A 7-year record of vertical profiles of radar measurements and
precipitation estimates at Dumont d'Urville, Adélie Land, East
Antarctica

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Abstract. S~~olid~~tudying precipitation ~~measurements in~~falling over Antarctica ~~are~~is crucial as snowfall
represents the main water input term for the
polar cap~~, and its probable increase in the coming century can mitigate sea-lev~~. However, precipitation
observations still remain scarce - and more particularly in the atmospheric column - due
to numerous experimental ~~ise caused by global warming. This paper~~sues related to the white continent.
This paper aims at helping to close this observation gap by
present~~s~~ing 7 years of Micro Rain Radar (Metek MRR-2) data at the Dumont d'Urville station in coastal
Adélie Land, East
5 Antarctica. Statistics are calculated on 3 radar variables (equivalent reflectivity, mean Doppler velocity and
signal-to-noise
5 ratio) to outline the main characteristics of the radar dataset. Seasonal and interannual variabilities are
also investigated, but no
significant temporal trends are detected except for the seasonal mean Doppler velocity which is higher in
summer and lower in
winter.

We then use the snowfall rate (S) data from a colocated snow-gauge to estimate the MRR precipitation
profile from the
10 radar equivalent reflectivity (Ze) through a locally derived Ze-S relation. We find the relation Ze = 43.3
S0.88. The processing
10
method used to obtain this relation, data quality and uncertainty considerations are discussed in the
manuscript.
In order to give an example of application of the dataset, a brief statistical comparison of the MRR
precipitation rate along
the vertical with model data from the ERA5 reanalysis and the LMDZ climate model is performed, and
notably shows that
models underestimate heavy precipitation events.

15 1 Introduction

15 Precipitation is the largest ~~positive~~input term for the surface mass balance of the Antarctic ice sheet
(Christopher et al. (1997), Krinner
et al. (2007)). It originates from evaporation over the
surrounding oceans, advection of water vapor to and over the ice sheet
by the atmospheric circulation, then condensation and
fall of condensed water to the surface. Various atmospheric processes
determine how much water vapor effectively condensates
above the ice sheet, how much falls all the way down to the surface,
20 and how much remains at the surface and effectively
contributes to accumulation and thus the ice sheet mass balance. Thomas

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et al. (2017) estimated from ice cores that the

20 Antarctic surface mass balance have increased in average by 14 ± 2.8 Gt per decade since 1900.

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Even concentrating on precipitation proper (ignoring post-deposition processes) raises a number of issues that may be
ignored in the most direct approaches to precipitation studies. In fact, many studies, and many available climatologies of
25 precipitation, focus on precipitation at the surface (e.g. the Global Precipitation Climatology Project (GPCP), Adler et al.
(2018)). This is sensible, as many issues with precipitation relate to the surface water budget, water resources at the surface
25 and mass balance of continental water bodies such as lakes and ice caps. One practical reason for concentrating on surface
precipitation is that it can be measured with ground-based instruments such as snow gauges (e.g., Seefeldt et al. (2021)). The
fate of precipitation in the atmospheric column, on the other hand, is more elusive due to the difficulty of monitoring the
30 atmosphere along the vertical dimension. Satellite-borne radars such as CloudSat, which operated from 2006 to 2011, enabled
the observation of precipitation above Antarctica on a continental scale (Palerme et al. (2014)), but with limited temporal
30 resolution (one orbit every 5 days), limited spatial coverage (north of 82°S), and without information below 1300 m above
ground level. Grazioli et al. (2017b) showed the importance of low-level processes such as the sublimation of precipitation
due to the dry air flowing from the Antarctic plateau, which was estimated to reduce snowfall by 17% in average all over the
continent35 continent, although other studies (Alexander et al. (2023), Bracci et al. (2022b)) find higher values of local snowfall reduction
(up to 50%) from surface remote sensing data at two coastal stations. This process can bias satellite estimates of precipitation
at the surface, and raises the necessity of ground-based measurements of the atmospheric column.
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Ground-based remote sensing using profiling techniques, such as meteorological radars and lidars, can provide valuable
additional data. Instrumental challenges (cost, technical expertise, energy requirements) tend to limit these applications to spe-
40 cific sites and contexts, e.g. for operational meteorology, or weather and hydrological risk predictions. The recent availability
of affordable, compact, low power consumption, relatively easy to use precipitation profiling radars has been a game changer
for the
study of the Antarctic precipitation in the atmospheric column rather than at the surface only. This has opened the possibility
40 of studying and documenting the processes occurring in the atmospheric column, from which surface precipitation results.
This has important added value for understanding the precipitation physics and evaluating meteorological and climate
45 models.

Numerical models are essential tools to forecast future climate changes, including the future contribution of Antarctic ~~pre-~~
precipitation evolution to global sea-level change. If Antarctica was to melt entirely, global sea-level would rise by ~~more than~~about 60
~~60~~ meters (Church et al. (2008)). This will not happen in a foreseeable future but the fact that realizing just 1% of this potential
would raise global
45 sea-level by 60 cm is a major source of concern (IPCC, Pörtner et al. (2022)). Conversely, an increase in accumulation due
to increasing precipitation over the continent, which is for example estimated at 51 ± 11 Gt yr−1 between
50 1991 and 2005 by
Lenaerts et al. (2018), has a mitigating effect on sea-level rise. Medley and Thomas (2019) estimated that precipitation over
Antarctica moderated sea-level rise by 2.5 mm per decade since 1979.

~~50~~ In recent years, Antarctica has significantly benefited from new approaches to observe precipitation. Measuring solid precip-
itation using traditional gauge methods is difficult (see SPICE project, Nitu et al. (2018)). It is particularly difficult in Antarctica
55 where the main issues of solid precipitation measurements are exacerbated : strong winds in the peripheral regions (Turner et al.

2
(2009) found more than 60 wind events of storm force or larger per year, i.e. over 24.5 m s−1, in three coastal stations), very
low precipitation rates in the interior (estimated at 36 mm yr−1 above 2250 m and north of 82°S by Palerme et al. (2014)),

~~55~~ problems with frost deposition on instruments, and low temperatures impacting electronic components.

~~2~~
Over the last decade, several research groups have deployed new generation of light precipitation radars at Antarctic stations:
60 at Princess Elisabeth (longitude~~ : 23.4~~, latitude~~ : -72.0,~~and altitude ~~:~~respectively 23.4◦, -72.0◦, 1392 m a.s.l., deployed in 2010, mostly sea~~-~~

sonal, Gorodetskaya
et al. (2015)), Mario Zucchelli (~~longitude :~~ 164.1◦ ~~latitude :~~ -74.7◦ ~~altitude :~~ 10 m a.s.l., deployed in December 2016, mostly
seasonal,
Bracci et al. (2022a)), Dumont d'Urville (140.0◦, -66.7◦, 41 m a.s.l., started in November 2015, Grazioli et al. (2017a),
~~60~~ Grazioli
et al. (2017b), Genthon et al. (2018)), and ~~other stations~~more recently at the Concordia station (123.3◦, -75.1◦, 3233 m a.s.l., Di Natale et al.
(2022)) and at the Davis station (78.0◦, -68.6◦, 27 m a.s.l., Alexander et al. (2023)). Radars are not influenced by most of the
65 problems that affect
the measurement of solid precipitation with gauges but there are other issues. The main one is that indirect information, such
as radar reflectivity resulting from the backscattering of microwaves by hydrometeors, has to be converted into hydrometeor
distributions and concentrations in the atmosphere, then to mass and fall speed to retrieve a precipitation ~~flux~~
flux (Peters et al. (2002)). This involves
hypotheses and tuning. In addition, these radars have been initially developed, and

are provided with processing tools, designed
65 for liquid precipitation. Obviously, for Antarctica, this has to be revised to access
70 solid precipitation (Maahn and Kollias (2012))

In this paper, we present 7 years of vertical profiling of precipitation at the Dumont d'Urville station in Adélie Land, East
Antarctica using a Metek Micro-Rain Radar (MRR-2) precipitation profiler. The setting, instruments, data processing methods
and datasets are presented in Sect. 2. The main characteristics of the MRR dataset, including variability, statistics and extremes
7005 are presented in Sect. 3.1. In Sect. 3.2, the mean MRR snowfall profile is derived from an empirical and local Ze-S relation,
enabling a vertical comparison with two climate models in section 3.3 as an example of application of the dataset. A general
conclusion with information on data access and format is provided in Sect. 4.

2 Setup, data and methods

2.1 Micro Rain Radar

7580 A Micro Rain Radar (Metek MRR-2, see Fig. 2a) transmitting in the K-band at 24 GHz was deployed at the Dumont d'Urville
Antarctic station in late 2015. Grazioli et al. (2017a) and Genthon et al. (2018) describe the setting, processing and first set of
of data from the instrument. The Dumont d'Urville (DDU) station is located on the Petrels Island longitude : 140.0014°, latitude
: -66.6628°, 41
m a.s.l., see Fig. 1), about 5 km off the coast of Adélie Land. As precipitation is essentially associated with synoptic extra-
tropical cyclones there (Jullien et al. (2020)), observations at DDU are representative of precipitation at the

85 nearby coast of the

80 Antarctic ice sheet. Setting the radar at DDU rather than on the ice sheet has the advantages that it provides
easy permanent
access to power and network, as well as servicing if necessary. It is installed within a unheated radome which
protects the instruments
from the fierce winds that blow in the region. On the other hand, the radome induces some attenuation of the radar transmitted
and reflected electromagnetic waves and thus some reduction of the sensitivity. This is in particular

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discussed in Grazioli et al.
(2017a) that describes the first year of MRR data, Durán-Alarcón et al. (2019) that compares 2
90 years of the DDU MRR to

85 another MRR deployed at the Princess Elizabeth station (longitude : 23.3°, latitude : -71.95°), and

lastly in Roussel et al. (2023)
that presents an analysis of precipitation at DDU during the YOPP (Year Of Polar Prediction) southern hemisphere special
observing period (see Bromwich et al. (2020)). However, no accumulated snow on the radome is reported by the winter-over staff, thanks to the strong winds and the radome's domed shape. A consequence of good operating

conditions at DDU station is that, to the authors' knowledge and albeit not

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the first MRR deployed in Antarctica, the DDU
95 MRR offers the longest quasi continuous data series for the Antarctic regionso far.

Figure 1. Topography of the Antarctic ice sheet and location of the Dumont d'Urville station.

~~(a)~~

~~(b)~~

~~Figure 2. Picture of the DDU MRR in its radome (a) and the DDU snow-gauge (b).~~
90 As most of precipitation at DDU falls as snow, the MRR data have been processed using the Maahn and Kollias (2012)

processing algorithm for snowfall, hereafter referred to as MK12. MK12 is especially suited for low signal-to-noise ratio (SNR)

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measurements such as those obtained in snowfall, as it improves noise removal and allows the detection of weak updrafts thanks
to a dynamic dealiasing procedure. Equivalent reflectivity Ze in dBz, mean Doppler velocity W in m s−1 and SNR in dB are
100 derived from the MRR minute-averaged raw spectrum, providing profiles up to 3 km a.g.l. with a vertical resolution of 100 m.
95 The two lowest and highest gates (below 300 m and above 2900 m) are considered too noisy by the algorithm and are therefore
discarded from this study. A quality flag described in the metadata is also provided to give information about masked spectra
not kept by the MK12 processing algorithm. We define the mean Doppler velocity as positive downward.

Due to various technical issues, the MRR was out of operation in about 6.4% of the total number of minutes in the record.
105 This occurred e.g. during maintenance or power outages. Furthermore, 0.1% of the precipitating timesteps (i.e., when the
100
minute reflectivity is not null along the vertical) are discarded as the quality flag indicates a raw spectrum dealiasing failure.

4
 (a)
(b)

Figure 2. Picture of the DDU MRR in its radome (a) and the DDU snow-gauge (b).

Lastly, equivalent reflectivities lower than -5 dBz are also discarded, in accordance with the threshold recommended by Maahn
and Kollias (2012), removing 10.5% of precipitating 1-min timesteps. For a full description of this method, which have been
used in numerous studies of snowfall in Antarctica (e.g., Scarchilli et al. (2020), Alexander et al. (2023)) or in the Arctic (e.g.,
110 Chellini et al. (2022)), we refer the reader
to Maahn and Kollias (2012).

The MRR being located inside a radome not optimized for the K-band, the signal is significantly attenuated.

This was quan-

105 tified by Grazioli et al. (2017a) by comparison with a nearby X-band radar. The regression between the measured reflectivity

values at X and K bands exhibited a slope close to 1, and an offset of about 6 dBz (to be added to the MRR data). This offset

was confirmed by Durán-Alarcón et al. (2019) by comparison with a second MRR deployed at DDU outside of the radome for

115 a short period of time. In the present paper, the radome attenuation is hence corrected by adding 6 dBz to the MRR reflectivity

values.

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Finally, the equivalent reflectivity, mean Doppler velocity and SNR are hourly-averaged, in accordance with the integration

time recommended by Durán-Alarcón et al. (2019) for climatological analysis, in order to remove short time perturbations

while keeping enough data for statistical significance. Hours with less than 10 valid minute timesteps were discarded to avoid

120 spurious spikes.

2.2 Snow-Gauge

115 Along with the MRR, an OTT Pluvio2 (model 400cm2) weighing gauge (with a wind shield, see Fig. 2b) was deployed during

the austral summer campaign 2015-16 at Dumont d'Urville. Hydrometeors falling into the bucket are measured by a very

sensitive weighing system, and converted in mm water equivalent. The weighing gauge hourly snowfall in mm hr−1 is then

125 obtained by summing the 1-minute bucket mass changes over one hour. These data are used in Sect. 3.2 to derive MRR snowfall

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profiles. Various limitations affect the gauge data, which are also discussed in Sect. 3.2. The gauge was deployed in the 2015-16

120 austral summer campaign, then removed in February 2016 and reinstalled in January 2017 until today. Moreover, it was out

of order between December 2021 and December 2022 included. These 2 main gaps are taken into account in the computation

of the MRR snowfall estimates in Sect. 3.2. For more information about the DDU snow-gauge, we refer the reader to Grazioli

130 et al. (2017a) and Genthon et al. (2018). The MRR and snow-gauge data range from November 2015 to June 2023, and the

instruments are still in operation.

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125 2.3 Météo-France Observations

Hourly surface meteorological variables such as 2-m temperature, 10-m wind speed and direction, and 2-m relative humidity

with respect to liquid are provided by the Meteo-France weather station at Dumont d'Urville, from January 2015 to June 2023

135 included. They are used in Sect. 3.2 for the computation of the MRR snowfall profile as a quality-control filter for the weighing

gauge data.

130 2.4 Models data

2.4.1 The ERA5 Reanalysis

Produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 is an atmospheric reanalysis which
140 combines a weather forecast model with meteorological observations from a large number of sources, through a 4-D data
assimilation system. It provides various meteorological variables over ~ 30 km resolution with 137 vertical levels, from 1979
~~135~~ to nowadays (Hersbach et al. (2020)). ERA5 supersedes ERA Interim, which stopped being produced in 2019.

While surface precipitation has been archived, the forecasted solid precipitation fluxes at the midpoint of the vertical layers
in the model have not been saved in the reanalysis archives at the time of the data extraction. To allow comparison with radar
145 vertical profiles of precipitation, we use the method to recalculate ERA5 snowfall rates described in Roussel et al. (2023), Sect.
S3. Hourly data from November 2015 to December 2021 included were extracted at the grid point nearest Dumont d'Urville,
~~140 of coordinates [140.0,~~ of longitude 140.0°and latitude -66.~~75]8~~°.

2.4.2 The LMDZ General Circulation Model

~~A~~Developed at the Laboratoire de Météorologie Dynamique (LMD) in Paris, the LMDZ model is the atmospheric component
150 of the ~~French~~ Institut Pierre-Simon Laplace Climate Model (IPSL-CM), see here), an atmosphere-land-ocean-sea ice global climate

model used in particular for the
Coupled Model Intercomparison Project exercises~~, the LMDZ General Circulation Model (~~. The Z in LMDZ stand~~ings~~ for its zooming
capabil-
ity~~), is developed at the Laboratoire de Météorologie Dynamique (LMD) in Pari~~i.e. a refinement of the mesh around an area of interest. Hourdin et al. (2020) describes the model's
~~145~~ generals, and
Madeleine et al. (2020) the clouds and precipitation physics. This model has already been used for various studies
in Antarctica
(Krinner et al. (2019), Vignon et al. (2018)) and in particular Lemonnier et al. (2021) that opens the way to the
evaluation of
155 the representation of the Antarctic precipitation in the model.

6
We use a simulation ranging from November 2015 to December 2021 included with a 96x95 horizontal grid and 95 vertical
levels. The grid is refined around Adélie Land, resulting in a resolution of approximately 50 km in the zoom center (see
Fig.
~~150~~ S1 of Roussel et al. (2023) for a map of the grid). The run was nudged with wind, temperature and humidity by the ~~ERA5~~
ERA5 reanalysis outside of the zoom area. For further details, we refer the reader to the very similar configuration in Roussel
160 et al.
(2023) that compared the precipitation at the surface and along the vertical of LMDZ and 5 other climate models with

the DDU
MRR and snow-gauge during the YOPP (Year Of Polar Prediction) period. We evaluate the model physics
used for CMIP-6,
the Sixth Coupled Model
Intercomparison Project exercise (CMIP-6), which has not been specifically adapted and calibrated on
Antarctic precipitation.
Hourly precipitation profiles are simply

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155 extracted at the grid cell nearest DDU of coordinates [140.4, longitude 140.4◦ and latitude -66.63]◦, as
the
most accurate representation of snowfall amounts
is that of the closest grid point regardless of the surface type (Roussel et al.
165 (2023)).

3 Statistical analysis

3.1 Characteristics of the 7-year record

In this section, before estimating the precipitation flux from the radar data in Sect. 3.2, the hourly-averaged
equivalent re-
160 flectivity Ze, the mean Doppler velocity W and the signal-to-noise ratio SNR are analyzed for the whole
7-year period, from

170 November 2015 to June 2023 included. The derivation of these variables with the MK12 processing
method is described in
Sect. 2.1.

Fig. 3 presents the daily-averaged 7 years of MRR reflectivity profiles, giving an overview of individual
precipitation events
and variability with respect to intensity over the whole period. The timeseries is quasi-continuous except for
several interrup-
165 tions identified on the figure by gray zones.

175 2-D joint distributions of equivalent reflectivity, mean Doppler velocity and SNR are presented in Fig.
4a, 4b and 4c. The
percentage of occurrence of those variables along each radar gate is color-coded (left blank for
occurrences below 1%), the
median is the solid-dotted black line and the 5th, 25th, 75th and 95th quantiles are the gray dashed lines.

The median equivalent reflectivity in Fig. 4a ranges from 5.5 dBz in altitude, then increases as ice crystals
grow through
170 deposition and aggregation and densify through riming (Planat et al. (2021)) towards a maxima of 10.2
dBz at 800 m. Then,

180 reflectivity decreases slightly to 9.7 dBz at 300 m due to snowflake sublimation by low-level dry air
blowing from the plateau
(katabatic flow). The physics of this process is discussed in Grazioli et al. (2017b). The 95th quantile
exceeds 20 dBz in the
lower gates, indicating the occurrence of rare but heavy snowfall events. There is no equivalent reflectivity
below 1 dBz, as K-
band reflectivities lower than -5 dBz have been discarded and an offset of +6 dBz was added to correct for
radome attenuation
175 (see Sect. 2.2). Hence, the radome attenuation correction reduces the MRR sensitivity.

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The mean Doppler velocity median decreases with height, going from 1.4 m s−1 at 300 m to 0.9 m s−1 at 2900 m. Even the

~~the~~ 95th quantile does not exceed 2.5 m s−1, supporting that rain events are very rare. In fact, only 0.7% of the hourly mean
Doppler
velocities exceed 3 m s−1. Vignon et al. (2021) found that the Dumont d'Urville station experiences in average only

~~180 1.8 days of rainfall per year, although that frequency may increase in the next decades~~.

~~All quantiles show a sharp increase of approximately 0.2 m s−1 at the lowest gate, which is probably due to noise in the~~
~~signal such as near-field effect, and despite the MK12 data quality masking. The 95th quantile also shows a suspicious increase~~
~~of the same magnitude at the highest gate (2900 m) probably due to noise in the signal. Most mean Doppler velocities above~~ 1.8 days

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 Figure 3. MRR equivalent reflectivity in dBz. Hatches indicate periods during which the MRR was not in operation. Periods with more than
10% of missing data are in gray shading.

of rainfall per year, although their projections from seven climate models indicate that rainfall events in coastal Antarctica will
190 increase in frequency and intensity in the next decades.

All quantiles show a sharp increase of approximately 0.2 m s−1 at the lowest gate, which is probably due to noise in the
signal such as near-field effect, and despite the MK12 data quality masking. The 95th quantile also shows a suspicious increase
of the same magnitude at the highest gate (2900 m) probably due to noise in the signal. Most mean Doppler velocities above

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 Figure 4. Median (black solid dotted line) and 5th, 25th, 75th and 95th quantiles (gray dashed lines) of the equivalent reflectivity Ze (fig. 3a),
the mean Doppler velocity W (fig. 3b) and the signal-to-noise ratio SNR (fig. 3c). The shading represents the occurrence along each radar
gate (left blank below 1%). Pay attention to the non-linear colorbar.

2000 m are smaller than 1 m s−1. There are a few rare events of negative W in altitude (75 over 12253 hourly timesteps)
18~~8~~9~~5~~ corresponding to weak updrafts, whose detection was made possible by the MK12 algorithm (see Sect. 2.1).

~~7~~
~~ Figure 3. MRR equivalent reflectivity in dBz. Hatches indicate periods during which the MRR was not in operation. Periods with more than~~
~~10% of missing data are in gray shading.~~

The SNR median in Fig. 4c is constant below 500 m, then decreases steadily with height, going from a ratio of -6.0 dB to
-15.6 dB. Most signal-to-noise ratios above 2000 m are below -10 dB. The SNR median is rather low, because the MRR has
a high noise level and solid precipitation corresponds to lower reflectivity than rainfall. It should be noted that the SNR 95th

19200 quantile ranges between 0 and +10 dB, indicating that heavy events fully stand out from the noise.

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~~Figure 4. Median (black solid dotted line) and 5th, 25th, 75th and 95th quantiles (gray dashed lines) of the equivalent reflectivity Ze (fig. 3a), the mean Doppler velocity W (fig. 3b) and the signal-to-noise ratio SNR (fig. 3c). The shading represents the occurrence along each radar gate (left blank below 1%). Pay attention to the non-linear colorbar.~~

Overall, the 2D joint distributions shown in Fig. 4 concur with Fig. 4a, 4d and 4g of Durán-Alarcón et al. (2019), which
plotted those 3 variables for the same instrument, although for a shorter period (2 years).

The maximum value of the equivalent reflectivity Ze reaches 31 dBz at 1900 m on February 9, 2022 at 6 pm UTC during a
19205 short and intense precipitation outburst of about 10 minutes, surrounded by longer and less intense events. Corresponding mean

Doppler velocity exceeds 6 m s−1, which suggests the presence of rain in altitude. Unfortunately, this event occurred during
local night and rain has not been reported by Météo-France staff at the station, although surface temperatures went above 0°C
for a few hours around that time. The snow-gauge was not operating (see Sect. 2.2) and cannot give further information about
the magnitude of this event.

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210 A reliable maximum value of the mean Doppler velocity could not be estimated because of various nonphysical peaks de-
tected by the algorithm and resulting from an imperfect dealiasing. Those peaks are not correctly filtered out by the data quality
masking of the MK12 algorithm. However, they do not seem to significantly shift the median and quantiles of Fig. 4.b, except
for the lowermost and uppermost gates (300 m and 2900 m).

2015 Interannual variability for the 7 years of data is investigated in Fig. 5, which presents the median yearly profiles from 2016
to 2022 of the equivalent reflectivity, mean Doppler velocity and SNR from the hourly-averaged data (8760 data points each

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year). Year 2023 is not shown as it was not complete at the time of extraction. We characterize the interannual variability over
those 7 years as the maximum profile minus the minimal profile. The equivalent reflectivity variability is 3 dBz (30% of the
median profile) and is rather constant along the vertical ; the mean Doppler velocity variability is 0.2 m s−1 near 300 m (15%

2240 of the median profile) and decreases towards 0.05 m s−1 in altitude ; and the SNR variability is 3 dB (50% of the average
profile). There is no statistically significant temporal trend of those variables over the 7 years of data (not shown).

Figure 5. Yearly median profiles of the MRR equivalent reflectivity (a), mean Doppler velocity (b) and SNR (c).
Seasonal variability is then considered in Fig. 6 for the same variables, whose medians have been

computed for each month

over the 7 years of data, thus providing a first estimation of the MRR climatology (around 5500 data points for each month).

2125 Here again, no visible trend is identifiable in Figs. 6a and 6c for the equivalent reflectivity and the signal-to-noise ratio. Seasonal

variability for those variables, if any, is masked by the substantial interannual variability seen above.

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Figure 6. Monthly median profiles of the MRR equivalent reflectivity (a), mean Doppler velocity (b) and SNR (c).

In contrast, a clear seasonal signal of the mean Doppler velocity appears throughout all the column in Fig. 6b. Ice crystals
and snowflakes fall slower in winter (June to September) than in summer (December to February), with inter-seasons in the
middle values. Indeed, relatively warmer and moister conditions in summer favor aggregation and riming, thus increasing the
2230 snowflakes density and fall speed (Garrett and Yuter (2014)). This signal remains when removing one year from the period at
a time (not shown), supporting that it is robust to interannual variability.

If we characterize seasonal variability as the maximal profile minus the minimal profile in Fig. 6, the equivalent reflectivity
variability is 3.5 dBz (around 40 % of the median profile) at 300 m and decreases slightly with altitude ; the mean Doppler

velocity variability is 0.3 m s−1 at 300 m (21 % of the median profile) and is divided by 2 in altitude ; whereas the SNR
2235 seasonal variability is 4.1 dB at 300 m (70 % of the median profile) and only 1.4 dB in altitude.

Both interannual and seasonal variability are larger near the surface than in altitude. In fact, we expect differences between
precipitation events to emerge during the aggregation and riming processes (Planat et al. (2021)) and thus be more pronounced
in the lower gates. Moreover, turbulence in the katabatic layer (below 1 km or so) is likely to impact the hydrometeors fall
speed, and to increase the mean Doppler velocity variability.

230 To quantify this effect, the spectrum width recorded by the MRR
240 can be used to estimate turbulence in the lower levels as described in Appendix A of Vignon et al. (2020), although such study
is beyond the scope of this paper.

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3.2 Estimation of snowfall rate profiles from the MRR data

3.2.1 Derivation of the Ze-S relation

In this section, the MRR snowfall rate profile is calculated by means of a power law relationship between the equivalent radar
245 reflectivity Ze (in mm6 m−3) and the snowfall rate S (in mm hr−1), i.e. Ze = aSb (eq. 1), whose

parameters a (prefactor) and
b (exponent) are estimated using the weighing gauge snowfall S (see Sect. 2.2). This is a common methodology for retrieving

235 snowfall rates from radar reflectivities (e.g., Grazioli et al. (2017a), Scarchilli et al. (2020), Souverijns et al. (2017), Schoger
et al. (2021)). Theoreti-
cal considerations about snowflakes shape, mass and velocity are discussed in Matrosov (2007) and Matrosov et al. (2009). The
equivalent reflectivity Ze at the usable gate closest to the surface (300 m a.g.l.) is processed as

250 described in Sect. 2.1, except
that it is converted in linear units (mm6 m−3) before the hourly averaging. The gauge hourly snowfall is computed as described

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in Sect. 2.2. We refer the reader to Sect. 4 for the processing code availability. The regression period spans from November

240 2015 to June 2023 included, which corresponds to a 5.5 year period when taking into account the two gaps in the snow-gauge

data mentioned in Sect. 2.2. 9456 hourly precipitating timesteps common for both instruments remain to perform the regression.

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At this stage, the scatter plot exhibits a large amount of statistical noise with many outliers (see gray dots of Fig. 7). This
issue motivated the application of several filters to reduce the noise. We present and use two of them in the following along with

245 their impact on the power-law parameters, as they were considered both mandatory and sufficient to obtain a robust regression.

Wind is the main source of uncertainty of snow-gauge measurements at Dumont d'Urville. It makes the gauge vibrate,

260 destabilizing its weighing system and leading to spurious precipitation records. Moreover, snow having already precipitated
may be remobilized from the surface into the atmosphere by the wind, and fall into the gauge bucket, leading to largely
overestimated snowfall rates and accumulation. Sugiura et al. (2003) showed that blowing snow can lead to an overestimation

250 of precipitation by 6 to 130% due to the increased number of aeolian snow particles in the atmosphere, a result supported
by numerous very large snow-gauge hourly snowfall rates suspiciously corresponding to low MRR reflectivities. In addition,

265 blowing snow particles are smaller than snowfall particles (Nishimura and Nemoto (2005), Naaim-Bouvet et al. (2014)) as
they originate from shattered snowflakes, and therefore have a different radar signature since radar reflectivity is dependent on
diameter to the sixth power. This impacts the Ze-S relation as part of the reflectivity signal does not correspond to precipitation.

255
Hourly wind speed provided by the Météo-France weather station (see Sect. 2.3) is thus used to discard all data points
corresponding to winds above 7 m s−1, in accordance with the threshold used in Scarchilli et al. (2020).

270 As a second filter, weighing gauge hourly snowfall lower than 0.1 mm hr−1 and exceeding 12 mm hr−1 have been discarded

to avoid respectively biases due to the instrument sensitivity and unrealistic values caused by maintenance operations on the
bucket, the second threshold originating from the snow-gauge documentation.

260

Data points removed by the application of these two filters are the small gray crosses in Fig. 7. The impact of the filters on
the Ze-S relation is discussed further below.

12

275 Hourly surface temperatures provided by Météo-France were also investigated to prevent liquid precipitation (above 0°C)
from impacting the Z-S relation, defined exclusively for snowfall. However, very few data points were affected by this filter
and the impact on the parameters was negligible, which is consistent with the rare rainfall occurrence found in Sect. 3.1 from
265 the mean Doppler velocity. Therefore, this filter was not retained in the final Ze-S relation computation.
Daily occurrences of blizzard and blowing snow from Météo-France weather reports were also tested as a filter, but proved

280 too coarse to efficiently clean out the noise in the correlation cloud. Again, this filter was not retained in the computation.
Only 503 data points are left after the application of these two filters, but they are quite evenly spread over the whole period
(not shown). A significant amount of information is thus lost in the filtering process, but we consider it mandatory to extract
270 the signal from the noise.

The 503 data point cloud resulting from the two filters described above still visually exhibits a dozen outliers, likely to affect
285 fits based on root mean square error minimization. It was therefore decided to convert equation (1) in log space, and to fit the

12

resulting equation :

ln(Ze) = b * ln(S) + ln(a) (2)

275 with a quantile linear regression method more robust to ouliers compared to the standard least-square method (Pedregosa et al.
(2011)).

Figure 7. MRR equivalent reflectivity and gauge snowfall rate scatter plot (black crosses) in log space filtered as described above, and the
resulting Ze-S relation derived with a robust quantile regression (blue solid line). The blue shading represents the regression RMSE. Ze-S
relations from Grazioli et al. (2017a) (red dashed line), Scarchilli et al. (2020) (yellow dashdot line) and Souverijns et al. (2017) (dotted
magenta line) are also represented. Small gray dots represent data points that have been filtered out. 290

Figure 7 presents the resulting scatter plot after filtering and the linear fit in log space. Converted back into linear space, the
relation obtained is Ze = 43.3 S0.88, with a R2 score in log space of 0.27. We estimate the regression uncertainty as the RMSE,
280 plotted in blue shading on Fig. 7. When the filter based on the wind speed threshold is deactivated, there is much more noise
in the scatter plot and the R2 score drops to 0.10, whereas parameters a and b change by -5% and -20%.

Thus, this filter allows

295 to remove a significant amount of outliers corresponding to high snow-gauge snowfall and low MRR reflectivity values typical
of blowing snow conditions, with a major impact on the R2 score and the regression slope b (see equation (2)). When the filter
based on the snow-gauge values is deactivated, parameters a and b decrease by -26% and -32%. Although the R2 score is better

~~13~~

~~285~~ (0.33) without this filter, it was retained as the weighing gauge snowfall very low values with high relative incertitude (>10%)
lead to a less realistic regression, as can be seen by the significant impact on the parameters. We made the choice of converting
300 the Ze-S relation in log space and using a robust quantile linear regression, as by reducing the impact of outliers it leads to a
regression that better fits the data, with almost no change to the R2 score (<0.01). Parameter a (b) changes by +17% (+15%)
compared with the standard linear regression, which is quite significant.

~~290~~

Compared to the Ze-S relation Ze = 76 S0.91 found by Grazioli et al. (2017a) (plotted in dashed red on Fig. 7) from the same
305 instruments although for a much shorter period, the slope b is very similar (inside the 95th confidence interval [0.78-1.09])
while the fit has an offset due to the much lower prefactor (outside the 95th confidence interval [69-83]), leading to a negative
R2 score. When our Ze-S relation is derived over the same period as Grazioli (from 2015-11-22 to 2016-01-29), although the
295 small number of data points does not allow to apply the filters, the two parameters fall back inside the 95% confidence interval

13
 Figure 7. MRR equivalent reflectivity and gauge snowfall rate scatter plot (black crosses) in log space filtered as described above, and the
resulting Ze-S relation derived with a robust quantile regression (blue solid line). The blue shading represents the regression RMSE. Ze-S
relations from Grazioli et al. (2017a) (red dashdot line), Scarchilli et al. (2020) (yellow dashed line), Souverijns et al. (2017) (magenta dotted
line) and Schoger et al. (2021) (green dashdot line) are also represented. Small gray dots represent data points that have been filtered out.

: a = 73.7 and b = 1.05. Small discrepancies persist due to different data processing methods such as the conversion of the
310 Ze-S relation in log space, the use of a robust quantile linear regression, or the initial processing of S and Ze. Over the whole
period, the parameters found in this study lead to higher MRR snowfall values than Grazioli et al. (2017a), as a given equivalent
reflectivity corresponds to a higher gauge snowfall. These considerations could be of interest for future studies using the DDU
300 MRR as an observation reference, as up to now, only parameters from Grazioli et al. (2017a) derived for a two-month period
in austral summer have been used (e.g., Lemonnier et al. (2019), Jullien et al. (2020), Roussel et al. (2023)).

315 The Ze-S relation of Scarchilli et al. (2020) Ze = 54 S1.15 (although for an integration time of 5 minutes) in dashed ~~ot~~ yellow

on Fig. 7 fairly well fits the data, although its R2 score is lower (0.20) as it does not take into account the outliers located
in the
lower right corner of the scatter plot. Souverijns et al. (2017) relation Ze = 18 S1.10 in dotted magenta is outside our
~~305~~ uncertainty
range in blue shading, with a negative R2 score. Likewise, our parameters a and b are both outside their uncertainty
range ([11-
43], [0.97-1.17]). This significant difference can be due to the location of the Princess Elizabeth station, 173 km off
the coast at
320 the other end of Antarctica with drier conditions and smaller particle diameters ; the much shorter sampling period
(January to
May 2016), or the instrument they used as snowfall reference (the Precipitation Imager Package). ~~The prefactor~~
Interestingly, Schoger et al.

14
 (2021) relation Ze = 77.61 S1.22 (in dashdot green) better fits our data despite the fact that their MRR is deployed at the other
end of the world (Ny-Ålesund, Svalbard in the Arctic) ; that could be related to more similar meteorological conditions. The
prefactor value a = 43.3 found by this study is consistent with those of the theoritical Ze-S relations of Matrosov et al. (2009)
325 which
~~310~~ range from 28 to 136, although the corresponding exponents exceed 1. However, definitive conclusions cannot be drawn ~~for a~~
for a or b individually, as they are not independent.

Despite the restrictive filtering steps listed above, the regression score R2 in log space remains low (0.27), which is mainly
due to outliers in the lower right corner of the scatter plot and probably not linked with blowing snow as they have not
3~~15~~30 been filtered out by the wind speed threshold. Furthermore, the precipitation flux at DDU may be explained by other factors
than radar reflectivity. Other explanatory variables, potentially season-dependent, could be used to derive better precipitation
estimates. This important issue will be addressed again in Sect. 4.

~~14~~
3.2.2 Sensitivity to integration time

Interestingly, the Ze-S relation obtained with the data processing detailed previously is robust to the integration time choice.
3~~20~~35 Table 1 presents the values of parameters a, b, the number of data points N and the score R2 for different integration times.

The hourly wind speed filter from Météo-France was linearly interpolated in time when the integration time was below 60
minutes. Although the shorter (5 minutes) and longer (180 minutes) integration times differ from the average with lower R2
scores due to respectively too much noise and undersampling effects, the parameters a and b are approximately independent
from the integration time. The hourly integration time exhibits the higher R2 score.

3̶2̶5̶40

Integration time (min)	a	b	N	R2
5	48.5	0.87	5712	0.19
15	44.6	0.88	1756	0.20
30	45.0	0.94	939	0.25
60	43.3	0.88	503	0.27
90	43.0	0.85	335	0.23
120	44.0	0.81	258	0.22
180	38.5	0.68	179	0.20

Table 1. Impact of the integration time on parameters a and b, the number of data points N and the R2 score.

Sensitivity of the Ze-S relation to interannual variability was also assessed by removing one year at a time in the computation.
The prefactor a varies between 42.3 and 44.1, whereas the exponent b varies between 0.85 and 0.95 (see Table 2). As these variations remain within 10% relative difference, this result supports that the derived Ze-S relation is also robust to interannual changes in the recordings.

15

Year removed	a	b	N	R2
2016	43.1	0.88	498	0.27
2017	43.2	0.95	418	0.30
2018	42.3	0.89	405	0.23
2019	43.2	0.86	405	0.23
2020	43.6	0.85	377	0.24
2021	43.2	0.89	458	0.33
2022	not in operation			
2023	44.1	0.86	464	0.27

Table 2. Impact of the interannual variability on parameters a and b, the number of data points N and the R2 score.

15
330345 In Sect. 3.3, the MRR snowfall profile is computed by inverting the equation $Ze = aS^b$:

$$S = \left(\frac{Ze}{a}\right)^{1/b} \quad (3)$$

with the parameters found for the whole dataset with an integration time of 1 hour. Doing so, we assume that the Z-S relation-
ship derived using the MRR data at 300 m is representative for the entire profile (up to 3 km), which may not hold true when
there is a large change in the hydrometeors structure and type along the vertical.

3350 3.3 Example of application to models evaluation

In this section, we show how the hourly MRR snowfall computed from the Ze-S relation described in Sect. 3.2 can be used to
evaluate the vertical profiles of precipitation as simulated by numerical models. The MRR is compared to the ERA5 reanalysis
and the LMDZ model (described in Sect. 2.4) for the period ranging from 2015-12-01 to 2022-01-01.

Firstly, the median and quantiles profiles of the three datasets in coastal Adélie Land are investigated. The model profiles
34055 are precipitation threshold-sensitive, as they produce a large number of very small precipitation events (below 0.01 mm hr−1).

Palerme et al. (2014) proposed a threshold of 0.07 mm per 6 hours to optimize the comparison of ERA-Interim precipitation
rates with CloudSat observations, which was also used in Roussel et al. (2023) for models evaluation. Converted to mm hr−1,
the models' threshold is 0.012 mm hr−1. The MRR snowfall threshold is derived from the equivalent reflectivity sensitivity of
-5 dBz, i.e. +1 dBz taking into account radome attenuation (see Sect. 2.1) and $10^{1/10} = 1.3$ mm6 m−3 in linear units. Equation
34560 (3) with the parameters a and b found in Sect. 3.2 gives a MRR threshold of 0.019 mm hr−1. To avoid sampling period biases
due to MRR missing data, only precipitating times (i.e., with a precipitation rate above the thresholds defined above) for the
three datasets have been retained, corresponding to 3717 data points. Figure 8 shows the profiles medians (solid lines with
dots) and the 10th and 90th quantiles (dotted lines).

The MRR 90th quantile stands out rather strikingly, peaking more than twice as large as the corresponding ERA5 and LMDZ
3650 profiles, while its median and 10th quantile remain of similar magnitude. This result suggests that models struggle to simulate

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Figure 8. Median (solid line with dots), 10th quantile and 90th quantile (dashed line) vertical profiles for the MRR (in red), ERA5 (in yellow)
and LMDZ (in blue) for the 3717 hourly data points of common precipitating timesteps.

heavy events. Maximum precipitation values reached at the surface (at 300 m for the MRR) for that period

are consistent with
that statement : ERA5 attains only 2.7 mm hr−1 and LMDZ 4.6 mm hr−1, whereas the MRR reaches 30 mm hr−1.

Although ERA5 and LMDZ reproduce the increase in precipitation from the top (3 km) down to a maximum around 800
m, as well as the decrease below due to sublimation of snowflakes, the slopes are not steep enough compared to the MRR.
3~~55~~570 This suggests that auto-conversion of ice crystals into snowfall as well as sublimation due to the katabatic flow may be un-
derestimated in the models, an issue already raised for ECMWF-IFS and LMDZ by Grazioli et al. (2017b) with one year of
data of the same instrument. Yet, the altitudes of maximum precipitation in ERA5 and LMDZ fairly well correspond to the
observations, with an ERA5 median profile peaking at 890 m and LMDZ at 740 m, while the MRR peaks at 800 m. Although
the MRR data do not extend below 300 m, the slopes of the model profiles below 800 m substantially overestimate surface
3~~60~~075 precipitation because of too weak sublimation. If sublimation is defined as the relative difference of the median snowfall rate
between the altitude of maximum precipitation and 300 m (including for the models), the MRR sublimation is 40%, whereas

~~16~~

~~Figure 8. Median (soli~~ERA5 (LMDZ) sublimation is only 12% (13%). This MRR sublimation is quite similar to Alexander et al. (2023) who found a
sublimation of 50% for a MRR deploye~~d line with dots), 10th quantile and 90th quantile (dashed line) vertical~~
profiles the Davis station and Bracci et al. (2022b) who found an order 30-40%~~for the~~a MRR ~~(in red), ERA5 (in yellow)~~
~~and LMDZ (in blue) for the 3717 hourly data points of common precipitating timesteps.~~

~~ERA5 (LMDZ) sublimation is only 12% (13%).~~

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 deployed at the Mario Zucchelli station.

380

The underestimation of strong events intensity by the models has a big impact on total snow accumulation. Indeed, Fig. 1
~~365~~ of Turner et al. (2019) indicates that extreme precipitation events contributes by more than 50% to total accumulation near the
DDU region. In the present dataset, almost 50% of the MRR total accumulation is due to snowfall larger than 2 mm hr−1,
whereas this contribution drops below 5% for ERA5 and LMDZ (not shown). This result is consistent with Fig. 11 of Grazioli
385 et al. (2017a) (upper panel) for one year of the same instrument, although the contribution of MRR snowfall rates larger than
2 mm hr−1 is only 30%. This difference can be explained by the larger MRR snowfall rates found by this study through the
~~370~~ revised Ze-S relation (see Sect. 3.2).

At the end of the period, after having removed the gaps in the MRR dataset, the MRR yearly average accumulation at 300m
is 1060 mm yr−1. It is larger than ERA5 by 44% with 737 mm yr−1 and than LMDZ by 53% with 691 mm yr−1 for the
390 same period and altitude. However, the models' accumulation at 300 m may be underestimated due to

their too smooth profile
shape (see Fig. 8). Conversely, the MRR snowfall rate may be overestimated due to remaining outliers in the Ze-S computation

~~17~~

~~375~~ despite the restrictive processing method described in Sect. 3.2. Grazioli et al. (2017a) estimated yearly accumulation from
October 2015 to October 2016 between 740 and 989 mm yr−1, i.e. 23% less in average than this study, which is consistent
again with lower snowfall rates obtained with the Grazioli et al. (2017a) Ze-S relation. Even so, precipitation has a high degree

395 of interannual variability (see Fig. 5a) and two different periods cannot be directly compared. Also, it is important to keep in
mind that the accumulation at the surface is probably much lower than 1060 mm yr−1 because of precipitation sublimation

~~380~~ below the MRR lowest gate at 300 m. Snow-gauge accumulation is not presented here as it is largely overestimated due to
contamination by blowing snow (not shown).

400 On the other hand, models precipitation occurrence is higher than the MRR, with 29% of hourly precipitating timesteps
for ERA5, 22% for LMDZ and only 15% for the MRR. Model snowfall events are also longer with a median of 13h (14h)
~~385~~ for ERA5 (LMDZ) compared to 7h for the MRR. However, this higher occurrence of model precipitation is not enough to
compensate for the larger MRR accumulation.

4 Conclusions

405 7 years of data from a Micro Rain Radar (MRR) deployed at the Dumont d'Urville station in Antarctica are presented. A
statistical analysis outlines the main characteristics of the MRR vertical profiles of the equivalent reflectivity, mean Doppler
~~390~~ velocity and signal-to-noise ratio, concurring with the results of Durán-Alarcón et al. (2019). No interannual or seasonal trend
have been clearly identified in the MRR profiles, except for the seasonal mean Doppler velocity which is larger in summer
and smaller in winter, suggesting an enhanced aggregation process. Nonetheless, the sample period is still short (7 years) to

410 possibly exhibit such climatic trends.

18

A Ze-S relation has been derived from the dataset to retrieve precipitation profiles, thus allowing to refine the relation found
~~395~~ by Grazioli et al. (2017a) for the same instrument but built on one summer season only. Despite a large amount of noise, the
7-year period made it possible to apply restrictive filters robust to integration time and interannual variability. The uncertainty
of the Ze-S relation is estimated as its RMSE in log space. The results have been compared with literature, and particularly
415 with the relation of Grazioli et al. (2017a) with whom an offset probably due to the sampling period has been found, leading
to smaller MRR snowfall rates than this study. However, Ze-S relations in the literature still present a significant degree of
~~400~~ uncertainty and makes it difficult to draw final conclusions. Although we chose to be very cautious, the

R2 score remains low
and other processing methods may be applied to the raw data (see data availability below) by future users. For instance, other
explanatory variables such as temperature, wind speed, or the mean Doppler velocity of hydrometeors could be combined to
420 the equivalent reflectivity to better constrain the Ze-S relation, but such considerations are beyond the scope of this study.

This Ze-S relation allowed the evaluation of two climate models (ERA5 and LMDZ) along the vertical as an application
405 example of the dataset. Models showed profiles too smooth, both in altitude and time, with a large underestimation of intense
snowfall events compared to the MRR leading to an accumulation twice as small. The weaker sublimation of precipitation by
the models is not enough to compensate for their smaller accumulation.

18
425 We believe that the 7 years of data presented in this paper are a great opportunity to evaluate and optimize climate models by
fostering future studies on the parameterization of snowfall along the vertical in Antarctica, as well as the representation of the
410 katabatic layer and its impact on precipitation sublimation. The dataset can also be used to complement and validate satellite
products by providing ground-based information, for instance to evaluate the effect of the blind range near the ground level to
obtain more accurate surface precipitation estimates.

430 Data availability. Data are available ~~here : https://web.lmd.jussieu.fr/~vwiener/MRRDATA/, and are furthermore currently under review on PANGAEA. A DOI and full data citation will be provided at the end of the process~~<ins>on the PANGAEA server here : https://doi.org/10.1594/PANGAEA.962727</ins>. The MRR 1-min profiles
of the source variables
415 (equivalent reflectivity, mean Doppler velocity, SNR and quality flag) are stored in zipped netCDF files from 2015-
11-23 to 2023-07-01
(one file per year). The MRR hourly snowfall profiles computed in Sect. 3.2 from the relation Ze = 43.3 S0.88 along
with the gauge 1-min
snowfall accumulation and the hourly wind speed and temperature from Météo-France observations are also available
for the same period.
The processing code in python used for the derivation of the Ze-S relation ~~is also attached as a Jupyter Notebook~~<ins>can be accessed here. Latest MRR data can</ins>

435 <ins>be retrieved upon direct request to VW</ins>.

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420 review. Christophe Genthon: instrument setting, writing, review, validation. Étienne Vignon: investigation, review. Jacopo Grazioli:
instrument setting, methodology, review. Alexis Berne: instrument setting, methodology, review, validation.

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