A New GPM-DPR Algorithm to Estimate Snowfall in Mountain Regions

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Abstract

Reliable precipitation forcing is essential for calculating the water balance, seasonal snowpack, glacier mass balance, streamflow, and other hydrological variables. However, satellite precipitation is often the only forcing available to run hydrological models in data-scarce regions, compromising hydrological calculations when unreliable. The IMERG product estimates precipitation quasi-globally from a combination of passive microwave and infrared satellites, which are intercalibrated based on GPM’s DPR and GMI instruments. Current GPM-DPR radar algorithms have satisfactorily estimated rainfall, but a limited consideration of PSD, attenuation correction, and ground clutter have degraded snowfall estimation, especially in mountain regions. This study aims to improve satellite radar snowfall estimates for this situation. Nearly two years (between 2019 and 2022) of aloft precipitation concentration, surface hydrometeor size, number and fall velocity, and surface precipitation rate from a high elevation site in the Canadian Rockies and collocated GPM-DPR reflectivities were used to develop a new snowfall estimation algorithm. Snowfall estimates using the new algorithm and measured GPM-DPR reflectivities were compared to other GPM-DPR-based products, including CORRA, which is employed to intercalibrate IMERG. Snowfall rates estimated with measured Ka reflectivities, and from CORRA were compared to MRR-2 observations, and had correlation, bias, and RMSE of 0.58 and 0.07, 0.43 and -0.38 mm h⁻¹, and 0.83 and 0.85 mm h⁻¹, respectively. Predictions using measured Ka reflectivity suggest that enhanced satellite radar snowfall estimates can be achieved using a simple measured reflectivity algorithm. These improved snowfall estimates can be adopted to intercalibrate IMERG in cold mountain regions, thereby improving regional precipitation estimates.

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Key Points:

- The proposed satellite radar algorithm outperforms the Combined Radar-Radiometer Algorithm snowfall estimates.
- Using Ka band measured reflectivity avoids overcorrection, resulting in improved light snowfall estimation.
- The proposed algorithm has global reproducibility if forced with Numerical Weather Prediction model outputs.
Abstract

Reliable precipitation forcing is essential for calculating the water balance, seasonal snowpack, glacier mass balance, streamflow, and other hydrological variables. However, satellite precipitation is often the only forcing available to run hydrological models in data-scarce regions, compromising hydrological calculations when unreliable. The IMERG product estimates precipitation quasi-globally from a combination of passive microwave and infrared satellites, which are intercalibrated based on GPM’s DPR and GMI instruments. Current GPM-DPR radar algorithms have satisfactorily estimated rainfall, but a limited consideration of PSD, attenuation correction, and ground clutter have degraded snowfall estimation, especially in mountain regions. This study aims to improve satellite radar snowfall estimates for this situation. Nearly two years (between 2019 and 2022) of aloft precipitation concentration, surface hydrometeor size, number and fall velocity, and surface precipitation rate from a high elevation site in the Canadian Rockies and collocated GPM-DPR reflectivities were used to develop a new snowfall estimation algorithm. Snowfall estimates using the new algorithm and measured GPM-DPR reflectivities were compared to other GPM-DPR-based products, including CORRA, which is employed to intercalibrate IMERG. Snowfall rates estimated with measured Ka reflectivities, and from CORRA were compared to MRR-2 observations, and had correlation, bias, and RMSE of 0.58 and 0.07, 0.43 and -0.38 mm h\(^{-1}\), and 0.83 and 0.85 mm h\(^{-1}\), respectively. Predictions using measured Ka reflectivity suggest that enhanced satellite radar snowfall estimates can be achieved using a simple measured reflectivity algorithm. These improved snowfall estimates can be adopted to intercalibrate IMERG in cold mountain regions, thereby improving regional precipitation estimates.

Plain Language Summary

Reliable precipitation input to hydrological models is essential to calculating the water balance, snow accumulation, glacier dynamics, river flow, and other water related variables. Satellites are sometimes the only way to estimate precipitation in regions lacking data, and if the algorithms that translate their observations into precipitation estimates are not properly designed, it can compromise water related calculations. Global satellite precipitation is calibrated based on radar observations. However, radar snowfall estimation is complicated because of the varied size and velocity of snowflakes and other limitations in current algorithms. This study aims to improve
satellite radar snowfall estimates for mountain regions. Nearly two years of surface radar and
snowflake size and velocity observations were used to develop an algorithm to estimate snowfall
using satellite radar observations. Satellite snowfall estimates with the developed algorithm were
better than estimates currently used to calibrate a widely used global precipitation product,
especially in observing light snowfall. These results suggest that the proposed algorithm can be
used as a reference to improve satellite snowfall in products dedicated to estimating mountain
precipitation worldwide. These better precipitation estimates can help reduce the uncertainty in
calculating water resources availability to communities and predict future drought and flood
conditions.

1 Introduction

Accurately estimating precipitation fields remains a grand challenge in mountain
hydrology due to the sparseness of gauges, blockage of ground-based weather radar, and
difficulties modelling precipitation in complex terrain. As the principal input to the terrestrial
hydrological cycle, precipitation accounts for the greatest uncertainty in calculating the water
balance, seasonal snowpacks, glacier mass balance, soil moisture and streamflows. Although
limitations remain in estimating satellite precipitation, it can be the sole source of precipitation
forcing in data-scarce mountain regions. Given that mountains are projected to provide over 50%
of worldwide water to downstream communities in the next decades (Viviroli et al., 2020), it is
important that mountain precipitation be better estimated to improve water resources prediction
and management.

Precipitation forcing establishes the input of water or snow to hydrological models;
hence, dictating the amount of water that will be redistributed in the basin by other hydrological
processes until it reaches the river channel. Unsurprisingly, simulations of surface runoff
(Bhuiyan et al., 2019; Fallah et al., 2020) and streamflow (Ehlers et al., 2019; Qi et al., 2020) are
known to be highly sensitive to precipitation forcing. In some instances, uncertainty can be
amplified when propagated from precipitation inputs to simulated streamflows (Biemans et al.,
2009; Kabir et al., 2022) and create seasonal errors in streamflow predictions (Biemans et al.,
2009), especially during high flows (Kabir et al., 2022; Salamon & Feyen, 2009). Precipitation
uncertainty is also known to worsen the quality of other hydrologically relevant variables, such
as soil moisture and evapotranspiration (Ehlers et al., 2019; Kabir et al., 2022), and icemelt and snowmelt contribution to streamflow in glacierized basins (Mimeau et al., 2019). Altogether, observational uncertainty is considered larger than predictive uncertainty related to model structure (Ehlers et al., 2019; Raleigh et al., 2015). Moreover, given the unarguable importance of precipitation forcing in modelling hydrological fluxes, properly providing accurate precipitation estimates becomes a foremost step for simulating streamflows in a future of climate-induced water resource change (Blöschl et al., 2017, 2019).

Precipitation can be estimated using a myriad of methods that are most useful to hydrologists when producing spatial fields. These spatial fields either try to predict precipitation in ungauged regions (interpolation), infer precipitation through atmospheric modelling (numerical weather prediction, NWP) or from indirect observations (remote sensing), or through a combination of these methods. Gauge-based precipitation interpolation works efficiently in dense networks (Fallah et al., 2020; Tang et al., 2020), but their quality usually deteriorates in remote locations where networks are sparse. For instance, the network quality is still subpar in many regions of Canada (Mekis et al., 2018), especially in the mountains, the Arctic, and coastal regions (Brunet & Milbrandt, 2023). Atmospheric modelling through NWPs is rapidly evolving due to better physics representation and computational power and can now reliably estimate precipitation fields (Bauer et al., 2015). High-resolution models such as the pan-Canadian Global Environmental Multiscale model (GEM) at 2.5 km can capture most of the small-scale mountain precipitation variability (Milbrandt et al., 2016), which can be combined with gauge observations into reanalysis products such as the Canadian Precipitation Analysis (CaPA) (Lespinas et al., 2015). Recently, high-resolution NWPs have been deemed to surpass the ability of distributed gauged products to estimate mountain precipitation (Lundquist et al., 2019). Ground-based weather radar is another alternative that can provide reasonable spatial precipitation estimates (Sikorska & Seibert, 2018), but they have limited coverage and can undergo beam blockage in mountain regions (Boluwade et al., 2017). In many parts of the world, dense precipitation networks, high-resolution NWPs, and ground-based weather radars are unavailable; hence, precipitation from satellite remote sensing becomes their sole solution. Current satellite-based precipitation estimates derived from the Tropical Rainfall Measurement Mission (TRMM) and the Global Precipitation Measurement Mission (GPM) have been useful at the global scale, but they need improvement to capture the high spatiotemporal variability and type of precipitation in
In snowfall-dominated mountain regions, the uncertainty in precipitation estimation is even larger than in lowlands. For instance, Canadian Rockies IMERG daily precipitation gauge evaluation correlations are ~ 0.3 when compared to the neighbouring Canadian Prairies with correlations of ~ 0.6 (Asong et al., 2017). High mountain precipitation uncertainty in interpolation products can arise from wind undercatch (Biemans et al., 2009; Mekis et al., 2018; Smith, 2007), weighing gauge problems caused by evaporation losses and temperature and wind fluctuations (Pan et al., 2016), and sparse networks of gauges capable of measuring snowfall (Brunet & Milbrandt, 2023; Mekis et al., 2018). Mountain precipitation spatiotemporal variability has posed considerable challenges to the development of NWP models (Barros & Lettenmaier, 1994; Houze, 2012). These models have recently overcome technical challenges to offer reliable precipitation estimates (Lundquist et al., 2019). However, high-resolution NWP models are not yet accessible worldwide. Moreover, mountain topography can limit the use of ground-based radar because of beam blockage (Boluwade et al., 2017; Villarini & Krajewski, 2010). Likewise, globally derived satellite products (coarser than ~ 10 km scale) cannot always resolve small-scale spatiotemporal variability in mountain precipitation (Lundquist et al., 2019; Mekis et al., 2018). In products derived from satellite radar data, ground-clutter contamination can limit the surface proximity to which precipitation can be estimated (Kulie & Bennartz, 2009).

Satellite precipitation offers a complementary solution for monitoring in ungauged mountain regions. Three main techniques of satellite precipitation estimation can be divided by their wavelengths. The first, and less accurate, is through thermal infrared radiation (IR), which estimates precipitation based on the relationship between cloud top temperature and precipitation rate. The second is via passive microwave radiation (PM), which measures the hydrometeor-attenuated thermal emission emanating from the top of the atmosphere. The third, and more accurate, is through active microwave radiation, i.e., radar, which measures the power backscattered from a series of transmitted pulses interacting with hydrometeors (Tapiador et al., 2012). IR estimates are usually limited to convective precipitation because the cloud-top temperature-precipitation relationship does not work efficiently in other forms of precipitation, such as those formed by stratiform clouds (Lettenmaier et al., 2015). Because Earth’s emissivity...
is low at the PM wavelengths, large pixels are required (~ 15-km at GPM-GPM Microwave Imager (GMI) sensor) to provide enough energy to sensibilize PM systems with reasonable antenna size (Tapiador et al., 2012). Radar technology, in contrast, provides the most accurate precipitation estimation and has well-established reflectivity-rainfall relationships. These relationships are based on the mechanism that makes reflectivity grow exponentially with rainfall droplet size, considering only one hydrometeor type (Atlas & Ulbrich, 1977). However, in the case of snowfall, different hydrometeor shapes have complicated this fairly simple relationship (Matrosov, 2007; Skofronick-Jackson et al., 2019).

Products like the Integrated Multi-satellitE Retrievals for GPM (IMERG) leverages multi-satellite IR and PM high frequency by intercalibrating their retrievals using precipitation estimates from the Combined Radar-Radiometer Algorithm (CORRA) product, which is mainly based on GPM’s Dual-frequency Precipitation Radar (GPM-DPR) reflectivities and also GMI observations (Hou et al., 2014; Skofronick-Jackson et al., 2017). GPM-DPR has been working satisfactorily as a reference for precipitation estimation at the global scale, but it has been challenged by variability in particle size distribution (PSD), attenuation correction, and ground-clutter in snowfall-dominated mountain regions (Arulraj & Barros, 2021; Asong et al., 2017; Skofronick-Jackson et al., 2019; Tang et al., 2020).

As the most accurate satellite precipitation estimate arises from radar, it is evident that improvements in PSD considerations need to be made in precipitation retrieval algorithms for snowfall-dominated mountain regions. Empirical power-law relationships like the one developed by Atlas and Ulbrich (1977) have been utilized to represent the relationship between reflectivity and snowfall ($Z_e$-$S$). However, their coefficients are highly dependent on the hydrometeor shape (Rasmussen et al., 2003), resulting in vastly different $Z_e$-$S$ relationships (Kulie & Bennartz, 2009; Rasmussen et al., 1999; Skofronick-Jackson et al., 2019; Schoger et al., 2021). Broadly speaking, reflectivity signals increase from dry dendrites to large aggregates (Matrosov, 2007). Using a generic $Z_e$-$S$ relationship for all the spectrum of hydrometeor shapes can cause differences in snowfall rates by a factor of ~ 2.5 when estimated from typical snowfall reflectivities (~ 20-30 dBZ) (Matrosov et al., 2009). Snowfall can also be estimated employing scattering models that relate reflectivity with the size of the particle for a given particle shape (Liu, 2008; Nowell et al., 2013); however, several microphysical property assumptions need to be made for these models to work satisfactorily (Skofronick-Jackson et al., 2019). Hence, simpler alternatives like the one
proposed by Rasmussen et al. (2003) can be more applicable where PSD information is not
directly available. In addition, globally developed radar precipitation algorithms, such as the one
for GPM-DPR retrievals, use attenuation correction algorithms that are not necessarily needed
for snowfall estimation at DPR wavelengths, which are usually larger than the observed solid
hydrometeors (Casella et al., 2017).

Further development of satellite radar snowfall algorithms is needed to broaden their
applicability in mountain regions hydrology. Most studies in satellite radar snowfall estimation
either tackle the problem using $Z_e$-$S$ relationships that are substantially dependent on PSDs
(Matrosov et al., 2009) or scattering models heavily based on microphysical assumptions
(Skofronick-Jackson et al., 2019). However, no studies have applied a combined approach that
uses measured satellite reflectivity and simple PSD information to derive dynamic $Z_e$-$S$
relationships that can be utilized to estimate snowfall rates operationally in mountain regions. In
addition, algorithms based on measured reflectivity can eliminate the effect of attenuation
correction on removing valid light snowfall reflectivity signals (Casella et al., 2017). Developing
more reliable satellite radar precipitation algorithms can be crucial in improving globally
developed multi-satellite and -sensor products, such as the IMERG, in snowfall-dominated
mountain regions.

The purpose of this study is to improve satellite radar snowfall estimates in cold
mountain regions. The specific objectives are (i) to develop an algorithm to estimate snowfall
based on surface observations of $Z_e$ and PSD, (ii) to apply this algorithm to GPM-DPR $Z_e$
observations, and (iii) to evaluate the newly developed algorithm against current global
operational algorithms capable of measuring snowfall. The algorithm was developed utilizing
approximately two years (inside the 2019-2022 period) of collocated Micro Rain Radar-2 (MRR-
2) observations of airborne hydrometeor concentrations, Parsivel$^2$ disdrometry observations of
near-surface hydrometeor size, concentration, crystal habit and fall velocity, and near-surface
Alter-shielded OTT Pluvio weighing gauge precipitation observations made at a sub-alpine, high
elevation site in the Front Ranges of the Canadian Rockies. The newly developed algorithm was
applied to multiple GPM-DPR reflectivities, and its snowfall estimates were evaluated against
readily available precipitation rates from the GPM-DPR, CORRA, and IMERG products.
2 Materials and Methods

2.1 Study Area

The study was conducted in the Fortress Mountain Research Basin (FMRB), Canadian Rockies, Alberta. FMRB is part of the Global Water Futures Observatories’ Canadian Rockies Hydrological Observatory (GWFO-CRHO), which is an effort to intensively monitor hydrologically relevant variables in Canada. The basin lies between 2000 and 2900 m above mean sea level (MSL), and it is covered at low elevations by a mix of Englemann spruce, lodgepole pine and sub-alpine fir, at mid-elevations a larch treeline zone, and at high elevations sparsely vegetated and rock covered alpine environments (Harder et al., 2020). FMRB has access and infrastructure to host advanced hydrometeorological instruments in a high mountain environment, more specifically at the Powerline (PWL) station at 2136 m MSL (Figures 1 and 2). A domain defined by physiographic features and containing the Canadian Rockies (within 114-117° W and 50-52° N) was adopted to limit satellite snowfall spatial analysis to mountain regions for this study (Figure 1b).
Figure 1. Fortress Mountain Research Basin study area map displaying stations with streamflow and precipitation gauges (a). The Canadian Rockies is shown in (b), as delimited by
physiographic features. North American major basins are also displayed in (b) and (c). PWL
station contains the advanced hydrometeorological instrumentation used in the study.

2.2 Instrumentation and Data

The PWL station is equipped to measure air temperature, relative humidity, wind speed,
and precipitation. Wind speed is measured with a Met One anemometer at the Alter-shielded
OTT Pluvio weighing precipitation gauge height. In addition, an MRR-2 and a Parsivel\textsuperscript{2} are also
available for reflectivity, particle Doppler velocity, and precipitation concentration aloft and
detailed characteristics of falling hydrometeors near the surface (size, number density, crystal
habit, fall velocity). The MRR-2 is mounted on a tower at 5.33 m height, and the Parsivel\textsuperscript{2} is
installed nearby on the ground at 3.12 m height. The station is in a mixed evergreen forest
clearing, which considerably reduces wind speed and, consequently, snowfall undercatch. Figure
2 displays the PWL station and its instruments.

The MRR-2 (METEK manufacturer) is a vertically profiling radar that can observe radar
power at 31 different atmospheric levels with a maximum 200 m vertical resolution. The MRR-2
operates at 24.23 GHz frequency, and it can measure the Doppler spectra of both liquid and solid
hydrometeors, providing that an antenna heater (used here) is employed for solid hydrometeors.
Radar reflectivity and Doppler velocity can be derived from the observed Doppler spectra using
different algorithms – the one used here is described in the next section (METEK, 2015). The
Parsivel\textsuperscript{2} disdrometer (OTT manufacturer) observes particle size and velocity using a 2D laser
sheet. The size and time of the particle obstruction crossing the laser sheet are measured at high
frequency (50 kHz) and used to estimate particle size and velocity, respectively. These two
variables and the number of particles for a given time step are used to calculate various PSD
parameters. The recording time step can be as short as 10 seconds (OTT Hydromet GmbH,
2018).

The MRR-2 and Parsivel\textsuperscript{2} are hosted by a military-grade single-board computer (SBC)
inside a box that is also mounted on the tower. This box was designed with a system that allows
for remote access to the SBC and contains a sub-system to power the MRR-2 and Parsivel\textsuperscript{2} with
a no-break power backup (Figure 2). The box is powered with AC from the Fortress Mountain
Resort main office. This office also hosts an internet network box that creates an independent
network that propagates a Wi-Fi signal to the PWL tower. The network box’s internet is provided via satellite. This system setup was important for monitoring devices and data download since, not unusually, AC power outages happened in the site, requiring the Parsivel\textsuperscript{2} software’s ASDO to be restarted.

![Figure 2. From left to right: MRR-2 (tower top), Alter-shielded OTT Pluvio gauge, and Parsivel\textsuperscript{2} at PWL. The picture was taken on 11 May 2023.](image)

The study period was defined according to MRR-2 and Parsivel\textsuperscript{2} data availability. This study also used data from Global Water Future’s Storms and Precipitation Across the Continental Divide Experiment (SPADE) since the PWL station was one of SPADE’s study sites (Thériault et al., 2021, 2022). SPADE took place between 24 April to 26 June 2019, and used the MRR-2 and Parsivel\textsuperscript{2} data, except that the Parsivel\textsuperscript{2} was in a different location ~ 200 m away.
from its original site displayed in Figure 2 (see Figure 2.d in Thériault et al. (2021)). The MRR-2 worked from 1 February 2019 until 30 June 2022. Parsivel\(^2\), after the SPADE period, was operational between 21 January 2020 and 30 June 2022. The MRR-2 recorded data every 10 s at a 200-m vertical resolution with 31 range gates (max altitude of 8341 m MSL) until 26 August 2019, and at 100-m vertical resolution (5241 m MSL) until 30 June 2022. Parsivel\(^2\) recorded data every 10 s during SPADE and every 1 min during the remaining period. In summary, this study’s ground-based and satellite-based portions were conducted when the Parsivel\(^2\) and MRR-2 were operational, respectively.

2.3 Ground-based Data Processing

The methodological steps hereafter are illustrated in Figure 3. MRR-2 .raw files were processed utilizing Maahn and Kollias (2012) software, which increases radar sensitivity to solid precipitation. Maahn and Kollias (2012)’s software employs a series of MRR-2 Doppler spectra noise removal steps especially suitable for snowfall observations, providing reliable estimates of hydrometeor effective reflectivity (\(Z_{e,t}\)) and Doppler velocity (\(W_t\)) at 1-minute time steps. The first two and the last range gates are excluded from the analysis due to the inability of the method to eliminate noise at these range gates.
Figure 3. Study methodological flowchart. The blue dashed box includes the ground-based steps. Parsivel$^2$ PSD parameter ($N_{0,t}$) and fall velocity ($V_t$) are used to calculate Eq. 3’s $a_t$ coefficient depending on particle type (dry or wet). MRR-2 effective reflectivity ($Z_{e,t}$) is then utilized to estimate MRR-2 & Parsivel$^2$ snowfall rate ($S_t$), which is employed in the ground-based evaluation against gauge observed snowfall rate. The green dashed box includes the satellite steps. This section uses GPM’s ancillary air temperature to estimate the ($N_{0,t,T}$) PSD parameter and calculate Eq. 3’s $a_t$ coefficient together with MRR-2 Doppler velocity ($W_t$). Four GPM-DPR based reflectivities are inputted to Eq. 3 to estimate snowfall rate, which are all evaluated against rates estimated with MRR-2 $Z_{e,t}$ at each satellite altitude bin. CORRA and DPR-P snowfall estimates are also evaluated using the latter. Satellite spatial estimates using $Z_{meas-Ka}$ are computed similarly, but using spatially distributed reflectivity and $N_{0,t,T}$ averaged inside the 1000-m layer above the clutter-free height. CORRA and IMERG spatial snowfall estimates are also used for comparison. GPM satellite picture is courtesy of NASA: https://science.nasa.gov/get-involved/toolkits/spacecraft-icons

Parsivel$^2$ data was processed using ASDO manufacture’s software. ASDO outputs particle size in 32 diameter ($D$) classes (0.062 to 24.5 mm) and 32 terminal velocities ($V$) classes (0.050 to 20.8 m s$^{-1}$) (OTT Hydromet GmbH, 2018). These two variables were employed to calculate PSD parameters described in this section. PSD number concentration ($ND_{i,t}$) at the $i^{th}$ diameter bin and $t^{th}$ time step in m$^3$ mm$^{-1}$ was calculated as follows,

$$ND_{e,t} = \sum_{j} \left( \frac{N_{i,j}}{A_i \Delta t V_j D w_i} \right)$$  \hspace{1cm} (1)

where, $N_{i,j}$ is the number of particles at the $i^{th}$ and $j^{th}$ velocity bin, $\Delta t$ is the time interval in seconds, $V_j$ is the particle terminal velocity in m s$^{-1}$, $D w_i$ is the diameter bin width in mm, and $A_i$ is the effective disdrometer sampling area in m$^2$,

$$A_i = A \left( 1 - \frac{D_i}{2w} \right)$$  \hspace{1cm} (2)

where, $A$ is the disdrometer laser beam sampling area in (0.0054 m$^2$) (from Parsivel$^2$ manual), and $w$ is the width of the disdrometer laser beam (0.03 m) (Angulo-Martínez et al., 2018).

Snowfall estimates from radar reflectivity can be calculated based on PSD parameters or on empirical power law relationships between measured snowfall rate ($S_t$ in mm h$^{-1}$) and radar reflectivity ($Z_{e,t}$ in mm$^3$ mm$^{-6}$),

$$Z_{e,t} = a_t S_t^b$$  \hspace{1cm} (3)
where, the $a_t$ coefficient and $b$ exponent are commonly fitted. However, $a_t$ has been known to be related to hydrometeor PSD parameters, and the variation in $b$ is small for snowfall estimation.

Rasmussen et al. (2003) developed a semi-empirical method to estimate the $a_t$ coefficient based on the intercept of the PSD ($N_{0,t}$ in cm$^{-4}$) and $V_t$ in cm s$^{-1}$ for dry ($a_{dry,t}$) and wet ($a_{wet,t}$) snowflakes,

$$a_{dry,t} = 3.36 \times 10^4 \left( \frac{N_{0,t}^{2/3} V_t^{5/3}}{} \right)$$

$$a_{wet,t} = 5.32 \times 10^4 \left( \frac{N_{0,t}^{2/3} V_t^{5/3}}{} \right)$$

while $b$ is set to be constant at 1.67. The value of $b = 1.67$ was theoretically derived by Rasmussen et al. (2003), aligning well with a compilation of studies that found the $b$ variation to be between 1.50 and 2.21 (Goodison et al., 1981). Here, the $a_t$ coefficient was calculated using the Parsivel$^2$ $V_t$, and $N_{0,t}$ is the intercept of the logarithmic regression model between $ND_{s,t}$ and $D_t$. The $a_t$ coefficient was calculated at an hourly time step. Hydrometeors were classified into rain, graupel, dry and wet snow adopting a pre-defined $V$-$D$ matrix based on the proximity to lines of $V$-$D$ empirical relationships for rain (Atlas & Ulbrich, 1977), graupel (Ishizaka et al., 2013), dry and wet snow (Rasmussen et al., 1999). All the above Parsivel variables in this section were calculated in their native temporal resolution (10 s or 1 min) and subsequently averaged to hourly for the remaining part of the analysis. The hydrometeor type was aggregated to hourly using the mode statistics because of its discrete nature.

Snowfall rate was estimated at near-surface utilizing $Z_{e,t}$ from the nearest available MRR-2 range gate (3rd bin above ground). $Z_{e,t}$ was averaged to hourly, and the snowfall rate in mm h$^{-1}$ was calculated using Eq (3). Quality-controlled precipitation from the Alter-shielded Pluvio weighing gauge was utilized to evaluate MRR-2’s snowfall rate estimate. Observed precipitation partitioning into snowfall and rainfall was made adopting Harder and Pomeroy (2013)’s energy balance psychrometric method and observations of air temperature and relative humidity. This partitioning was used to determine environmental conditions to form snowfall at the surface.

Snowfall was adjusted for gauge undercatch due to the wind utilizing wind speed measurements at gauge height (Smith, 2007). Gauged snowfall was also aggregated to hourly from 15-min timesteps before evaluation, and only non-zero precipitations were used.
2.4 Satellite-based Data Processing

Seven satellite-derived products were utilized in this study: GPM-DPR Ka and Ku measured ($Z_{\text{meas-Ka}}$ and $Z_{\text{meas-Ku}}$) and corrected ($Z_{\text{cor-Ka}}$ and $Z_{\text{cor-Ku}}$) reflectivities, GPM-DPR dual-frequency precipitation rate (DPR-P), CORRA precipitation rate, and IMERG precipitation rate. The 2A.GPM.DPR.V9 product version was employed, hereinafter GPM-DPR. The GPM-DPR overpasses were selected based on a 5 km window from the PWL station – the radar’s spatial resolution. Among other variables, GPM-DPR provides measured ($Z_{\text{meas}}$) and corrected ($Z_{\text{cor}}$) radar reflectivity in dBZ from Ku (13.6 GHz) and Ka (35.5 GHz) bands, DPR-P, quality-controlled outputs, and other environmental variables at 5-km spatial resolution and every 125 m of altitude from 0 to 22 km MSL (Hou et al., 2014). Each type of measured ($Z_{\text{meas}}$) and corrected ($Z_{\text{cor}}$) reflectivity for each band (Ka or Ku) is used as input to $Z_e$ in Eq. 3 to estimate snowfall rate ($S_t$). Although there are currently two main orbital platforms able to observe snowfall globally, GPM-DPR and CloudSat-Cloud Profiling Radar (CPR), GPM-DPR was used because of its better ability to detect larger snowfall rates at an extensively wider swath (Skofronick-Jackson et al., 2019). In addition, GPM-DPR observes a larger number of mountain snowfall returns than CloudSat-CPR because of its scanning capabilities (Tang et al., 2017). CORRA estimates precipitation based on an optimal physically consistent forward model that uses GPM-DPR Ka reflectivities, GPM-GMI brightness temperatures, path-integrated attenuation, and ancillary geophysical variables (Grecu et al., 2016). CORRA provides precipitation rates at every 250-m layer and 5-km spatial resolution, and it has been adopted to intercalibrate IMERG’s multi-satellite estimates (Huffman et al., 2019). Therefore, it is crucial to understand if the newly developed algorithm using GPM-DPR reflectivities can surpass CORRA’s ability to estimate mountain snowfall. IMERG was also used to check spatial consistency with the new algorithm.
Table 1. Product names that were employed in this study with their respective spatial and vertical resolutions, variables used, product provider naming and version.

<table>
<thead>
<tr>
<th>Product</th>
<th>Spatial Res.</th>
<th>Vertical Res.</th>
<th>Variable</th>
<th>Provider naming/version</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zmeas-Ka</td>
<td>5-km</td>
<td>125-m</td>
<td>Z_e,t [dBZ]</td>
<td>2A.GPM.DPR/V9</td>
</tr>
<tr>
<td>Zmeas-Ku</td>
<td>5-km</td>
<td>125-m</td>
<td>Z_e,t [dBZ]</td>
<td>2A.GPM.DPR/V9</td>
</tr>
<tr>
<td>Zcor-Ka</td>
<td>5-km</td>
<td>125-m</td>
<td>Z_e,t [dBZ]</td>
<td>2A.GPM.DPR/V9</td>
</tr>
<tr>
<td>Zcor-Ku</td>
<td>5-km</td>
<td>125-m</td>
<td>Z_e,t [dBZ]</td>
<td>2A.GPM.DPR/V9</td>
</tr>
<tr>
<td>DPR-P</td>
<td>5-km</td>
<td>125-m</td>
<td>P [mm h(^{-1})]</td>
<td>2A.GPM.DPR/V9</td>
</tr>
<tr>
<td>CORRA</td>
<td>5-km</td>
<td>250-m</td>
<td>P [mm h(^{-1})]</td>
<td>2B.GPM.DPRGMI.CORRA/V07A</td>
</tr>
<tr>
<td>IMERG</td>
<td>0.1 º</td>
<td>Surface</td>
<td>P [mm h(^{-1})]</td>
<td>IMERG/precipitationUncal/V6</td>
</tr>
</tbody>
</table>

2.5 Snowfall Estimates at Satellite Altitudes

The newly proposed algorithm is a modification of Rasmussen et al. (2003)’s methodology to derive \( Z_e,t-S_t \) relationships from ground-based measurements, described in 2.3. The main difference from the latter is that instead of utilizing a \( N_{0,t} \) calculated from measured PSD, it adopts an air-temperature estimated \( N_{0,t,T} \) (\( N_{0,t,T} \) in cm\(^{-4}\)) based on Field et al. (2005):

\[
N_{0,t,T} = 5.65 \times 10^{-2} \exp (-0.107 T_{a,t})
\]  

where, \( T_{a,t} \) is the air temperature in ºC.

The algorithm inputs are all taken at the satellite observation altitude bin: reflectivity (either \( Z_{\text{meas}} \) or \( Z_{\text{cor}} \)), Doppler velocity from MRR-2, and air-temperature from GPM-DPR’s ancillary environmental variables. It is important to note that snowfall rates were calculated only above the clutter-free altitude, also provided as GPM-DPR ancillary data. To avoid receiver noise, minimum reflectivity thresholds of 12 (Hou et al., 2014) and 13 dBZ (Hamada & Takayabu, 2016) were set for \( Z_{\text{meas}}-\text{Ka} \) and \( Z_{\text{meas}}-\text{Ku} \), respectively. Because hydrometeor type cannot be derived at satellite observation altitudes accurately, a threshold of -5 ºC was employed to determine whether to use Eq. 4 or 5. The -5 ºC threshold excludes any fractional rain.
indicative of hydrometeor wetness in the region (Harder and Pomeroy, 2013). Spatial estimates were calculated in the 1000 m layer above the clutter-free altitude, and the respective inputs where averaged inside that layer. In addition, the precipitation flag product (flagPrecip) from GPM-DPR was utilized to mask non-precipitating radar profiles while computing the spatial snowfall rates. Aside from MRR-2 Doppler velocity, all inputs are spatially distributed. Hence, snowfall rate uncertainty related to $V_t$ in Eqs. 4 and 5 should increase away from the study site in the spatial estimates shown in Figure 7. Rasmussen et al. (2003)’s algorithm in combination with Field et al. (2005) air temperature estimation of the PSD parameter $N_{0,t}$ was chosen to allow the calculation of the $a_t$ coefficient accounting for PSD at satellite altitudes where direct observations of PSD are not available. The Field et al. (2005) equation to derive the $N_{0,t}$ PSD parameter was chosen due to its air temperature parameterization, ease of application and its coverage of environmental conditions that encompass those found in the study area and many other cold mountain regions, in which clouds between -55 to 10 °C were sampled for solid hydrometeor PSDs.

2.6 Evaluation of the Proposed Algorithm

The proposed algorithm snowfall estimates were evaluated near the surface using MRR-2 $Z_{e,t}$, Parsivel$^2$ $V_t$, and either Parsivel$^2$ observed $N_{0,t}$ or air-temperature estimated $N_{0,t}$ (described in section 2.5) against wind undercatch-corrected precipitation rates from the Pluvio Alter-shielded weighing gauge. MRR-2 $Z_{e,t}$ near the surface was extracted from the 3rd radar bin above ground, which could be at 300 m or 600 m AGL, depending on the vertical resolution utilized. The first two returns are excluded by the Maahn and Kollias (2012) method due to excessive noise. For satellite evaluations, MRR-2 snowfall rates aloft were matched to each satellite altitude bin, including that of CORRA estimates. Satellite evaluations used MRR-2 $W_t$ and air-temperature estimated $N_{0,t}$. Standard evaluation statistics such as correlation coefficient, Root Mean Squared Error (RMSE), and mean bias were employed. Student’s t-tests were also used to determine whether the analyzed products differed statistically from CORRA. In addition, qualitative spatial evaluation including the IMERG product was performed to make sure the proposed algorithm maintained spatial consistency of snowfall accumulation.
3 Results and Discussions

3.1 Ground-based Snowfall Estimates Evaluation

Ground-based snowfall rates, as estimated by MRR-2 and Parsivel\(^2\) data, are shown in Figure 4. Snowfall rate estimated employing MRR-2 \(Z_{e,t}\) and Parsivel\(^2\) \(V_t\) and \(N_{0,t}\) had a 0.75 correlation, -0.13 mm h\(^{-1}\) bias, and 0.45 mm h\(^{-1}\) RMSE (Figure 4a). Snowfall rate estimated using air temperature-derived \(N_{0,t}\) instead (Eq. 6) had a decreased accuracy with a 0.67 correlation, -0.25 mm h\(^{-1}\) bias, and 0.57 mm h\(^{-1}\) RMSE (Figure 4b). Although accuracy worsened for air temperature-derived \(N_{0,t}\) snowfall rates, the decrease in accuracy was a necessary compromise for not being able to rely on Parsivel\(^2\) data, as this is not available at satellite observation altitudes. These results suggest that the method can be broadly employed by satellite-observed reflectivities at high altitudes.

Figure 4. Ground-based snowfall rate evaluation utilizing MRR-2 \(Z_{e,t}\) and Parsivel\(^2\) \(N_{0,t}\) and \(V_t\) (a) and air temperature-derived \(N_{0,t}\) instead (b). The x-axes represent the snowfall rate observed by the precipitation gauge. The red dashed line is the 1:1 line, and the shaded grey is the regression standard error.

3.2 Satellite-based Snowfall Estimates Evaluation

The evaluation statistics between satellite and MRR-2 estimated snowfall rates are displayed in Table 2. \(Z_{\text{meas}}-\text{Ka}\) made the best snowfall rate estimation with a correlation, bias, and RMSE of 0.58, 0.43 mm h\(^{-1}\), and 0.83 mm h\(^{-1}\), respectively. The CORRA product made the
worst snowfall rate estimation \((r = 0.07, \text{ bias} = -0.38 \text{ mm h}^{-1}, \text{ RMSE} = 0.85 \text{ mm h}^{-1})\). Table 2 also displays the Student’s t-test results utilized to define whether each product differed significantly from CORRA. Every analyzed product but DPR-P was statistically different from CORRA at a significance level of \(p < 0.05\), suggesting that they can all be well suited to replace CORRA in the intercalibration of IMERG mountain snowfall estimates.

**Table 2.** Snowfall rate evaluation statistics per product. MRR-2 snowfall rates were used as ground truth. T-tests were performed between each product and CORRA to determine if their means were different. A t-test p-value < 0.05 represents different means. \(n\) is the number of matched returns between MRR-2 and each product – same as the number of data points in Figure 5.

<table>
<thead>
<tr>
<th>Product</th>
<th>Correlation</th>
<th>Bias [mm h(^{-1})]</th>
<th>RMSE [mm h(^{-1})]</th>
<th>(n)</th>
<th>t-test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Z_{\text{meas}-Ka})</td>
<td>0.58</td>
<td>0.425</td>
<td>0.827</td>
<td>97</td>
<td>-7.444</td>
<td>7.63E-12</td>
</tr>
<tr>
<td>(Z_{\text{meas}-Ku})</td>
<td>0.49</td>
<td>1.117</td>
<td>1.800</td>
<td>94</td>
<td>-8.517</td>
<td>8.32E-14</td>
</tr>
<tr>
<td>(Z_{\text{cor}-Ka})</td>
<td>0.52</td>
<td>1.088</td>
<td>1.752</td>
<td>92</td>
<td>-8.334</td>
<td>2.59E-13</td>
</tr>
<tr>
<td>(Z_{\text{cor}-Ku})</td>
<td>0.50</td>
<td>1.167</td>
<td>1.845</td>
<td>92</td>
<td>-8.539</td>
<td>9.38E-14</td>
</tr>
<tr>
<td>DPR-P</td>
<td>0.17</td>
<td>-0.306</td>
<td>0.645</td>
<td>92</td>
<td>0.303</td>
<td>0.762</td>
</tr>
<tr>
<td>CORRA</td>
<td>0.07</td>
<td>-0.383</td>
<td>0.846</td>
<td>81</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 5 gives more insight into the evaluation of satellite-derived snowfall rates. All products originated from GPM-DPR reflectivities overestimate snowfall, especially at large rates. \(Z_{\text{meas}-Ka}\) had better statistics because the overall snowfall overestimation is lower than the other products and does not increase at high rates. Surprisingly, all \(Z_{\text{cor}}\) and \(Z_{\text{meas}-Ku}\) had similar snowfall rates. This similarity can be attributed to the GPM-DPR reflectivity attenuation correction algorithm that raises \(Z_{\text{meas}-Ka}\) reflectivities close to \(Z_{\text{meas}-Ku}\) through their optimization process, resulting in three similar reflectivities. The Ku instrument is known to overestimate precipitation rates when compared to Ka (Petracca et al., 2018). The snowfall rate outliers in Figure 5b, c, and d are also a result of these accentuated reflectivities. DPR-P and
CORRA were both unable to correctly estimate snowfall rates above ~ 1.5 mm h\(^{-1}\), the difference between the two being that CORRA underestimation was not as systematic as for DPR-P. The agreement between CORRA and DPR-P is expected because the CORRA precipitation algorithm is mainly influenced by GPM-DPR observations (Skofronick-Jackson et al., 2019). The inability of CORRA to estimate larger snowfall rates could be one of the reasons IMERG significantly underestimates precipitation in snowfall-dominated regions (Asong et al., 2017; Tang et al., 2020).
Figure 5. Satellite-based snowfall rate evaluation as compared to MRR-2 estimated snowfall rate for $Z_{\text{meas}}$-$Ka$ ($Z_m$-$Ka$) (a), $Z_{\text{meas}}$-$Ku$ ($Z_m$-$Ku$) (b), $Z_{\text{cor}}$-$Ka$ ($Z_c$-$Ka$) (c), $Z_{\text{cor}}$-$Ku$ ($Z_c$-$Ku$) (d), DPR-P.
Corresponding authors: S. L. A. Asong and J. C. Lundquist.

1. Data Description

1.1 Data Sets

GPM-DPR (Global Precipitation Measurement - Deep Precipitation Radar) is a satellite radar system that provides high-resolution precipitation data globally. The data used in this study are from the DPR multispectral radar, which measures reflectivity at four frequencies: Ka, Ku, C, and X. The focus is on the Ka band, which is known for its high reflectivity and ability to penetrate precipitation, making it particularly useful for snowfall estimation.

1.2 Data Processing

The data were processed using standard algorithms to estimate precipitation rates. These estimates were then compared with ground-based observations to assess the accuracy of the DPR data.

2. Methods

2.1 Profile-Based Snowfall Estimation

Profile-based snowfall estimation involves analyzing the precipitation rate over a vertical profile. This method is particularly useful in mountainous regions where spatial variability can be high.

2.2 Intercomparison

Intercomparison is used to evaluate the performance of different satellite precipitation products. In this study, GPM-DPR, CORRA, and IMERG (Integrated Multi-satellite Retrievals for GPM) were compared to estimate snowfall rates.

3. Results

3.1 Profile-Based Snowfall Rates

Profile-based snowfall rates from GPM-DPR were compared with ground-based observations. The results showed that GPM-DPR was able to estimate snowfall rates with higher accuracy than the other analyzed products. Z\textsubscript{meas}-Ka was also capable of providing spatial estimates that are more in agreement with mountain snowfall literature while portraying many observations. Z\textsubscript{meas}-Ku, Z\textsubscript{cor}-Ka, and -Ku snowfall are very similar and tend to overestimate snowfall rates, especially for larger rates. Aside from having better quantitative estimates, Z\textsubscript{meas}-Ka (n = 97) had 20% more observations that can be employed for the intercalibration of multi-satellite estimates in cold mountain regions compared to CORRA (n = 81). Figure 6 shows the cumulative distribution function (CDF) of Z\textsubscript{meas}-Ka (best GPM-DPR product), CORRA, and IMERG. This figure illustrates the gridded snowfall rate distribution of 34 snowfall events observed during the 302 analyzed GPM-DPR overpasses. It is worth noting that two events were not included because the temperature at satellite observing altitudes was above 0°C. The CDFs demonstrate that the newly developed product can measure a wider range of snowfall rates.

Z\textsubscript{meas}-Ka had 50% of its observations below ~ 1.0 mm h\textsuperscript{-1} and 90% below ~ 2.6 mm h\textsuperscript{-1}, spanning a wider range of snowfall rates. Conversely, CORRA had 50% of its observations below ~ 0.6 mm h\textsuperscript{-1} and 90% below 1.4 mm h\textsuperscript{-1}, which shows a concentration towards low rates. Likewise, IMERG seems to have observed mainly small snowfall rates, with 50% of its observations below ~ 0.2 mm h\textsuperscript{-1} and 90% below ~ 1.8 mm h\textsuperscript{-1}, but was capable of observing larger rates than CORRA. The difference between CORRA and IMERG’s ability to measure high snowfall rates could be a result of IMERG being a surface precipitation estimate, which might even include rain and mixed precipitation when compared to CORRA’s observed clutter-free altitude. Even with that considered, Z\textsubscript{meas}-Ka was still able to observe larger snowfall rates than IMERG, suggesting that it can be utilized to improve the underestimation of IMERG in mountain regions (Asong et al., 2017; Lundquist et al., 2019).
Figure 6. Cumulative distribution functions (CDFs) of spatial snowfall rates for 34 events within the Canadian Rockies domain (same as in Figure 1b). The CDFs represent $Z_{meas} - K_a$ ($Z_{m} - K_a$), CORRA, and IMERG snowfall rate pixel values.

Figure 7 displays the maps of accumulated snowfall during the 34 events for $Z_{meas} - K_a$, CORRA, and IMERG. To focus only on the Canadian Rockies (such as in Figure 1b), areas outside this region are masked from the maps in Figure 7. The first noticeable feature is the large difference in accumulation between $Z_{meas} - K_a$ and the other two products. $Z_{meas} - K_a$ had a maximum snowfall accumulation of 28.4 mm, while CORRA and IMERG maximum accumulations were 9.0 and 19.3 mm, respectively. These accumulations represent that $Z_{meas} - K_a$ can observe three times more snowfall than CORRA and 1.5 times more than IMERG. This difference in accumulation portrays how using $Z_{meas} - K_a$ could improve the underestimation of IMERG. In addition, Figure 7 shows that $Z_{meas} - K_a$ accumulates more snowfall closer to the continental divide compared to CORRA and IMERG, which is more aligned with precipitation orographic enhancement theory (Barros & Lettenmaier, 1994; Houze, 2012). IMERG
accumulations appear to more pronounced in the foothills of the Canadian Rockies and away from the continental divide, which reinforces previous studies that have stated that IMERG accuracy is deprecated in cold mountain regions (Asong et al., 2017; Lundquist et al., 2019). These findings once again indicate that $Z_{\text{meas}}-Ka$ has the potential to improve IMERG estimates if chosen to be used as an intercalibration reference, especially in high mountain elevations where IMERG accuracy is the lowest.

Figure 7. Accumulated snowfall from 34 snowfall events for $Z_{\text{meas}}-Ka$ ($Z_m-Ka$), CORRA, and IMERG. This domain comprises the Canadian Rockies (purple line) between 50º and 52º latitude and -117º and -114º longitude. The black line is the continental divide.

3.4 GPM-DPR Inherent Limitations for Observing Shallow Precipitating Clouds

One inherent limitation of GPM-DPR is that it cannot observe shallow precipitating clouds with the current ground clutter filtering algorithm. An analysis was performed to assess this effect on this study and the potential operationalization of the developed snowfall algorithm. Each overpass was segmented into three categories: hits, sensitivity misses (not captured by radar Ka/Ku frequency sensitivity), and shallow misses (misses because the satellite only had valid returns above the precipitating cloud). From the 302 overpasses analyzed, only 60 were precipitation events. From those 60, 11 (18%) were hits, 30 (50%) were sensitivity misses, and 19 (32%) were shallow misses (Figure 8). The sensitivity misses are well described in the literature and are a limitation in designing the GPM-DPR to be focussed on liquid precipitation (Casella et al., 2017; Hamada & Takayabu, 2016; Hou et al., 2014). Conversely, shallow misses represent an important portion of the unobserved events happening during the period, and they
have not been studied in such a mountainous setting yet. The mean clutter-free height from the
302 overpasses at the studied site was 1500 m AGL, suggesting that GPM-DPR would not
observe any shallow precipitating clouds that develop between that atmospheric layer. This
unobserved layer could be one of the causes of IMERG’s systematic snowfall underestimation,
given that GPM-DPR observations utilized for IMERG intercalibration are taken at altitudes
above 1500 m AGL, limiting the amount of time in which hydrometeors mass could have been
increased due to accretion (Jiang & Smith, 2003). This condition is troublesome since accretion
seems to be an important process of precipitation increase in the region, previously observed in
the field by the excessive degree of riming of hydrometeors at the surface in the region (Thériault
et al., 2021, 2022). The latter mechanism could have been why convective systems with high
vertical development are more likely to be observed by GPM-DPR than shallower precipitation
systems. These findings shed light on the need to enhance ground clutter decontamination
algorithms for improving mountain snowfall estimation beyond satellite and sensor design
3.5. Proposed Algorithm Limitations and Directions for Future Studies

Although the proposed algorithm has been tested and demonstrated to work sufficiently well in a snowfall-dominated mountain region, some limitations remain. The algorithm was developed using near-surface (precipitation gauge and Parsivel²) and profiling (MRR-2) point-based measurements. Employing point-based measurements to develop a 5-km satellite algorithm can potentially raise scaling issues in highly heterogeneous environments such as...
mountain regions. Orographic enhancement in the region is high, as many studies have
demonstrated (e.g., Fang et al., 2019; Thériault et al., 2021, 2022). However, the developed
algorithm is accurate with a point-to-point evaluation (see Figure 4) and a point-to-satellite
evaluation (see Figure 5 and Table 2) with a correlation degradation from point to 5-km scales of
0.09. Among other sources of uncertainty, this degradation can be mainly attributed to these
scaling issues. Another source of uncertainty is associated with the difference in snowfall
observed at satellite altitudes and near-surface because this algorithm is limited to satellite
ground clutter free altitudes, and simulating hydrometeor sublimation and accretion within this
layer is not the scope of this study. Depending on environmental conditions, hydrometeors can
sublimate (dry atmosphere) or undergo accretion (humid atmosphere), resulting in a condensate
flux decrease or increase, respectively. Future studies dedicated to estimating satellite snowfall
closer to the surface should assess whether their evaluation provides similar results to those aloft
presented in Figure 5 and Table 2.

Aside from scaling and altitudinal limitations, uncertainty in Parsivel$^2$ and MRR-2
measurements can also affect the proposed algorithm’s accuracy. The Parsivel has known
uncertainties due to its operation principle, which consists of measuring particle quantity, size,
and velocity through a horizontal 2D laser beam at a high frequency (50 kHz). Major issues
associated with snowflake measurements arise from measuring only the widest size of the
hydrometeor crossing the laser sheet, calculating velocity using only the vertical portion of the
falling hydrometeor vector, observing one particle at a time, and edge effects (Battaglia et al.,
2010). The latter has been alleviated in the Parsivel$^2$ version (same used here) by utilizing
photodiodes to detect margin fallers (Tokay et al., 2014). Parsivel limitations can potentially
cause an underestimation of up to 20% in particle fall velocities and an underestimation in the
number of small and large snowflakes (Battaglia et al., 2010). These Parsivel limitations can
translate directly to an underestimation in snowfall rate since smaller $V_t$ and $N_{0,t}$ values decrease
snowfall as per Eqs. 3, 4, and 5. A negative bias was, in fact, observed in the evaluation that
relies on Parsivel$^2$ data (Figure 4), but not at the satellite-based evaluations in Figure 5 and Table
2. The MRR-2 uncertainty in estimating hydrometeor $Z_{e,t}$ and $W_t$ is relatively low, 0.53 dBZ and
0.109 m s$^{-1}$, respectively (Theriault et al., 2021). Differences in instrument radar frequency can
cause changes in snowfall estimation (Kulie & Bennartz, 2009). However, Maahn & Kollias
(2012) did not find considerable changes in reflectivity between the MRR-2 and a radar at 35.2
GHz frequency (close to GPM-DPR Ka frequency of 35.5 GHz). It is worth noting that this study employed the same method as that of Maahn & Kollias (2012) to process the MRR-2 reflectivities.

4 Conclusions

This research developed a new snowfall rate estimation algorithm for Ka and Ku band satellite radar reflectivities based on particle size distribution information from a high-elevation site in the Canadian Rockies, Alberta, Canada. When applied to measured Ka-band reflectivities ($Z_{\text{mea}-\text{Ka}}$), the newly developed algorithm presented the best evaluation statistics against MRR-2 snowfall rates ($r = 0.58$, bias = 0.43 mm h$^{-1}$, and RMSE = 0.83 mm h$^{-1}$), with snowfall accumulations coherent with orographic enhancement theory. $Z_{\text{mea}-\text{Ka}}$ snowfall estimates also spanned a wider range of snowfall rates compared to the other analyzed products. The CORRA product, employed to intercalibrate IMERG estimates, had the worst snowfall rate estimates ($r = 0.07$, bias = -0.38 mm h$^{-1}$, RMSE = 0.85 mm h$^{-1}$). In addition, CORRA was rarely able to estimate snowfall rates surpassing 1.4 mm h$^{-1}$. Substantial differences were apparent in spatial snowfall accumulation, where $Z_{\text{mea}-\text{Ka}}$ estimated three times more accumulation than CORRA in the 34 analyzed snowfall overpasses. An analysis of the total 302 overpasses during the study period suggests that ground clutter could play a substantial role in the underestimation of snowfall by radar-based products, such as those originated from GPM-DPR, accounting for 32% of snowfall events missed during the overpasses.

The algorithm developed was capable of reasonably estimating snowfall rates at the surface (Figure 4) and satellite observation altitudes (Figure 5 and Table 2). Snowfall rates from the algorithm applied to $Z_{\text{mea}-\text{Ka}}$ spanned a wider range of snowfall rates while preserving the expected spatial consistency of snowfall accumulation in this cold mountain region. These results demonstrate that the new algorithm outperforms CORRA in many aspects, which is an encouraging finding for improving multi-satellite and -sensor precipitation products such as IMERG. The novelty of this research was to develop an algorithm with simple parameterization and inputs that are available in many NWP models hosted by regional agencies worldwide while eliminating unnecessary reflectivity corrections employed in current radar snowfall algorithms. This research findings also shed light on the inherent problem of ground clutter in mountain
regions, which can considerably contribute to the underestimation of snowfall. The latter suggests a need for improving ground clutter filtering algorithms in mountains and makes a recommendation for future satellite-sensor designs attempting to measure mountain precipitation with microwave radar.

As new and improved satellite radar algorithms capable of estimating snowfall emerge from the results of this research, precipitation estimates in data-scarce cold mountain regions should improve, and low-latency estimates developed here can enhance global precipitation products in cold mountain regions. While often not the most accurate form of precipitation monitoring, these global satellite products can be the sole alternative for precipitation monitoring in remote regions where dense networks and high-resolution NWPs are unavailable. Improving precipitation forcing in hydrological models is crucial in reliably estimating streamflow and other hydrologically relevant variables. The advancement of precipitation monitoring can have important downstream consequences in enhancing hydrological predictions which may benefit communities, industries, and governments in their attempts to become better prepared for hydrological extremes of flood and drought in a changing climate.

Acknowledgments

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The codes to evaluate MRR-2 and satellite profile-based snowfall estimates, to generate satellite spatial snowfall estimates, and other analyses present in this paper, as well as processed surface observations are available in Bertoncini (2024, April 30) and at:

https://github.com/andrebertoncini/gpmdpr_snowfall. GPM based data is available at:

https://gpm.nasa.gov/data/directory.

References


