1	How much snow falls in the world's mountains?					
2	A first look at mountain snowfall estimates in A-train observations and reanalyses.					
3	Anne Sophie Daloz ^{1,2,3} , Marian Mateling ⁴ , Tristan L'Ecuyer ^{2,4} , Mark Kulie ⁵ , Norm B. Wood ¹ ,					
4	Mikael Durand ⁶ , Melissa Wrzesien ⁷ , Camilla W. Stjern ³ and Ashok P. Dimri ⁸ .					
5	1. Space Science and Engineering Center (SSEC), University of Wisconsin-Madison,					
6	1225 West Dayton Street, 53706 Madison, WI, USA					
7	2. Center for Climatic Research (CCR), University of Wisconsin-Madison,					
8	1225 West Dayton Street, 53706 Madison, WI, USA					
9	3. Center for International Climate Research (CICERO)					
10	Gaustadalleen 21, 0349, Oslo, Norway					
11	4. Department of Atmospheric and Oceanic Sciences (AOS), University of Wisconsin-					
12	Madison					
13	1225 West Dayton Street, 53706 Madison, WI, USA					
14	5. NOAA/NESDIS/STAR/Advanced Satellite Products Branch					
15	1225 West Dayton Street, Madison, WI 53706, USA					
16	6. School of Earth Sciences and Byrd Polar and Climate Research Center, Ohio State					
17	University					
18	108 Scott Hall, 1090 Carmack Rd, Columbus OH, 43210, USA					
19	7. Department of Geological Sciences, University of North Carolina at Chapel Hill					
20	Chapel Hill, NC 25799, USA					
21	8. School of Environmental Sciences, Jawaharlal Nehru University,					
22	New Delhi, 110067, India					
23						

24 Abstract

25 CloudSat estimates that 1773 cubic km of snow falls, on average, each year over the world's mountains. This amounts to five percent of the global snowfall accumulations. This study 26 27 synthetizes mountain snowfall estimates over the four continents containing mountains (Eurasia, 28 North America, South America and Africa), comparing snowfall estimates from a new satellite 29 cloud radar based dataset to those from four widely used reanalyses: Modern-Era Retrospective 30 analysis for Research and Applications (MERRA), MERRA-2, Japanese 55-year Reanalysis (JRA-31 55) and European Center for Medium-Range Weather Forecasts Re-Analysis (ERA-Interim). 32 Globally, the fraction of snow that falls in the world's mountains is very similar between all these 33 independent datasets (4-5%), providing confidence in this estimate. The fraction of snow that falls 34 in the mountains compared to the continent as a whole is also very similar between the different 35 datasets. However, the total of snow that falls globally and over each continent – the critical factor governing freshwater availability in these regions – varies widely between datasets. The consensus 36 37 in fractions and the dissimilarities in magnitude could indicate that large-scale forcings may be 38 similar in the five datasets while local orographic enhancements at smaller scales may not be 39 captured. This may have significant implications for our ability to diagnose regional trends in 40 snowfall and its impacts on snowpack in the rapidly evolving alpine environments.

41

42

43

44

45

47 **1. Introduction**

Falling snow transfers moisture and latent energy between the atmosphere and the surface. 48 49 Snow impacts the surface radiant energy transfer by modifying albedo and emissivity. 50 Accumulated snow can also act as a thermal insulator that modifies sensible heat fluxes and how 51 surface temperature responds to changes in atmospheric conditions. Furthermore, it acts as a 52 surface water storage reservoir (Rodell et al., 2018), providing seasonal runoff that provides fresh 53 water supplies for both human populations and water-dependent ecosystems. Billions of people 54 around the world depends on these resources. These water supplies are recognized as being at risk 55 from climate change and rising global temperatures (Barnett et al., 2005; Mankin et al., 2015).

56

57 The advent of satellite-borne instruments capable of detecting falling snow and of reanalysis 58 products that diagnose snowfall have made possible a global examination of how snowfall is 59 distributed and its contribution to atmospheric and surface processes. Precipitation gauge 60 measurements of snowfall for meteorological and hydrological purposes provide valuable data but 61 have historically suffered shortcomings related to spatial sampling and gauge performance (Kidd 62 et al., 2017). Shortcomings in the accuracy of such measurements and methods to improve that 63 accuracy have been the focus of a number of studies (Goodison et al., 1998; Kochendorfer et al., 64 2018). Beyond accuracy issues, these gauge networks are necessarily of limited spatial coverage 65 potentially biasing climatologies over large domains. Coverage of ocean regions is not possible. 66 Over land, gauges tend to be located near inhabited areas, leading to spare or nonexistent coverage 67 in more remote locations (Groisman and Legates, 1994). These remote locations include areas 68 such as the high latitudes and mountains, where snowfall can be the dominant form of 69 precipitation. Even when these areas have relatively dense gauge networks such as the CONUS

(Contiguous United States) mountains, gridded datasets have their limitations, most notably gauge
under catchment issues and large snowfall accumulation gradients in complex terrain that are often
insufficiently sampled by existing in situ networks (Henn et al., 2018).

73

74 Given these shortcomings in snowfall surface observations, studies on snowfall in remote 75 locations commonly rely on reanalyses (e.g. Bromwich et al., 2011). Reanalyses utilize numerical 76 weather prediction models to integrate observations of large-scale geophysical fields (e.g., 77 temperature and water vapor). One strength of reanalysis datasets is their continuous spatial and 78 temporal coverage. However, the veracity of reanalysis snowfall datasets depends strongly on the 79 underlying model and the assimilated datasets, which often exhibits systematic and varied biases 80 (Daloz et al. 2018). In addition, their low spatial resolutions can be a limitation especially in 81 regions of complex topography and reanalyses should therefore be used with caution. For example, 82 Wrzesien et al. (2019) showed that reanalyses have large biases in terms of snow water equivalent 83 (SWE) over North America. Wang et al. (2019) compared the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5th generation (ERA5) and ERA-Interim snowfall 84 85 estimates over Arctic sea ice and showed higher snowfall in ERA5 compared to ERA-Interim 86 resulting in a thicker snowpack for ERA5. Orsolini et al. (2019) focused on the Tibetan Plateau 87 and evaluated snow depth and snow cover estimates from reanalyses (ERA-5, ERA-Interim, 88 Japanese 55-year Reanalysis (JRA-55), and Modern-Era Retrospective analysis for Research and 89 Applications 2 (MERRA-2)), in situ observations and satellite remote sensing observations. They showed that reanalyses can represent the snowpack of the Tibetan Plateau but tend to overestimate 90 91 snow depth or snow cover. Snow accumulation measurements from automatic weather stations are 92 compared to reanalysis datasets (ERA-Interim and National Center for Environmental Prediction

-2 (NCEP-2)) over the Ross Ice Shelf in Antarctica in Cohen and Dean (2013). While both
reanalysis datasets miss a number of accumulation events, ERA-Interim is able to capture more
events than NCEP-2. Liu and Magulis (2019) evaluated snowfall precipitation biases over Hign
Mountain Asia in MERRA-2 and ERA-5. The results show that, at high altitudes, snowfall is
underestimated in both reanalyses. In this current study, four reanalysis datasets will be examined:
MERRA, MERRA-2, ERA_Interim and JRA-55.

99

100 As an alternative to reanalyses, snowfall rates can now be assessed using satellite observations 101 (with sufficient spatio-temporal coverage) provided by CloudSat's Cloud Profiling Radar (CPR). 102 CloudSat observations, nearly continuous since 2006 (Stephens et al., 2002, 2008), have been 103 applied to produce near-global estimates of snowfall occurrence and intensity (Liu 2008; Kulie 104 and Bennartz, 2009; Wood and L'Ecuyer, 2018). The resulting datasets have been examined 105 extensively from local to global scales (Liu 2008; Kulie and Bennartz, 2009; Hiley et al., 2011; 106 Palerme et al., 2014; Smalley et al., 2015; Chen et al., 2016; Behrangi et al., 2016; Norin et al., 107 2015; Milani et al., 2018; Lemonnier et al., 2019a, b). CloudSat has substantially extended the spatial extent of precipitation measurements compared to existing gauge or radar networks. In 108 109 particular, these instruments have greatly enhanced the observations of light precipitation 110 including snowfall over oceans, over remote high latitude regions and over inaccessible land areas 111 (e.g., Behrangi et al., 2016; Milani et al., 2018; Smalley et al., 2015; Norin et al., 2017; Lemonnier 112 et al. 2019a, b).

113

However, satellite-based retrievals also have inherent uncertainties related, for example, totheir limited temporal coverage. For instance, they might miss some heavy events such as

116 atmospheric rivers in Western North and South America (Ralph et al., 2005; Neiman et al., 2008; 117 Viale and Nunez, 2011). Therefore, CloudSat snowfall retrievals have been extensively assessed 118 against a wide range of independent ground-based measurements. Hiley et al. (2011) seasonally 119 compared CloudSat snowfall estimates with Canadian surface gauge measurements, showing 120 better results for higher versus lower latitudes - especially lower latitude coastal sites. They 121 speculated that the latitudinal differences might be due to CloudSat sampling (more observations 122 at higher latitudes), snow microphysical differences associated with warmer snow events that 123 could affect CloudSat estimates (e.g., wetter snow, rimed snow, and/or mixed phase precipitation), 124 or precipitation phase identification issues associated with snow events in the 0-4°C temperature 125 range. CloudSat's 2C-SNOW-PROFILE (2CSP) product also displayed excellent light snowfall 126 detection capabilities when compared against the National Multi-Sensor Mosaic QPE System 127 (NMQ) dataset, a hydrometeorological platform which assimilates different observational 128 network. Still, CloudSat did not produce higher snowfall rates as frequently as NMQ (Cao et al., 129 2014). Further comparisons between CloudSat and the National Centers for Environmental 130 Prediction (NCEP) merged NEXRAD and rain gauge Stage IV dataset illustrated consistent 131 CloudSat-Stage IV performance when near-surface temperatures are below freezing (Smalley et 132 al., 2014). The CloudSat 2CSP product was also compared to a ground-based radar network in Sweden, showing consistent agreement in the $0.1 - 1.0 \text{ mm h}^{-1}$ snowfall rate range (Norin et al., 133 2015). However, 2CSP snowfall rate counts were lower above the 1 mm h⁻¹ threshold. 2CSP 134 135 retrievals have also been rigorously compared to ground-based profiling radars in Antarctica, with 136 CloudSat outperforming ERA-Interim grid-averaged results when MRR-derived retrievals are 137 used as a reference dataset (Souverijns et al., 2018). Comparisons between CloudSat and existing 138 reanalysis datasets are however scarce, and mostly limited to the poles (Palerme et al., 2014, 2017;

Milani et al., 2018; Behrangi et al., 2016). Together, these independent analyses provide confidence that CloudSat observations may deliver realistic accumulations on seasonal scales. The CloudSat snowfall dataset has also been proven useful for isolating distinct modes of snowfall variability on global scales. For instance, over-ocean convective snow has been comprehensively studied using CloudSat products (Kulie et al., 2016; Kulie and Milani, 2018). CloudSat also exhibits enhanced snowfall observational capabilities in mountainous regions compared to groundbased radar networks, partially due to scanning radar beam blockage issues (Smalley et al., 2014).

146

In spite of the noted shortcomings in snowfall datasets from gauge, radar and reanalyses,
mountain snowfall has not yet been thoroughly studied using multiple reanalyses and the CloudSat
data set. In this study, we derive mountain snowfall from five datasets (CloudSat 2CSP, MERRA,
MERRA-2, ERA-Interim and JRA-55) to answer the following questions:

151 1. How much snow falls on the World's mountains?

152 2. What percentage of continental snow falls on mountainous regions?

153 Given the challenges in retrieving snowfall from single-frequency radar observations, especially 154 in complex terrain, the CloudSat estimates are not treated as the "reference" dataset, though we 155 note that they are the only estimates derived directly from observations. All five sources are treated 156 as providing valid independent estimates of the fraction of snow that falls in mountainous 157 compared to all continental regions to document the current state of knowledge in this field. The 158 next section presents the different datasets employed in this study, as well as methodological 159 information such as the mountain and continental masks. Section 3 compares mountain snowfall 160 fraction and magnitudes between the different datasets while the following section, Section 4

discusses the differences in absolute magnitude of snowfall estimates. Finally, Section 5summarizes the results of this study and offers concluding remarks.

163

164 2. Data and Methodology

165 **2.1 Satellite observations**

For this work, the CloudSat data are spatially gridded onto a 1° x 3° (lat/lon) grid. The 166 167 nadir-pointing CPR onboard NASA's CloudSat satellite is the first spaceborne W-band (94-GHz) 168 radar. CloudSat's high inclination orbit (98°) provides a unique coverage of observed global 169 snowfall (Kulie et al., 2016). In addition to providing near-global sampling, the CPR has a 170 minimum detectable radar reflectivity of approximately -29 dBZ and is consequently sensitive to 171 lighter precipitation events (Tanelli et al., 2008). The CPR has a fixed field of view pointed at 172 near-nadir and measures over a spatial resolution of approximately 1.7 km along-track and 1.4 km 173 cross-track (Tanelli et al., 2008). The orbit is such that CloudSat revisits particular locations every 174 16 days. While this observing strategy limits sampling on short time-scales, CloudSat has observed 175 more than 120 million snowing profiles over its 10+ year mission providing a rich dataset from 176 which to derive snowfall frequency and cumulative snowfall over the large domains analyzed here. 177 CloudSat data are available from 2007.

178

179 CloudSat's 2CSP snowfall product, version R04 (Wood et al., 2013), provides estimates 180 of instantaneous surface snowfall rates (S) for each of these pixels derived from the observed 181 vertical profiles of radar reflectivity (Z). A version R05 is now available however, the snow 182 retrieval status variable is evaluated in the same way in the two versions of the product. The global 183 snowfall amount is very similar in R04 and R05 so the results should only differ slighly with the

184 new version of CloudSat. The data are spatially gridded onto a 1° x 3° (lat/lon) grid to ensure robust 185 sampling by the narrow CloudSat ground track. This means that the satellite data are sampled onto 186 the spatial grid desired and then averaged within each grid. The product derives instantaneous data 187 twice per month from an optimal estimation retrieval (Rodgers, 2000). They are then applied to 188 individual reflectivity profiles to obtain vertical profiles of snow microphysical properties. Ground 189 clutter affects radar bins nearest the surface, so the retrieval is applied only to the clutter-free 190 portion of the profile, i.e., that portion of the profile that is above the extent of likely ground clutter 191 effects, typically about 1.2 km over land. Surface snowfall rate is estimated as the rate in the lowest 192 clutter-free radar bin. The cumulative snowfall presented here are, thus, not true surface snowfall rates. Grazioli et al. (2017) compared the vertical profile of precipitation from the ECMWF 193 194 Integrated Forecasting System (IFS) model with satellite-borne radar measurements. They showed 195 some noticeable differences between the different datasets in the vertical structure. Clutter limits 196 CloudSat's ability to detect shallow snow events or capture strong variations in snow profiles near 197 the surface (Maahn et al, 2014; Souverijns et al, 2018; Palerme et al, 2017). While this introduces 198 uncertainty in the snowfall estimates presented here, the analysis of ground-based vertically-199 pointing radar in East Antarctica and in Svalbard (Norway) by Maahn et al. (2014) show that the 200 effects of this observing system limitations may be compensated by the competing effects of 201 evaporation and undetected shallow snowfall. It should also be noted that on November 1 2011, 202 there was a change in CloudSat's operating mode, leading to daytime-only operations, which can 203 lead to some uncertainty in the snowfall estimates.

204

Snow and rain are discriminated based on the CloudSat 2C-PRECIP-COLUMN product
(Haynes et al., 2013), which applies a melting layer model driven by the ECMWF analyses
temperature profiles. Snow particles are assumed to melt following the model of melted mass

fraction described by Haynes et al. (2009). All profiles with melted fractions less than about 15% at the surface (<1.2km) are considered snowing. Those with melted fractions greater than 90% are considered raining. Melted/frozen fractions between 15-90% are labeled "mixed" category considered to be a catch-all uncertainty for profiles that cannot be unambiguously classified as rain or snow using W-band reflectivity alone. Only snowing profiles are considered in this study.

213

214 2.2 Reanalyses

215 This study also considers four modern reanalyses: MERRA, MERRA-2, ERA-Interim and JRA-55. MERRA (Rienecker et al., 2011; 0.67° x 0.5° x 42 levels) uses the Goddard Earth 216 217 Observing System version 5 (GEOS-5) and the data assimilation system (DAS). MERRA-2 218 (Gelaro et al., 2017; Bosilovich et al., 2015; 0.635° x 0.5° x 42 levels) was recently introduced to 219 replace MERRA. ERA-Interim (Dee et al., 2011; 0.75° x 0.75° x 37 levels) is developed by the 220 ECMWF. ERA-Interim replaced the previous reanalysis dataset from the ECMWF, ERA-40. The 221 Japanese Meteorological Agency (JMA) has recently developed their second reanalysis dataset 222 after JRA-25: JRA-55 (Kobayashi et al., 2015; 0.56° x 0.56° x 60 levels). Both MERRA 223 (Rienecker et al., 2011) and MERRA-2 (Gelaro et al., 2017) use 3D variational assimilation 224 systems, where JRA-55 (Kobayashi et al., 2015) and ERA-Interim (Dee et al., 2011) use 4D. The 225 spatial and temporal modeling of snowfall alone is different in these reanalyses, as are some of the 226 physical mechanisms within. The MERRA-2 reanalysis is based on an updated version of the 227 GEOS-5 atmospheric model. Reichle et al. (2017) showed that the snow amounts are generally 228 better represented in MERRA-2 than MERRA. However, MERRA-2 precipitation has a known 229 deficiency over high topography due to issues in categorizing precipitation mode as large-scale 230 instead of convective (Gelaro et al., 2017). The results from these previous studies make the

231	comparison between MERRA and MERRA-2 particularly interesting in this case. JRA-55
232	assimilates the same observations that were used for the predecessor to ERA-Interim, ERA-40, as
233	well as archived observations from JMA. Both JRA-55 and ERA-Interim use their own forecast
234	models.

CloudSat has not been assimilated in any of the four reanalyses so it can be considered as
independent. All datasets used in this study are bilinearly interpolated from their native resolution
to match the 1° x 3° (lat x lon) grid of CloudSat. The data are examined over the time period 20072016 with a monthly temporal resolution. The production of MERRA data ended in February 2016,
as MERRA-2 is now the preferred dataset while CloudSat started in 2007.

241

242 2.3 Masks and definitions

243 Snowfall estimates from all sources are partitioned between the different continents using 244 the "continental mask" shown in Figure 1a. The continental mask was first used in L'Ecuyer et al. 245 (2015). Then, the mountain and non-mountain regions are separated using the "mountain mask" 246 presented in Figure 1b. Based on the Kapos et al. (2000) definition, grid cells are classified as 247 mountainous based on elevation, slope, and local elevation range. They used the global digital 248 elevation model GTOPO30 and ARC-INFO to identify areas above particular altitudes and 249 generate grids containing the slope and the local elevation range. Then, they combined these 250 variables, with adapted criteria, to define mountainous regions. The original mask was produced 251 using with a spatial resolution of 30 arc-seconds (~1 km). Our version of the mountain mask has been aggregated to 1° x 3° (lat/lon) grid to match the spatial resolution of the gridded CloudSat 252

253 2SCP. The combination of these two masks is used to subdivide the snowfall estimates over the254 four continents that contain mountains: North America, South America, Eurasia and Africa.

255

In this article, total mountain snowfall is equal to the cumulative snow falling over North America, South America, Africa and Eurasia. Greenland and Antarctica are considered as ice sheets and therefore do not qualify as continents with mountains. Global snowfall is the cumulative snow falling over all lands in the world, which includes the four continents already cited plus Greenland, Australia and Antarctica.

261

3. Mountain snowfall estimates in CloudSat observations and reanalyses

263 **3.1** Global spatial distribution of mountain snowfall

264 Table 1 shows the snowfall estimates for mountain and non-mountain snowfall for CloudSat and the reanalyses, over each continent and globally. According to CloudSat 265 266 observations, 1773 cubic km of snow falls over global mountains per year. This number is an 267 average over the volume of snow falling during the time period from 2007 to 2016. From CloudSat 268 estimates, 5% of global snowfall is within mountainous areas. It is encouraging that the fraction 269 of snow falling in the mountains occupies a narrow range from 4% for MERRA's reanalyses and 270 JRA-55 to 5 % for ERA-Interim and CloudSat. This good agreement between the different datasets 271 (Table 1) allows us to state with some confidence that 5% of all continental snow falls in the 272 mountains globally. In the reanalyses, while the fraction of snow within the mountains is similar 273 across all datasets, the amount of snow falling over the mountains varies depending on the dataset 274 examined (cf. Table 1). MERRA and MERRA-2 global mountain snowfall estimates are close to

CloudSat with 1763 and 1891 cubic km per year, respectively, while ERA-Interim and JRA-55
show much lower amounts, with 1041 and 489 cubic km per year, respectively.

277

278 To visualize where the snow is falling, Figure 2 presents the geographical distribution of 279 the mountain snowfall estimates in CloudSat and the reanalyses. As expected, in all datasets a 280 majority of the mountain snow falls in the Northern Hemisphere (Himalayas and Rockies; 95-281 99%), with little snowfall (<5%) in the Southern Hemisphere. The geographical patterns exhibited 282 by MERRA, MERRA-2 and CloudSat seem to resemble each other while ERA-Interim and JRA-283 55 tend to show different geographical distributions with generally lower snow rates. However, 284 when focusing on specific regions, we can see that MERRA-2 has also major differences compared 285 to MERRA and CloudSat: For example, over South America or Eastern Russia, MERRA-2 286 produces much more snow than all the other datasets. Another interesting difference appears when 287 comparing the datasets over North America versus Asia. ERA-Interim has higher snow rates in 288 the Rockies compared to the Himalayas while for the other datasets they are comparable. To go 289 deeper into the comparison of the datasets, Figure 3 presents the differences in geographical 290 distribution of mountain snowfall between CloudSat and the reanalyses over the High-mountain 291 Asia. This figure clearly shows very large differences between CloudSat and the reanalyses, 292 reaching +/- 10 mm/month/gridbox at some locations. In general, both ERA-Interim and JRA-55 293 present much lower snow accumulations compared to CloudSat. On the other hand, MERRA and 294 MERRA-2 present lower snow accumulations on the southern part of the domain and higher on 295 the northern part. These differences in snowfall distribution have major implications in terms of 296 mountain runoff, millions of people in the surrounding regions depend on these resources. The 297 systematically lower mountain snowfall estimates in ERA-Interim and in JRA-55, as well as the

tendency for MERRA-2 to produce higher mountain snowfall rates over some continents will befurther discussed below.

- 300
- 301

3.2 Contribution of mountain snowfall to continental snowfall

302 Table 1 also shows the contribution of mountain snowfall to total snowfall for CloudSat 303 and each reanalysis over each continent. To get a better sense of the contribution of orography to 304 snowfall, the percentage of mountainous grid points over each continent is provided in the last 305 column of the table. Eurasia has the highest fraction of mountainous grid boxes with 33% of its 306 grid boxes considered as mountains. North and South America have a quarter of their grid boxes 307 covered with mountains and only 14% of the African continent is considered mountainous. The 308 contribution of mountain snowfall does not vary substantially between continents. For Eurasia, 309 South America and Africa, it is around 10 % while for North America it represents around 5% of the snow falling over the continent. Over all the continents, the agreement between the reanalyses 310 311 and CloudSat observations is very good with differences under 4%.

312

313 Coherently with the previous section, the magnitude of mountain snowfall estimates over 314 the four continents vary a lot depending on the datasets examined. MERRA's datasets and 315 CloudSat present similar magnitude in terms of mountain and continental snowfall while ERA-316 Interim and JRA-55 present much lower estimates than the other datasets. For example, over 317 Eurasia the values for mountain snowfall vary between 379 for JRA-55 and 1440 cubic km per 318 year for CloudSat. Over North America, it varies from 105 cubic km per year for JRA-55 to 378 319 cubic km per year for MERRA-2 and for South America from 5 for JRA-55 to 86 cubic km per 320 year for MERRA-2. Unfortunately, the high range of differences observed for mountain snowfall

also applies for the magnitude of total snowfall over each continent. In all cases, JRA-55 shows the lowest magnitude estimates and MERRA-2 the highest. It is also interesting to point out that CloudSat is always part of the higher range of snowfall estimates for each continent. Due to its limited temporal coverage, it might be missing some heavy snow events such as atmospheric rivers in Western North America (Rutz and Steenburgh, 2012; Lavers and Villarini, 2015; Molotch et al. 2010). These few events contribute to a large part of the water year precipitation but as the analysis has been done over several years, this should have a limited impact on the total accumulated snow.

329 4. Examination of the differences in snowfall magnitude

330 The previous section showed a very good agreement between all the datasets in terms of 331 mountain snowfall fractions. However, the spatial maps presented in Figure 2 and the absolute 332 snowfall amounts in Table 1 showed substantial differences in magnitude between the different 333 datasets. This is further demonstrated in Figure 4 that summarizes the snowfall estimates in 334 mm/month/grid box over Eurasia, North America, South America and Africa and its partitioning 335 between mountainous (blue) and non-mountainous areas (yellow) for the five datasets. To ease the 336 comparison between the different datasets, here the snowfall amounts are normalized by the 337 number of mountain and non-mountain grid boxes respectively. There is some consistency in the 338 relative behavior of the various datasets between the regions. Consistently with the results in 339 Section 3, JRA-55 always has the lowest estimates of snowfall per grid box (cf. Table 1). For 340 example, over North America and Eurasia, JRA-55 produces 68% less snowfall than the average of the four other datasets (Fig. 4). Even so, when looking at Figure 5, which presents the frequency 341 342 of snowfall occurrences for each continent for all datasets, the frequency of snowfall occurrences 343 for JRA-55 is very close to the other products. This indicates that JRA-55 underestimates the

344 intensity of many snowfall events. ERA-Interim also tends to be on the lower end of the spectrum 345 concerning snowfall, compared to the other datasets (Fig. 4). This can be at least partly attributed 346 to its systematic lower frequency of snowfall occurrences (cf. Figure 5). With the exception of 347 North America, MERRA-2 generally has the highest total snowfall compared to the other datasets (Fig. 4). Again, this is consistent with the results shown in the previous section. This overestimate 348 349 is related to the way this dataset represents the frequency of snowfall events. MERRA-2 produces 350 much more snowfall events than the other datasets (cf. Figure 5). This bias might be similar to the 351 bias identified for precipitation in climate models, producing too frequent and too lightly-352 precipitating events, referred to as "perpetual drizzle" (Stephens et al., 2010). This could be 353 happening for snowfall events in MERRA-2.

354

355 The differences in snowfall among datasets is especially prominent over Africa and South 356 America. Over Africa (Fig. 4d), both MERRA and MERRA-2 produce much more snow than the 357 other datasets, with MERRA-2 producing nearly twice as much snowfall as MERRA. MERRA 358 produces 75% more snowfall than the average of the three remaining datasets (ERA-Interim, JRA-359 55 and CloudSat) while MERRA-2 produces 85% more. For the same reasons, over South America 360 MERRA-2 produces 73% more snowfall than the average of the other datasets. Furthermore, it 361 highly exceeds the mountain and non-mountain snowfall compared to the other datasets. However, 362 as most of the snow over South America is mountainous, the excess in mountainous snowfall has 363 a stronger impact on the differences in total accumulated snowfall. The seasonal cycle of mountain 364 snowfall over South America (not shown) provides another interesting explanation for this specific 365 bias. From January to December, MERRA-2 overestimates the other datasets but with a similar 366 seasonal cycle in the first part of the year. However, during the second part (after June), the

behavior of MERRA-2 is very different – instead of a decrease in mountain snowfall, snowfall
accumulations remain very high and steady. This is clearly a major contributor to the high snowfall
estimates of MERRA-2 over South America.

370

371 Overall, these results are coherent with previous studies comparing different reanalysis 372 datasets (Daloz et al. 2018, Sebastian et al. 2016, Thorne and Vose 2010). They all show that 373 reanalyses are able to represent some general patterns but also show very important differences. 374 For example, Sebastian et al. (2016) compared atmospheric budgets for the computation of water 375 availability in different reanalyses. They showed considerable variations in the individual 376 components of the different budgets and suggested that part of these variations could be attributed 377 to differences in the representation of clouds and convective schemes for precipitation. 378 Furthermore, Daloz et al. (2018) showed significant differences in the representation of clouds in 379 the reanalyses examined in this article, confirming the hypothesis of Sebastian et al. (2016). More 380 specifically, they showed that JRA-55 exhibits some strong deficiencies in the representation of 381 clouds and that MERRA-2 introduces some biases that were not evident in MERRA. These results 382 may partly explain the deficiencies observed for these two datasets.

383

384 5. Summary and conclusion

Snowfall plays an important role in a number of atmospheric and surface processes that impact energy and hydrological cycles and can influence Earth's climate. To understand these processes, and how they will be influenced by future climate change, it is imperative to have reliable observations of present-day mountain snowfall. This study is a preliminary step towards an estimate of mountain snowfall from CloudSat satellite observations and four reanalyses
(MERRA, MERRA-2, JRA-55 and ERA-Interim). In this work we answer the following questions:

391 1. How much snow falls on the World's mountains?

1773 cubic km per year of snow falls on the World's mountains in CloudSat observations, 1763
cubic km per year in MERRA, 1891 cubic km per year in MERRA-2, 1041 cubic km per year in
ERA-Interim and 489 cubic km per year in JRA-55 (cf. Table 1).

395 2. What percentage of continental snow falls on mountainous regions?

4 to 5% of snow falls over the mountains (cf. Table 1).

397

One aim of this research is to provide context for researchers who want to use snowfall 398 399 estimates globally or on specific continents from reanalyses and/or satellite observations. The 400 results of the discussion clearly emphasize the necessity of using several datasets, including different platforms such as reanalyses and satellite observations. Results presented here can help 401 402 future analyses select validation datasets for specific continents, since we show that some datasets 403 behave differently than the others for continental snowfall estimates. For instance, modelers have 404 difficulties accurately representing snowfall over South American mountains (Gelaro et al., 2017), 405 and it is suspected that MERRA-2 is not the optimal dataset to use for this continent. However, 406 this study and Wrzesien et al. (2019) showed that over North America, MERRA-2 is certainly a 407 realistic dataset with substantial skills. Generally, there is no good or bad dataset, however some 408 datasets may outperform others over certain continents. These different abilities in the reanalyses 409 and satellite products can lead to issues when validating climate models, for example. We therefore 410 recommend to use an ensemble of the products just like it is recommended to use several models 411 or simulations. This study also suggests that estimates of the fraction of snow that falls in the 412 mountains compared to all-continental snowfall may be more reliable than estimates of the 413 absolute magnitude of mountain snow accumulations. A hypothesis behind this result could be that 414 the datasets presented here have a similar representation of the large-scale forcings but differences 415 at local/smaller scales, which could be due to differences in the physical parameterizations of the 416 models, subgrid-scale parameterizations of orographical effects. Indeed, even if the reanalyses are 417 based on different models, they should simulate similar and realistic large-scale forcings. For 418 CloudSat, its ability to capture these forcings would come from its relatively good level of temporal 419 and spatial coverages. This could explain the consensus between the different datasets in terms of 420 snowfall fractions. On the other hand, at smaller scales, both types of datasets experience different limitations which would explain the dissimilarities in snowfall magnitude. For example, for 421 422 CloudSat, its spatial coverage could lead it to miss some heavy snow events like atmospheric 423 rivers.

424

425 In the future, this work will expand in several directions. First, a deeper and more process-426 oriented analysis of the differences observed during the different datasets should be done over each 427 continent. While this study is confined to mountain snowfall produced by CloudSat and reanalysis 428 datasets, it also serves as a foundation for studying cloud microphysical and dynamical processes 429 operating within snow-producing clouds forced by orography. Because different modes of 430 snowfall have varying impacts on the environment and potentially unique remote sensing 431 fingerprints, identifying specific types of snowfall could lead to better measurements of snowfall. In addition, this could also improve forecasting by representing different snowfall modes more 432 433 realistically within numerical weather models. Also, to evaluate the ability of climate models to

represent snowfall estimates, this same analysis could be realized for climate models such as theCMIP5 ensemble, or the forthcoming CMIP6 ensemble.

436

437 Acknowledgments and Data

438 For ASD, this research was supported by a seed grant from the Center of Climatic Research of the 439 University of Wisconsin-Madison. Parts of this work by TL was performed at the University of 440 Wisconsin-Madison for the Jet Propulsion Laboratory, California Institute of Technology, 441 sponsored by the National Aeronautics and Space Administration (NASA) CloudSat program. 442 This work by MK was also partly supported by a NASA grant award NNX16AE21G. Parts of this 443 research by NBW were performed at the University of Wisconsin - Madison for the Jet Propulsion 444 Laboratory, California Institute of Technology, sponsored by the National Aeronautics and Space 445 Administration. CloudSat data used herein were acquired from the CloudSat Data Processing 446 Center (DPC) and time of writing can be accessed online at the at 447 http://www.cloudsat.cira.colostate.edu; we acknowledge the support of the DPC in providing the 448 data. MERRA and MERRA-2 data were provided by NASA's Global Modeling and Assimilation 449 Office (GMAO) and obtained through the Goddard Earth Sciences Data and Information Services 450 Center (GES DISC). JRA-55 data was provided by the Japanese Meteorological Agency and 451 obtained through the National Center for Atmospheric Research's (NCAR) Research Data 452 Archive. ERA-Interim data was provided by the European Centre for Medium-Range Weather 453 Forecasts (ECMWF) and obtained via the ECMWF WebAPI. The views, opinions, and findings 454 contained in this report are those of the author(s) and should not be construed as an official 455 National Oceanic and Atmospheric Administration or U.S. Government position, policy, or 456 decision.

References

458	Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming								
459	climate on water availability in snow-dominated regions. Nature, 438(7066), 303-309.								
460	http://doi.org/10.1038/nature04141								
461	Behrangi, A., M. Christensen, M. Richardson, M. Lebsock, G. Stephens, G. J. Huffman,								
462	D. Bolvin, R. F. Adler, A. Gardner, B. Lambrigtsen, and E. Fetzer (2016), Status of high-latitude								
463	precipitation estimates from observations and reanalyses, J. Geophys. Res. Atmos., 121, 4468								
464	4486, doi: 10.1002/2015JD024546.								
465	Bosilovich, M.G., J. Chern, D. Mocko, F.R. Robertson, and A.M. da Silva, 2015:								
466	Evaluating Observation Influence on Regional Water Budgets in Reanalyses. J. Climate, 28, 3631-								
467	3649, https://doi.org/10.1175/JCLI-D-14-00623.1								
468	Bromwich, D. H., J. P. Nicolas, and A. J. Monaghan, 2011: An assessment of precipitation								
469	changes over Antarctica and the Southern Ocean since 1989 in contemporary global reanalyses, J.								
470	Clim., 24, 4189-4209, doi:10.1175/2011JCLI4074.1								
471	Cao, Q, Y. Hong, S. Chen, J.J. Gourley, J. Zhang and P.E. Kirstetter, 2014: Snowfall								
472	Detectability of NASA'S CloudSat: The first cross-investigation of its 2C-Snow-Profile Product								
473	and National Multi-sensor Mosaic QPE (NMQ) Snowfall Data. Progress in Electromagnetics								
474	Research, Vol. 148, 55-61.								
475	Chen, T., J. Guo, Z. Li, C. Zhao, H. Liu, M. Cribb, F. Wang, and J. He, 2016: A CloudSat								
476	Perspective on the Cloud Climatology and Its Association with Aerosol Perturbations in the								
477	Vertical over Eastern China. J. Atmos. Sci., 73, 3599–3616, https://doi.org/10.1175/JAS-D-15-								
478	0309.1								

Cohen L. and S. Dean, 2013: Snow on the Ross Ice Shelf: comparison of reanalyses and
observations from automatic weather stations. The Cryosphere, 7, 1399-1410. Doi:10.5194/tc-71399-2013.

Daloz, A.S., E. Nelson, T. L'Ecuyer, A.D. Rapp, and L. Sun, 2018: Assessing the Coupled
Influences of Clouds on the Atmospheric Energy and Water Cycles in Reanalyses with A-Train
Observations. *J. Climate*, **31**, 8241–8264, https://doi.org/10.1175/JCLI-D-17-0862.1

Dee, D. P., and Coauthors (2011), The ERA-Interim reanalysis: configuration and
performance of the data assimilation system, *Quart. J. Roy. Meteor. Soc.*, *137*, 553-597, doi:
10.1002/qj.828.

Gelaro, R., and Coauthors (2017), The Modern-Era Retrospective Analysis for Research
and Applications, Version 2 (MERRA-2), *J. Climate*, *30*, 5419-5454, doi: 10.1175/JCLI-D-160758.1.

Goodison B., P.Y.T. Louie and D. Yang, 1998 : WMO solid precipitation measurement
intercomparison : Final report. WMO/TD No. 872. WMO, Geneva 88pp. plus annexes 212pp.

493 Grazioli J., J.-B. Madeleine, H. Gallée, R.M. Forbes, C. Genthon, G. Krinner, A. Berne,

494 2017: Katabatic winds diminish Antarctic precipitation. Proceedings of the National Academy of

495 Sciences, 201707633; DOI: 10.1073/pnas.1707633114

496 Groisman, P. Y., and D. R. Legates, 1994: The accuracy of United States precipitation497 data. Bull. Am. Meteorol. Soc., 75, 215-227.

Guan, B., Molotch, N. P., Waliser, D. E., Fetzer, E. J., and Neiman, P. J. (2010), Extreme
snowfall events linked to atmospheric rivers and surface air temperature via satellite
measurements, *Geophys. Res. Lett.*, 37, L20401, doi:10.1029/2010GL044696.

Haynes, J. M., T. S. L'Ecuyer, G. L. Stephens, S. D. Miller, C. Mitrescu, N. B. Wood, and
S. Tanelli, 2009: Rainfall retrieval over the ocean with spaceborne W-band radar. J. Geophys.
Res., 114, D00A22, doi:10.1029/2008JD009973.

Haynes, J. M., and co-authors, 2013: Level 2-C Precipitation Column algorithm product
process description and interface control document, version P2_R04. CloudSat Project technical
document, National Aeronautics and Space Administration, 17 pp. Available from
http://www.cloudsat.cira.colostate.edu/sites/default/files/products/files/2C-PRECIP-

508 COLUMN_PDICD.P2_R04.20130124.pdf, last access 20 June 2019.

Henn, B., Newman, A. J., Ben Livneh, Daly, C., & Lundquist, J. D. (2018). An assessment
of differences in gridded precipitation datasets in complex terrain. Journal of Hydrology, 556,
1205–1219. http://doi.org/10.1016/j.jhydrol.2017.03.008

Hiley, M.J., M.S. Kulie, and R. Bennartz, 2011: Uncertainty Analysis for CloudSat
Snowfall Retrievals. *J. Appl. Meteor. Climatol.*, 50, 399–418,
https://doi.org/10.1175/2010JAMC2505.1

Kapos, V., J.Rhind, M. Edwards, M.F. Price and C. Ravilious, 2000: Developing a map of
the world's mountain forests. In: Forests in Sustainable Mountain Development: A State-ofKnowledge Report for 2000, M.F. Price and N. Butt (eds.), CAB International, Wallingford: 4–9.
Kidd, C., A. Becker, G.J. Huffman, C.L. Muller, P. Joe, G. Skofronick-Jackson, and D.B.

519 Kirschbaum, 2017: So, How Much of the Earth's Surface Is Covered by Rain Gauges?. *Bull. Amer.*

520 *Meteor. Soc.*, **98**, 69–78, https://doi.org/10.1175/BAMS-D-14-00283.1

521 Kobayashi, S., and Coauthors (2015), The JRA-55 Reanalysis: General Specifications and
522 Basic Characteristics, *J. Meteor. Soc. Japan*, *93*, 5-48, doi: 10.2151/jmsj.2015-001.

- Kochendorfer J. and Co-authors, 2018: Testing and development of transfer functions for
 weighing precipitation gauges in WMO-SPICE. Hydrol. Earth. Syst. Sc., 22, 1437-1452,
 doi:10.5194/hess-22-1437-2018.
- 526 Kulie, M. S., and R. Bennartz, 2009: Utilizing spaceborne radars to retrieve dry snowfall.
 527 J. Appl. Meteorol. Clim. 48, 2564-2580.
- Kulie, M.S., L. Milani, N.B. Wood, S.A. Tushaus, R. Bennartz, and T.S. L'Ecuyer, 2016:
 A Shallow Cumuliform Snowfall Census Using Spaceborne Radar. *J. Hydrometeor.*, 17, 1261–
 1279, https://doi.org/10.1175/JHM-D-15-0123.1
- Kulie, MS, Milani, L. Seasonal variability of shallow cumuliform snowfall: A Cloud-Sat
 perspective. *Q J R Meteorol Soc* 2018; 144 (Suppl. 1): 329–343. https://doi.org/10.1002/qj.3222
 Lavers, D.A., and G. Villarini, 2015: The contribution of atmospheric rivers to
 precipitation in Europe and the United States, Journal of Hydrology, Volume 522, Pages 382-390,
 ISSN 0022-1694, https://doi.org/10.1016/j.jhydrol.2014.12.010.
- Lemonnier F., J.-B. Madeleine, C. Claud, C. Palerme, C. Genthon, T. L'Ecuyer, N. Wood
 , 2019a: CloudSat-inferred vertical structure of snowfall over the Antarctic continent. JGR.
 Atmospheres, doi:10.1029/2019JD031399.
- Lemonnier F., J.-B. Madeleine, C. Claud, C.Genthon, C. Durán-Alarcón, C. Palerme, A.
 Berne, N. Souverijns, N. van Lipzig, I. V. Gorodetskaya, T. L'Ecuyer, N. Wood, 2019b:
 Evaluation of CloudSat snowfall rate profiles by a comparison with in-situ micro rain radars
 observations in East Antarctica. The Cryosphere Discuss., doi: 10.5194/tc-2018-236.
- L'Ecuyer, T.S., H.K. Beaudoing, M. Rodell, W. Olson, B. Lin, S. Kato, C.A. Clayson, E.
 Wood, J. Sheffield, R. Adler, G. Huffman, M. Bosilovich, G. Gu, F. Robertson, P.R. Houser, D.
 Chambers, J.S. Famiglietti, E. Fetzer, W.T. Liu, X. Gao, C.A. Schlosser, E. Clark, D.P.

546 Lettenmaier, and K. Hilburn, 2015: The Observed State of the Energy Budget in the Early Twenty-

547 First Century. J. Climate, 28, 8319–8346, https://doi.org/10.1175/JCLI-D-14-00556.1

Liu, G., 2008: Deriving snow cloud characteristics from CloudSat observations. J.
Geophys. Res., 113, D00A09, doi:10.1029/2007JD009766.

Liu Y. and S.A. Magulis, 2019: Deriving bias and uncertainty in MERRA-2 snowfall precipitation over High Mountain Asia. Front. Earth. Sci., https://doi.org/10.3389/feart.2019.00280

Maahn, M., C. Burgard, S. Crewell, I. V. Gorodetskaya, S. Kneifel, S. Lhermitte, K. Van
Tricht, and N. P. M. van Lipzig (2014), How well does the spaceborne radar blind zone affect
derived surface snowfall statistics in polar regions?, *J. Geophys. Res. Atmos.*, *119*, 132604-132620,
doi: 10.1002/2014JD022079.

Mankin, J.S., D. Viviroli, D. Singh, A.Y. Hoekstra, and N.S. Diffenbaugh, 2015: The
potential for snow to supply human water demand in the present and future. *Environ. Res. Lett.*,
10, no. 11, 114016, doi:10.1088/1748-9326/10/11/114016.

Milani, L., and Co-authors, 2018: CloudSat snowfall estimates over Antarctica and the
Southern Ocean: An assessment of independent retrieval methodologies and multi-year snowfall
analysis. Atmospheric Research 213, DOI:10.1016/j.atmosres.2018.05.015.

Neiman, P. J., F. M. Ralph, G. A. Wick, J. D. Lundquist, and M. D. Dettinger, 2008:
Meteorological characteristics and overland precipitation impacts of atmospheric rivers affecting
the west coast of North America based on eight years of SSM/I satellite observations. *J. Hydrometeor.*, 9, 22–47.

567 Norin, L., Devasthale, A., L'Ecuyer, T. S., Wood, N. B., and Smalley, M.: Intercomparison
568 of snowfall estimates derived from the CloudSat Cloud Profiling Radar and the ground-based

569 weather radar network over Sweden, Atmos. Meas. Tech., 8, 5009-5021,
570 https://doi.org/10.5194/amt-8-5009-2015, 2015.

Orsolini, Y., Wegmann, M., Dutra, E., Liu, B., Balsamo, G., Yang, K., de Rosnay, P., Zhu,
C., Wang, W., Senan, R., and Arduini, G.: Evaluation of snow depth and snow cover over the
Tibetan Plateau in global reanalyses using in situ and satellite remote sensing observations, The
Cryosphere, 13, 2221–2239, https://doi.org/10.5194/tc-13-2221-2019, 2019.
Palerme, C., C. Claud, A. Dufour, C. Genthon, N. B. Wood, and T. L'Ecuyer (2017),
Evaluation of Antarctic snowfall in global meteorological reanalyses, *Atmos. Res.*, *190*, 104-112,

577 doi: 10.1016/j.atmosres.2017.02.015.

Palerme, C., J. E. Kay, C. Genthon, T. L'Ecuyer, N. B. Wood, and C. Claud (2014), How
much snow falls on the Antarctic ice sheet?, *The Cryosphere*, *8*, 1577-1587, doi: 10.5194/tc-81577-2014.

Ralph, F. M., P. J. Neiman, G. A. Wick, S. I. Gutman, M. D. Dettinger, D. R. Cayan, and
A. B. White, 2006: Flooding on California's Russian River: Role of atmospheric river. *Geophys. Res. Lett.*, 33, L13801, doi:10.1029/2006GL026689.

Reichle, R.H., Q. Liu, R.D. Koster, C.S. Draper, S.P. Mahanama, and G.S. Partyka, 2017:
Land Surface Precipitation in MERRA-2. *J. Climate*, 30, 1643–1664,
https://doi.org/10.1175/JCLI-D-16-0570.1

587 Rienecker, M. M., and Coauthors (2011), MERRA: NASA's Modern-Era Retrospective
588 Analysis for Research and Applications, *J. Climate*, *24*, 3624-3648, doi: 10.1175/JCLI-D-11589 00015.1.

Rodell, M., J.S. Famiglietti, D. N. Wiese, J.T. Reager, H.K. Beaudoing, F.W., Landerer
and M.-H. Lo, 2018: Emerging trends in global freshwater availability. Nature 557, 651-659.

592	Rodgers, C. D. (2000), Inverse Methods for Atmospheric Sounding: Theory and Practice.
593	Series on Atmospheric and Oceanic and Planetary Physics, Vol. 2, World Scientific, 256.
594	Rutz, J. J. and Steenburgh, W. J. (2012), Quantifying the role of atmospheric rivers in the
595	interior western United States. Atmosph. Sci. Lett., 13: 257-261. doi:10.1002/asl.392
596	Sebastian, D., Pathak, A. & Ghosh, S. Use of Atmospheric Budget to Reduce Uncertainty
597	in Estimated Water Availability over South Asia from Different Reanalyses. Sci Rep 6, 29664
598	(2016). https://doi.org/10.1038/srep29664
599	Smalley, M., L'Ecuyer, T., Lebsock, M., and Haynes, J. (2014), A comparison of
600	precipitation occurrence from the NCEP Stage IV QPE product and the CloudSat cloud profiling
601	radar, J. Hydrometeorol., 15, 444-458, doi:10.1175/JHM-D-13-048.1.
602	Smalley, M. and T. S. L'Ecuyer, 2015: A global assessment of the spatial scale of
603	precipitation occurrence. J. Appl. Meteor. and Climatol., 54, 2179-2197.
604	Souverijns, N., Gossart, A., Lhermitte, S., Gorodetskaya, I. V., Grazioli, J., Berne, A.,
605	Duran-Alarcon, C., Boudevillain, B., Genthon, C., Scarchilli, C., and van Lipzig, N. P. M.:
606	Evaluation of the CloudSat surface snowfall product over Antarctica using ground-based
607	precipitation radars, The Cryosphere, 12, 3775-3789, https://doi.org/10.5194/tc-12-3775-2018,
608	2018.
609	Stephens, G. L., and Coauthors (2002), The CloudSat mission and the A-Train, Bull. Amer.
610	Meteor. Soc., 83, 1771-1790, doi: 10.1175/BAMS-83-12-1771.
611	Stephens, G. L., and co-authors, 2008: CloudSat mission: Performance and early science
612	after the first year of operation. J. Geophys. Res., 113, D00A18, doi:10.1029/2008JD009982.
613	Stephens et al., 2010, "Dreary state of precipitation in global models", JGR, 115, D24211,
614	doi:10.1029/2010JD014532.

615	Tanelli, S., S. L. Durden, E. Im, K. S. Pak, D. G. Reinke, P. Partain, J. M. Haynes, and F									nd R	
616	T. Marchan	d (200	08), CloudSa	t's Clo	ud Profil	ling Rada	r after tw	vo years	in o	rbit: Perform	ance
617	calibration,	and	processing,	IEEE	Trans.	Geosci.	Remote	Sens.,	46,	3560-3573,	doi
618	10.1109/TG	RS.20	008.2002030.								

Thorne, P.W. and R.S. Vose, 2010: <u>Reanalyses Suitable for Characterizing Long-Term</u>
Trends. *Bull. Amer. Meteor. Soc.*, **91**, 353–362, https://doi.org/10.1175/2009BAMS2858.1

Viale, M. and M.N. Nuñez, 2011: Climatology of Winter Orographic Precipitation over the
Subtropical Central Andes and Associated Synoptic and Regional Characteristics. *J. Hydrometeor.*, 12, 481–507, https://doi.org/10.1175/2010JHM1284.1

Wang, C., Graham, R. M., Wang, K., Gerland, S., and Granskog, M. A.: Comparison of
ERA5 and ERA-Interim near-surface air temperature, snowfall and precipitation over Arctic sea
ice: effects on sea ice thermodynamics and evolution, The Cryosphere, 13, 1661–1679,
https://doi.org/10.5194/tc-13-1661-2019, 2019.

Wood, N., T. L'Ecuyer, D. Vane, G. Stephens, and P. Partain, 2013: Level 2C Snow
Profile Process Description and Interface Control Document, Algorithm Version P_R04. NASA
JPL CloudSat project technical document revision 0, 21 pp. Available from
http://www.cloudsat.cira.colostate.edu/sites/default/files/products/files/2C-SNOW-

632 PROFILE_PDICD.P_ R04.20130210.pdf, last access 3 August 2015.

633 Wood, N. B., and T. S. L'Ecuyer, 2018: Level 2C Snow Profile Process Description and

634 Interface Control Document, Product Version P1_R05. NASA JPL CloudSat project document

635 revision 0., 26 pp. Available from

- 636 http://www.cloudsat.cira.colostate.edu/sites/default/files/products/files/2C-SNOW-
- 637 PROFILE_PDICD.P1_R05.rev0_.pdf, last access 20 June 2019.

638	Wrzesien, M. L., Durand, M. T., & Pavelsky, T. M., 2019: A reassessment of North
639	American River basin cool-season precipitation: Developments from a new mountain climatology
640	data set. Water Resources Research, 55. https://doi.org/10.1029/2018WR024106
641	
642	
643	
644	
645	
646	
647	
648	
649	
650	
651	
652	
653	
654	
655	
656	
657	
658	
659	
660	

661 Tables

662

663

Snowfall estimates	MERRA	MERRA-2	ERA- Interim	JRA-55	CloudSat	Percentage of mountain grid boxes per continent
Eurasia	1416/11176 11%	1426 / 13104 10%	808 /8112 9%	379 / 3916 9%	1440 / 10764 12%	33%
North America	312 / 4500 6%	378/5800 6%	223 /3450 6%	105 / 1725 6%	303 / 7325 4%	24%
South America	30 / 270 10%	86 / 662 12%	10 / 100 9%	5 / 46 10%	30 / 236 11%	21%
Africa	0.5 / 6 8%	0.8 / 11 7%	0.1 / 1 9%	0.07 / 0.5 12%	0.2 / 2 9%	14%
Global	1763/ 43403 4%	1891/47127 4%	1041/21363 5%	489/11288 4%	1773/35027 5%	

664

Table 1: The table summarizes the snowfall estimates of mountain and non-mountain 665 666 snowfall for MERRA, MERRA-2, ERA-Interim, JRA-55 and CloudSat for the time period 2007-667 2016, for Eurasia, North America, South America, Africa and globally. Global snowfall is the cumulative snow falling over all lands in the world, which includes the four continents already 668 669 cited plus Greenland, Australia and Antarctica. For each area and dataset, a table cell shows: the 670 amount of mountain (top left), non-mountain snow (top right; cubic km per year) and the 671 contribution of mountain snow to the total amount of snow falling over a continent (bottom, %). The last column shows the percentage of grid boxes considered as mountain by the mountain mask 672 over each continent. 673 674

675

677 Figures



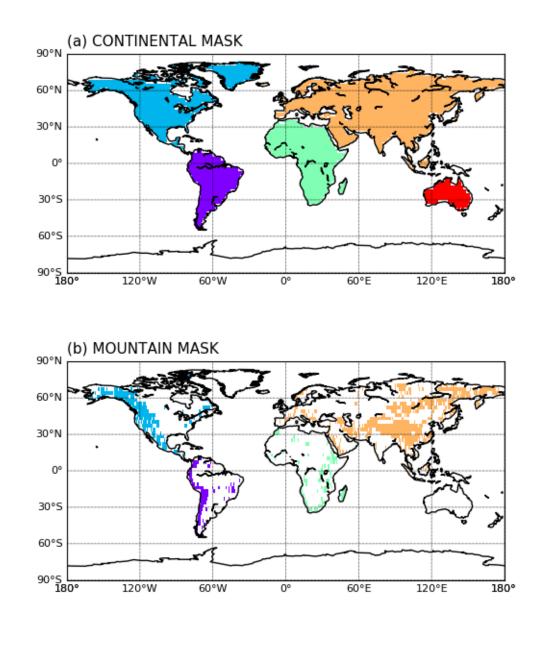


Figure 1: Spatial maps of the continental mask (a) with specific colors for each continent: blue for
North America, pink for South America, orange for Eurasia, green for Africa, red for Australia
and white for Antarctica; and the associated mountain mask (b) for each continent containing
mountains.

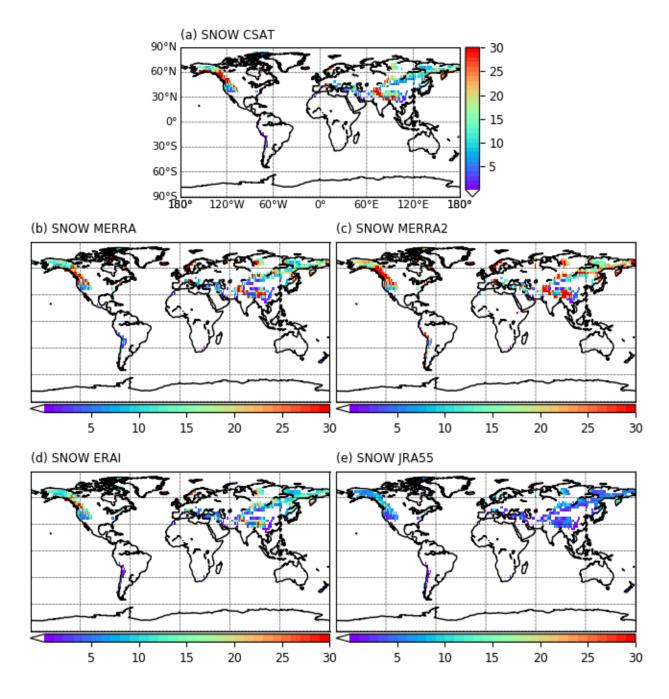


Figure 2: Spatial maps of global cumulative mountain snowfall (mm/month/gridbox) for a)
CloudSat, b) MERRA, c) MERRA-2, d) ERA-Interim and d) JRA-55, averaged over the time
period 2007-2016.

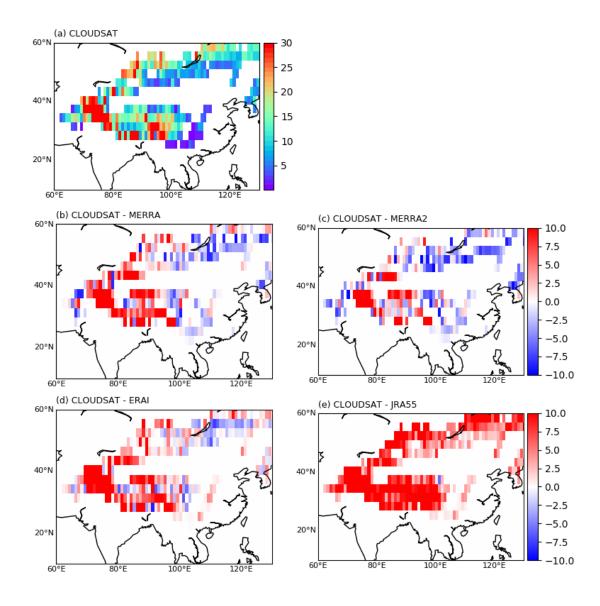


Figure 3: Spatial maps of the global cumulative mountain snowfall (mm/month/gridbox) over the
High-mountains Asia for a) CloudSat, b) CloudSat minus MERRA, c) CloudSat minus MERRA2, d) CloudSat minus ERA-Interim and d) CloudSat minus JRA-55, over the time period 20072016.

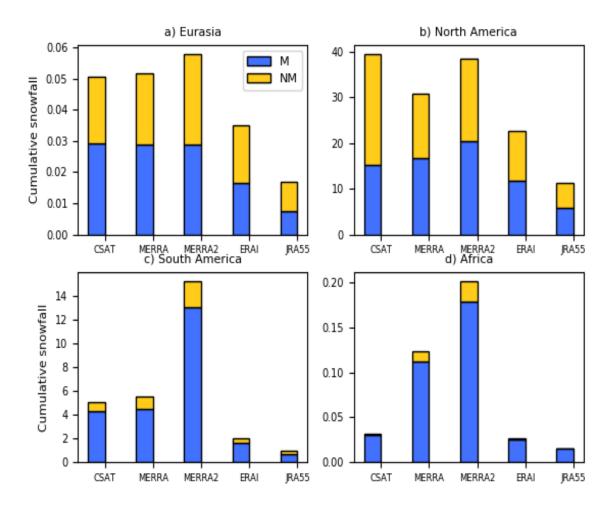


Figure 4: Snowfall estimates (mm/month/grid box) over: a) Eurasia, b) North America, c) South
America and d) Africa for CloudSat, MERRA, MERRA-2, ERA-Interim and JRA-55 over the
time period 2007-2016. Mountain snow is in blue and non-mountain snow is in yellow.

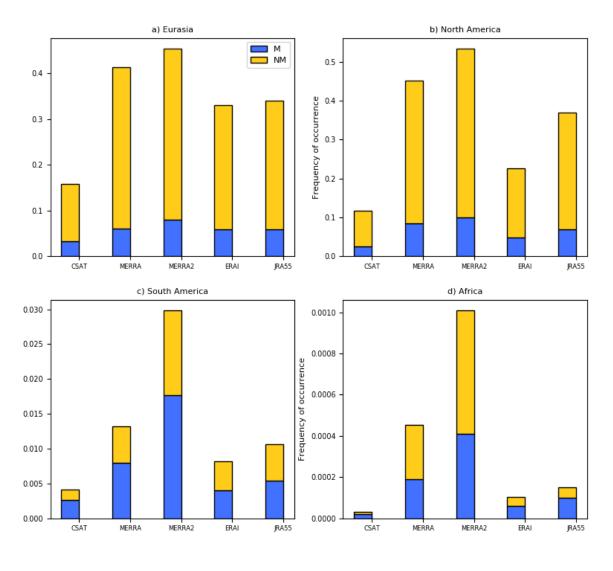


Figure 5: Frequency of occurrence of snowfall estimates over: a) Eurasia, b) North America, c)
South America and d) Africa for CloudSat, MERRA, MERRA-2, ERA-Interim and JRA-55 over
the time period 2007-2016. Mountain snow is in blue and non-mountain snow is in yellow.