 88(3), 271–282.

Déry, S. J., & Brown, R. D. (2007). Recent Northern Hemisphere snow cover extent trends and implications for the snow-albedo feedback. Geophysical Research Letters, 34, L22S04. https://doi.org/10.1029/2007GL031474

Duffy, G., & Bennartz, R. (2018). The role of melting snow in the ocean surface heat budget. Geophysical Research Letters, 45, 9782–9789. https://doi.org/10.1002/2018GL079182

ECCC (2017). Technical documentation—Digital archive of Canadian Climatological Data. Environment and Climate Change Canada Document, 35.

Elder, K., Dozier, J., & Michaelson, J. (1991). Snow accumulation and distribution in an Alpine Watershed. Water Resources Research, 27(7), 1541–1552.

Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., et al. (2017). The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). Journal of Climate, 30(14), 5419–5454.

Hansen, B. B., Isaksen, K., Benestad, R. E., Kohler, J., Pedersen, Å. O., Loe, L. E., et al. (2014). Warmer and wetter winters: Characteristics and implications of an extreme weather event in the High Arctic. Environmental Research Letters, 9(11), 114021.

Haynes, J. M., L’Ecuyer, T. S., Stephens, G. L., Miller, S. D., Mitrescu, C., Wood, N. B., & Tanelli, S. (2009). Rainfall retrieval over the ocean with spaceborne W-band radar. Journal of Geophysical Research: Atmospheres, 114, D00A22. https://doi.org/10.1029/2008JD009973

Hiley, M. J., Kulie, M. S., & Bennartz, R. (2010). Uncertainty analysis for CloudSat snowfall retrievals. Journal of Applied Meteorology and Climatology, 50(2), 399–418.

Hudak, D., Rodriguez, P., & Donaldson, N. (2008). Validation of the CloudSat precipitation occurrence algorithm using the Canadian C band radar network. Journal of Geophysical Research, 113, D00A07. https://doi.org/10.1029/2008JD009992

Kochendorfer, J., Rasmussen, R., Wolff, M., Baker, B., Hall, M. E., Meyers, T., et al. (2017). The quantification and correction of wind-induced precipitation measurement errors. Hydrology and Earth System Sciences, 21(4), 1973–1989.

Koyama, T., & Stroeve, J. (2019). Greenland monthly precipitation analysis from the Arctic System Reanalysis (ASR): 2000–2012. Polar Science, 19, 1–12.

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