Experimental Quantification of the Sampling Uncertainty Associated with Measurements from PARSIVEL Disdrometers

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(Manuscript received 25 November 2009, in final form 1 November 2010)

ABSTRACT

The variability of the (rain)drop size distribution (DSD) in time and space is an intrinsic property of rainfall, which is of primary importance for various environmental fields such as remote sensing of precipitation, for example. DSD observations are usually collected using disdrometers deployed at the ground level. Like any other measurement of a physical process, disdrometer measurements are affected by noise and sampling effects. This uncertainty must be quantified and taken into account in further analyses. This paper addresses this issue for the Particle Size Velocity (PARSIVEL) optical disdrometer by using a large dataset corresponding to light and moderate rainfall and collected from two collocated PARSIVELs deployed during 15 months in Lausanne, Switzerland. The relative sampling uncertainty associated with quantities characterizing the DSD—namely the total concentration of drops \( N_t \) and the median-volume diameter \( D_0 \)—is quantified for different temporal resolutions. Similarly, the relative sampling uncertainty associated with the estimates of the most commonly used weighted moments of the DSD (i.e., the rain-rate \( R \), the radar reflectivity at horizontal polarization \( Z_h \), and the differential reflectivity \( Z_{\text{dr}} \)) is quantified as well for different weather radar frequencies. The relative sampling uncertainty associated with estimates of \( N_t \) is below 13% for time steps longer than 60 s. For \( D_0 \), it is below 8% for \( D_0 \) values smaller than 1 mm. The associated sampling uncertainty for estimates of \( R \) is on the order of 15% at a temporal resolution of 60 s. For \( Z_h \), the sampling uncertainty is below 9% for \( Z_h \) values below 35 dBZ at a temporal resolution of 60 s. For \( Z_{\text{dr}} \) values below 0.75 dB, the sampling uncertainty is below 36% for all temporal resolutions. These analyses provide relevant information for the accurate quantification of the variability of the DSD from disdrometer measurements.

1. Introduction

The microstructure of rainfall (i.e., the characteristics of individual raindrops) is controlled by the complex interactions between cloud microphysics and atmosphere dynamics (Testik and Barros 2007). The microstructure of rainfall is of primary importance for remote sensing of precipitation but also for numerical weather modeling, rainfall infiltration, or soil erosion (e.g., Salles et al. 2002). In the present paper, the focus is on weather radar remote sensing; therefore, the size, shape, and fall velocity of raindrops are of particular interest. The shape and fall velocity of a raindrop can be accurately derived from its equivolume diameter (e.g., Beard 1977; Andsager et al. 1999). Therefore, a fundamental property of rainfall for the investigation of its microstructure is the (rain)drop size distribution (DSD). Rain, and hence DSD, is highly variable in time and space at inter- and intraevent scales as well as for different geographic locations (Tokay and Short 1996; Jameson and Kostinski 2001; Uijlenhoet et al. 2003; Miriovsky et al. 2004; Lee and Zawadzki 2005; Lee and Zawadzki 2005; Lee et al. 2009).

To further our understanding of the microstructure of rainfall, reliable DSD measurements are of primary importance. Information about the DSD is usually collected at ground level using disdrometers. Different types of disdrometers have been developed. The Joss–Waldvogel (JW) electromechanical disdrometer (Joss and Waldvogel 1967) is the most popular sensor to collect DSD measurements. Numerous studies have compared JW disdrometer measurements with those of other instruments such as rain gauge (Tokay et al. 2001, 2003, 2005; Sieck et al. 2007), optical spectropluviometer (Campos and Zawadzki 2000; Salles and Creutin 2003), microrain radar (Peters et al. 2005), Precipitation Occurrence

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DOI: 10.1175/2010JHM1244.1

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Sensor System (POSS) Doppler radar (Sheppard and Joe 1994; Campos and Zawadzki 2000), or 2D video disdrometer (Tokay et al. 2001). The fluctuations observed at the ground level result from the combination of two signals: the natural variability of the physical process and the sampling fluctuations induced by the instrument (e.g., Gertzman and Atlas 1977). Numerous studies have pointed out the difficulties in distinguishing between these two sources of variability in rainfall observations (e.g., Joss and Waldvogel 1969; Gertzman and Atlas 1977; Smith et al. 1993; Gage et al. 2004; Miriovsky et al. 2004; Berne and Uijlenhoet 2005; Uijlenhoet et al. 2006).

Any analysis of the DSD variability must take into account the sampling uncertainty associated with DSD measurements in order to better characterize the natural variability of the DSD, which is the environmental phenomenon of interest. For instance, Krajewski et al. (2006) pointed out the observed significant differences between DSD measurements from disdrometers of different types deployed in the same 100-m² area. Such strong instrumental differences can lead to significant differences in higher-order moments of DSD and must be quantified and integrated in DSD analyses.

The optical disdrometer considered in this study is the Particle Size and Velocity (PARSIVEL; manufactured by OTT-Germany) described by Löffler-Mang and Joss (2000). In previous studies, PARSIVEL was mostly used to investigate snowfall measurements (Löffler-Mang and Blahak 2001; Yuter et al. 2006; Tokay et al. 2007; Egli et al. 2009) because of the capability of the instrument to distinguish between solid and liquid precipitation. Recently, a critical evaluation of PARSIVEL snow measurements based on the comparison with a collocated 2D-video disdrometer was presented by Battaglia et al. (2010).

The objective of the present study is to quantify and characterize the sampling uncertainty associated with the PARSIVEL disdrometer in rain. In this context, the sampling uncertainty is defined as the uncertainty due to the limited sampling area of the PARSIVEL that collects measurements about a spatially and temporally varying process (rainfall). Two collocated PARSIVELs will sample two distinct subsets of the same population of raindrops and will hence provide slightly different measurements (Steiner et al. 2003; Berne and Uijlenhoet 2005). This sampling uncertainty does not include all sources of error (Jones et al. 1997); for example errors related to signal processing issues and limited representativeness. Therefore, the present approach is different from investigations about the “total” uncertainty affecting rainfall gauges (e.g., Sevruk et al. 2009), which have to deal with the issue of the impossible access to the true rainfall characteristics.

The experimental setup and the dataset are described in section 2. Section 3 presents the comparison between rain-rate measurements from disdrometers and from nearby tipping-bucket (TB) rain gauges. The sampling uncertainty associated with PARSIVEL measurements is quantified for the total concentration of drops, the median-volume diameter, the rain rate, the radar reflectivity, and the differential reflectivity in section 4. Finally, summary and conclusions are provided in section 5.

2. Experimental setup

Following the approach proposed in previous works (Gage et al. 2004; Tokay et al. 2005; Krajewski et al. 2006; Sieck et al. 2007), two PARSIVELs (PARSIVEL 01 and PARSIVEL 02) were collocated (about 50 cm apart) and deployed at the École Polytechnique Fédérale de Lausanne (EPFL) campus in Lausanne, Switzerland, from late January 2008 to mid-April 2009 (about 15 months). A third one (PARSIVEL 03) has been deployed perpendicularly to the two previous ones in order to investigate the effect of the wind on PARSIVEL measurements. Additional meteorological information was provided by a weather station deployed a few meters away.

A picture of the experimental setup is presented in Fig. 1. In agreement with the local climatology, the wind speeds observed during rainfall were limited (below 6 m s⁻¹).

Figure 2 presents the rain-rate differences between PARSIVEL 01 and 03 as a function of wind speed and direction. As highlighted by the negligible values of the correlation coefficient (−0.08 and −0.05, respectively), the comparison of measurements from the two orthogonal PARSIVELs did not show a significant influence of the wind (speed and direction) on the deviation of the rain-rate measurements from collocated PARSIVELs. Similar results were obtained when comparing PARSIVEL 02 and 03. It must be noted that wind effects are investigated for collocated PARSIVELs at the same height; consequently, wind influence on PARSIVELs at different locations and elevations is not considered in the present paper. Because of a later deployment and technical problems, PARSIVEL 03 has missed about 140 h of rain, which is about 20% of the rainy period recorded by PARSIVEL 01 and 02, corresponding to a loss of about 170 mm of rain amount. Because the dataset is large, considering two or three PARSIVELs leads to similar results (see section 4b). Consequently, data from PARSIVEL 03 have not been considered in the analyses presented hereafter.

Similarly, two collocated TB rain gauges have been deployed near the pair of PARSIVELs (about 3 m away), providing independent measurements of rain rates and rain amounts (Fig. 1). The Précis Mécanique
tipping-bucket rain gauges (model 3029), with a catching area of 400 cm$^2$, are connected to dataloggers that record tipping times (corresponding to 0.1 mm) with an accuracy of 0.1 s. From visual inspection, splashing does not seem to have a significant impact on TB rain gauge measurements. Because the focus of the present work is on the sampling uncertainty, the fact that our experimental setup does not strictly follow the recommendations from the World Meteorological Organization (WMO 2008) is not considered an issue.

PARSIVEL is an optical disdrometer with a horizontal laser beam of 54 cm$^2$ that provides DSD measurements as well as information about quantities derived from the DSD (e.g., rain rate $R$ and radar reflectivity factor $Z$) and information about the type of precipitation. When a particle crosses the laser beam, the attenuation in the received voltage and the time for the particle to leave the beam are used to estimate the equivolume diameter $D$ and the terminal fall speed $v$ of the drop. The particle diameter is calculated from the maximum shadowed area that is related to the maximum output voltage attenuation, assuming the shape of the particle is known. Because drops larger than 1 mm are not spherical, the calculation of the equivolume diameter is based on different axis ratio (vertical over horizontal axis) relationships. Drops smaller than 1 mm are assumed to be spherical (axis ratio = 1), contrary to particles with a diameter larger than 5 mm, for which the axis ratio is set to 0.7. For drops between 1 and 5 mm, the axis ratio varies linearly from 1 to 0.7. PARSIVEL retrieval rationale is described in detail in Battaglia et al. (2010). The estimated size and fall speed of the particles are stored in a $32 \times 32$ matrix corresponding to 32 nonequidistant classes of diameter (from 0 to 25 mm) and 32 nonequidistant classes of fall speed (from 0 to 22.4 m s$^{-1}$).

All drops in a given class are assigned the values corresponding to the center of the size and velocity classes. Because of their low signal-to-noise ratio, the first two classes of diameter (0.062 and 0.187 mm) are always empty. Therefore, sampled diameters start at the lower bound of the third class—that is, 0.25 mm. According to Löffler-Mang and Joss (2000) and Battaglia et al. (2010), taking into account falling drops that are at the margins (i.e., particles partly detected), the effective sampling area of PARSIVEL can be estimated as a function of drop diameter:

$$S_{\text{eff}}(D_i) = L \times \left( W - \frac{D_i}{2} \right),$$

where $L$ and $W$ are respectively the length (180 mm) and the width (30 mm) of the laser beam, and $D_i$ is the center of the $i$th diameter class. Concentrations of drops are hence calculated using the effective sampling area $S_{\text{eff}}$.

Because our investigations focus on rainfall, solid or mixed precipitation is disregarded. The rainy periods (i.e., as soon as a strictly positive rain rate is recorded by at least one of the PARSIVELs) represent about 990 h of rain. To avoid the effect of very weak rainfall on the statistical descriptors, data have been filtered—only time steps for which both PARSIVELs measure a rain-rate $R$ larger than 0.1 mm h$^{-1}$ are considered. For consistency, the same time steps are considered for TB rain gauges. It must be noted that the employed filter ($R > 0.1$ mm h$^{-1}$) will remove different time steps depending on the temporal resolution considered. At a time resolution of 20 s, this threshold of 0.1 mm h$^{-1}$ removes about 27% of the rainy measurements. This proportion increases to 48% for a 1-h time step. Nevertheless, the removed time steps represent a loss of...
only 2\% and 3\% of the total rain amount at 20 s and 1 h, respectively.

To identify and remove suspicious measurements (due to splashing, multiple drops at a time, margin fallers, insects, spiders, etc.), a filter based on drop velocity–diameter relationship, similar to the one used by Kruger and Krajewski (2002) and Thurai and Bringi (2005), is applied to the raw PARSIVEL measurements ($32 \times 32$ drop counts). The drop velocity model is taken from Beard (1977). After comparison with the rain gauges, the

$$\left| v(D)_{\text{meas}} - v(D)_{\text{Beard}} \right| \leq 0.6 \cdot v(D)_{\text{Beard}}$$

(2)

are considered, where $v(D)_{\text{meas}}$ is the velocity measured by PARSIVEL, and $v(D)_{\text{Beard}}$ is the velocity for a drop of diameter $D$ according to Beard’s model. Such a filter removes about 25\% of the total number of particles detected. The filtered drops are mainly below 0.5 mm (about 71\%) and between 0.5 and 1 mm (about 28\%). In terms of rain amount, the filtered drops represent only 3.5\% of the total rain amount recorded over the period.

All the estimates of DSD and rainfall variables used in the present study are calculated from DSDs expressed as concentrations of drops per diameter classes (expressed in m$^{-3}$ mm$^{-1}$) computed from the filtered raw DSDs. Figure 3 presents the scatterplot of the rain rate computed from DSD (denoted by $R'$) versus the rain rate provided by PARSIVEL (denoted by $R$) at a time resolution of 300 s. The correlation coefficient is about 1 and the ratio of the means is about 1.04. $R'$ is slightly lower than $R$ because of a larger number of time steps with rain-rate values below 0.5 mm h$^{-1}$. Figure 3 shows a very good agreement between $R'$ and $R$, and results obtained in this study for $R'$ will be assumed valid for $R$ (as this parameter is likely to be more frequently employed by PARSIVEL users).
The dataset involved in this study (after the filtering process) corresponds to about 725 h of rainfall over 15 months from 19 January 2008 to 14 April 2009. The average rain amount measured by the two PARSIVELs (TB rain gauges) is about 900.3 (941.2) mm. Figure 4 presents the average rain rate from the two PARSIVELs and the two rain gauges, as well as the cumulative amount for each sensor, at a time resolution of 300 s. It indicates that this dataset corresponds to light and moderate rainfall with limited maximum rain rate (below 40 mm h$^{-1}$).

Figure 5 shows the concentration of drops at 300 s averaged over 15 months for each PARSIVEL. It shows a slight underestimation of the concentration of drops recorded by PARSIVEL 01 compared to PARSIVEL 02 for drops between 1.8 and 5 mm. This underestimation explains the slightly lower rain amount recorded by PARSIVEL 01 over the 15 months.

PARSIVEL 01 (02) detected 20 (24) drops in the class 6.5 mm, 10 (12) in the class 7.5 mm, and 1 (2) in the classes 8.5 and 9.5 mm. Drops larger than 7 mm are considered unrealistic and were removed from the dataset. Nevertheless, their influence on the results is negligible because of their very low numbers (≤15).

Table 1 presents the total number of drops measured by PARSIVEL 01 over the 15 months as well as some statistics on drop sizes at 60 s temporal resolution. The 90% quantile of $D$ is about 1.375 mm, which highlights...
the limited number of big drops in the dataset. These statistics are very similar for PARSIVEL 02. Because the experiment lasted 15 months, the derived statistics are assumed to be robust and representative of the local climatology.

3. Comparison between optical disdrometers and tipping-bucket rain gauges

Prior to the quantification of the sampling uncertainty, PARSIVEL and gauge rain-rate values are compared to check if there is any significant bias in PARSIVEL measurements, considering rain gauge as the reference instrument. For rain gauge measurements, the intensity resolution—0.1 mm per tip—is too coarse for time steps shorter than 5 min (one tip over 5 min corresponds to 1.2 mm h⁻¹), which will be the temporal resolution for the comparison of PARSIVEL and rain gauge data in this section. From Fig. 4, we see that the two PARSIVELs have collected 863.2 and 937.3 mm respectively, which is a difference of about 8%. The two TB rain gauges have collected 928.7 and 953.7 mm respectively, which is a difference of about 3%. On average, PARSIVEL and TB rain gauges have recorded total rain amounts of 900.3 and 941.2 mm respectively, corresponding to a difference of 4.3% over 15 months. Moreover, considering individual disdrometers and TB rain gauges, the maximum deviation in terms of rain amount between an individual PARSIVEL and an individual TB is about 9.5%, which is reasonable with respect to the 15 months the experiment lasted.

Figure 6 presents the scatterplot of the rain rates recorded by PARSIVEL 01 and 02 as well as the comparison between rain rates recorded by PARSIVEL 01 and TB rain gauges 02 (the two sensors between which the bias is the largest) at a resolution of 300 s. The other comparisons between individual sensors show similar agreements but with lower bias. Figure 7 presents the difference of rain-rate values between the two PARSIVELs over the 15 months at a time resolution of 300 s. From March to June 2008, PARSIVEL 01 provides slightly larger rain rates than PARSIVEL 02. From July 2008 to February 2009, PARSIVEL 02 provides larger rain rates than PARSIVEL 01. Finally, between January and February 2009 as well as between February and April 2009, there is no clear bias between the two PARSIVELs. Overall, we will consider that the bias between the two PARSIVELs is negligible, and that the difference between the two PARSIVELs can be correctly described as a white noise with zero mean. Hence, sampling uncertainty, as defined in section 1, is likely the main source of error in the measurements from the two PARSIVELs. Spider webs and insects as well as laser inhomogeneity could explain some of the bias, although there is no clear reason for this timing.

These comparisons show that rain-rate estimates derived from DSD measurements provided by PARSIVEL are reliable. The next section is devoted to the quantification of the sampling uncertainty associated with measurements from a single PARSIVEL.

4. Quantification of the sampling uncertainty

a. Integral quantities related to the DSD

While TB rain gauges only provide information about rain rate, the main benefit of disdrometers is the access to information about the microstructure of rain. For
quantitative applications, the statistical moments of the DSD (e.g., rain rate and radar reflectivity) are of major interest. Any analysis based on DSD measurements must take into account the uncertainty induced by the sampling process.

The DSD can be seen as the product of the drop concentration $N_t$ (m$^{-3}$) and a probability density function $f$:

$$N(D) = N_t f(D).$$  \hfill (3)

The total drop concentration $N_t$ is the sum of the DSD over the range of sampled diameters of drops:

$$N_t = \int_{D_{\text{min}}}^{D_{\text{max}}} N(D) \, dD. \hfill (4)$$

Moreover, a quantity commonly used to characterize (at least partly) the probability density $f$ is the median-volume diameter $D_0$ (mm), which is defined as the 50% quantile of the normalized distribution of liquid water content over all drop diameters:

$$\int_{D_{\text{min}}}^{D_0} N(D) D^3 \, dD = \int_{D_0}^{D_{\text{max}}} N(D) D^3 \, dD. \hfill (5)$$

In other words, drops smaller (respectively larger) than $D_0$ contribute to half of the total rainwater content in the sampled volume. $D_0$ is sensitive to the concentration of large drops.

Similarly to Tokay et al. (2005), the rain-rate $R$, the radar reflectivity $Z$, and the differential reflectivity $Z_{\text{dr}}$ (the most commonly used moments of the DSD) are considered:

$$R = 6\pi 10^{-4} N_t \int_{D_{\text{min}}}^{D_{\text{max}}} f(D) \nu(D) D^3 \, dD, \hfill (6)$$

$$Z_{hv} = \frac{\lambda^4 10^6}{\pi^4 |K_w|^2} \int_{D_{\text{min}}}^{D_{\text{max}}} f(D) \sigma_{R,hv}(D) \, dD, \quad \text{and} \hfill (7)$$

$$Z_{\text{dr}} = 10 \log_{10} \left( \frac{Z_h}{Z_v} \right), \hfill (8)$$

where $\nu$ is the drop terminal fall velocity (m s$^{-1}$), $\lambda$ is the wavelength (cm), $K_w$ is the dielectric factor for liquid water (dimensionless), $D$ is the equivolume diameter (mm), and $\sigma_{R,hv}$ is the backscattering cross section for horizontal (vertical) polarization (cm$^2$). With respect to the DSD, $R$ and $Z_h$ depend on both the drop concentration $N_t$ and the probability density function $f$, while $Z_{\text{dr}}$ only depends on $f$.

The sampling uncertainty will be quantified for $N_t$ and $D_0$, as well as for $R$, $Z_h$, and $Z_{\text{dr}}$. Because the dataset is representative of the local climatology characterized by light-to-moderate rainfall, the corresponding values of specific attenuation and specific differential phase are low. The sampling uncertainty for these ranges of values is of limited interest and is, therefore, not considered in the present paper.

**b. Method**

Following Tokay et al. (2005), we consider that $n$ colocated sensors sample the same population (the two...
PARSIVELs are 50 cm apart. We denote $m_{i,t}$ the variable of interest, derived from the DSD spectrum measured by sensor $i$ at time step $t$. In the following, $S_k$ denotes a subset of $k$ instruments among $n$. The arithmetic mean of $m_{i,t}$ for $i$ in $S_k$ at time step $t$, denoted by $m_{S_k,t}$, is expressed as

$$m_{S_k,t} = \frac{1}{k} \sum_{i \in S_k} m_{i,t}. \quad (9)$$

Similarly, the mean over $n$ sensors at time step $t$ is

$$\overline{m}_{n,t} = \frac{1}{n} \sum_{i=1}^{n} m_{i,t}. \quad (10)$$

As proposed in Chandrasekar and Gori (1991), Gage et al. (2004), Berne and Uijlenhoet (2005), and Tokay et al. (2005), using the difference between two collocated sampled values of a quantity removes the natural variability and enables the quantification of the sampling variability alone. To limit the influence of large absolute uncertainty values and to ease comparison with other sensors, we will consider the relative sampling uncertainty. Assuming that the mean over $n$ instruments is representative of the true value, the normalized difference between Eqs. (9) and (10), denoted by $s_{S_k,t}^\prime$, is defined as

$$s_{S_k,t}^\prime = \frac{m_{S_k,t} - \overline{m}_{n,t}}{\overline{m}_{n,t}}. \quad (11)$$

A similar approach based on the relative error has been used previously by Habib et al. (2001) and Ciach (2003), considering the specific case of one sensor ($k = 1$) among $n$ collocated ones for tipping-bucket rain gauge measurements.

Moreover, we consider that a given variable related to the DSD spectrum measured by sensor $i$ at time step $t$ can be seen as the sum of the real value of the variable at time $t$ (denoted by $M_i$) — which is of interest but not known — and a sampling uncertainty, denoted by $\omega_{i,t}$, associated with the measurement process and considered as a Gaussian white noise,

$$m_{i,t} = M_i + \omega_{i,t}. \quad (12)$$

Because the considered sensors are identical, the distribution of $\omega_i$ is supposed to be identical for all sensors. As a Gaussian white noise, $\omega_i$ is supposed to be 0 on average, so the sampling uncertainty is fully characterized by its standard deviation $\sigma_\omega$. Hence, $\sigma_\omega$ must be derived from the collected data. Replacing Eqs. (9), (10), and (12) in Eq. (11) leads to

$$s_{S_k,t}^\prime = \frac{1}{k} \sum_{i \in S_k} (M_i + \omega_{i,t}) - 1. \quad (13)$$

As suggested for radar reflectivity measurements (Gage et al. 2004; Berne and Uijlenhoet 2005), the relative sampling uncertainty affecting $m_{S_k}$ is quantified by $s_{S_k}^\prime$—the standard deviation of $s_{S_k}$:

Assuming the collocated instruments sample the same DSD population, the relative sampling uncertainty $\sigma_{s_s}^\prime$ ($r$ standing for relative) can be calculated from $s_{S_k}$ (see appendix A for details):

$$\sigma_{s_s}^\prime = \frac{\sigma_\omega}{E(M)} \simeq \sigma_{s_S} \sqrt{\frac{nk}{n-k}}. \quad (14)$$

Considering that the sampling uncertainty may depend on the value of $M$, $\sigma_\omega$ is estimated for different classes of $M$, within which $M$ and $\omega$ are assumed to be

![FIG. 7. Differences between rain-rate values recorded by the two PARSIVELs ($R_{01} - R_{02}$) over the 15 months at a temporal resolution of 300 s.](image-url)
uncorrelated. Figure 8 shows the distribution of $\varepsilon_i(D_0)$ values for $D_0$ between 0.6 and 0.7 mm at a temporal resolution of 60 s. Solid vertical line represents the mean while dashed vertical lines represent the 10% and 90% quantiles.

Nevertheless, outliers cannot be excluded, especially for classes with a low number of $\varepsilon_i$ values. The classical estimation of the standard deviation is sensitive to possible outliers, while quantiles are more robust. The difference between quantiles $Q_{90\%}$ and $Q_{10\%}$ corresponds to 80% of the distribution that is in the interval $[-1.28\sigma; +1.28\sigma]$ for a Gaussian distribution. Consequently, a more robust estimation of $\sigma_{\varepsilon_k}$ can be derived from the quantiles as

$$
\sigma_{\varepsilon_k} = \frac{Q_{90\%}(\varepsilon_k) - Q_{10\%}(\varepsilon_k)}{2 \times 1.28}.
$$

As mentioned in section 3, the limited bias between the two disdrometers (about 8%) is neglected.

To check the validity of Eq. (14), four additional disdrometers were collocated next to the two considered ones for a period of about 2 months (all sensors gathered over about 10 m$^2$). Figure 9 shows $\sigma_{\varepsilon_k}$ and $\sigma_{\varepsilon_{sk}}$ as functions of the number of sensors for $R$ between 0.1 and 2 mm h$^{-1}$. As expected, the number of collocated instruments has a significant impact on $\sigma_{\varepsilon_k}$. On the contrary, the relative uncertainty $\sigma'_{\varepsilon_{sk}}$ does not significantly depend on the number of sensors deployed. The same computation was performed as well for $N_t$, $D_0$, $Z_{dr}$, and $Z_{hi}$ with similar results. This experimentally demonstrates that Eq. (14) is at least valid for the local climatology. Because the approximation used in Eq. (A2) may cause problems when the considered number of samples (denoted by $n_t$) is small (Stuart and Ord 1994,
p. 351), this 2-month dataset is too limited to check the validity of this approximation for higher R classes (the quantile 95% is about 3 mm h$^{-1}$). Eq. (A2) will nevertheless be assumed to hold for higher R (and other quantities of interest). To provide reliable quantification of the relative sampling uncertainty, $s_{rv}$ is calculated only if there are more than 30 values in a given class ($n_t \geq 30$). Comparison between results obtained by considering data from two or three PARSIVELs shows that working with only two has a limited effect on the derived sampling errors. Therefore, the analyses are conducted on data from PARSIVELs 01 and 02, which have the longest record.

Because time resolution has a strong impact, $\sigma_{rv}$ is estimated at 11 different time resolutions ranging from 20 s to 1 h. The analyses were also conducted for three typical frequencies of weather radar systems: 2.8 GHz (S band), 5.6 GHz (C band), and 9.4 GHz (X band).

The sampling error has been investigated and quantified for TB rain gauges (e.g., Habib et al. 2001; Ciach 2003) as well as for the Joss–Waldvogel disdrometer (e.g., Chandrasekar and Gori 1991; Tokay et al. 2005). Although our approach is similar to these last two (in particular by considering collocated stations as well as by using the standard deviation to quantify the sampling uncertainty), we focus on the relative sampling error per class of the considered quantity. Hence, direct comparison with these studies is not possible.

c. Sampling uncertainty associated with total drop concentration estimates

Because the sampling uncertainty may vary with the total concentration of drops, the range of observed $N_t$ values was divided into nine non-equidistant classes in order to have a sufficient number of values in each class ($n_t \geq 30$). The $N_t$ values range from 0 to 2000 drops per cubic meter. Figure 10 presents the relative sampling uncertainty $\sigma_{rv}(N_t)$ associated with $N_t$ estimates from a single PARSIVEL. The corresponding values of the uncertainty for the different classes and temporal resolutions are provided in Table B1 in appendix B. For $N_t$ estimates, the relative sampling uncertainty is between 3% and 25%. It is decreasing with increasing $N_t$ classes and increasing time steps. For time steps longer than 300 s, the relative sampling uncertainty is below 10% independently of $N_t$. The highest values of $\sigma_{rv}(N_t)$ are observed for the first class—that is, for $N_t$ below 50 drops per cubic meter. For low $N_t$ values, a few missed drops will have a stronger effect on the uncertainty than for larger $N_t$ values, independent of the time resolution.

d. Sampling uncertainty associated with median-volume diameter estimates

Similarly to $N_t$, 10 non-equidistant classes of $D_0$ have been defined from 0.6 to 2.5 mm. The map of relative sampling uncertainty associated with $D_0$ estimates is presented in Fig. 11 [the corresponding values of $\sigma_{rv}(D_0)$ are provided in Table B2 in appendix B] according to the different $D_0$ classes and temporal resolutions. The relative sampling uncertainty associated with $D_0$ estimates would be...
is between 1% and 27%. Here $\sigma_{\text{rel}(D_0)}$ is decreasing for decreasing $D_0$ and increasing time steps. For $D_0$ about 1.75 mm and below, the relative sampling uncertainty is below 20% independently of the temporal resolution. Figure 12 presents the median of the number of drops with a diameter $D$ larger than $D_0$ for each $D_0$ class. This number decreases with increasing $D_0$ classes, illustrating the decreasing number of big drops [recall that $D_0$ is sensitive to big drops; see Eq. (5)]. The larger sampling uncertainty for small time steps (i.e., 20 and 60 s) and higher $D_0$ classes is hence due to the limited number of drops in these classes. Therefore, a few missed big drops will induce a large relative sampling uncertainty.

e. Sampling uncertainty associated with rain-rate estimates

Following the same approach, nine rainfall intensity classes have been defined from 0.1 to 30 mm h$^{-1}$. Because of the large number of low rain-rate values, the first classes are thinner than the higher ones. Figure 13 presents the relative sampling uncertainty $\sigma_{\text{rel}(R)}$ associated with rain-rate measurements from a single sensor for both types of instrument (i.e., PARSIVEL and TB rain gauges). The corresponding values of the relative sampling uncertainty for the different classes and temporal resolutions are provided in Table B3 in appendix B.

For PARSIVEL measurements, the relative sampling uncertainty is between 7% and 25%. It is globally decreasing with increasing rain-rate classes and increasing time steps. At a temporal resolution of 300 s, the relative sampling uncertainty is below 12% for all $R$ values. At high temporal resolutions (e.g., 20 s), the sampling uncertainty is below 20% for rain rates higher than 6 mm h$^{-1}$ and between 20% and 25% for light rain rates (i.e., below 6 mm h$^{-1}$). Figure 14 presents the median of the number of drops measured as well as the mean diameter as a function of $R$ classes at a 60 s temporal resolution. As expected, the measured number of particles is increasing with increasing rain rates. The larger values of sampling uncertainty at high temporal resolutions and for low $R$ values can be related to the lower number of drops measured compared to higher $R$ values. Therefore, $\sigma_{\text{rel}(R)}$ is more sensitive to a difference of a few drops for low than for large $R$ values. The slight
increase for higher classes is due to the influence of a few big drops (with low concentrations) as illustrated by the increasing mean diameter in Fig. 14. Similarly, the decrease of $\sigma_{w(R)}$ for increasing time steps can be related to the larger number of drops for larger time steps (see Table 1). The relative sampling uncertainty is then less affected by a few missed drops.

For TB rain gauge measurements, the relative sampling uncertainty is between 4% and 110%. The quantity $\sigma_{w(R)}$ shows a similar pattern with decreasing $\sigma_{w(R)}$ for increasing rain-rate classes and time steps. The TB rain gauge measurements are globally affected by a sampling uncertainty that is larger than PARSIVEL’s for temporal resolutions below 15 min (e.g., greater than 25% for $R < 4$ mm h$^{-1}$ at temporal resolutions < 5 min). Large sampling uncertainty at low rainfall rates and short integration intervals is directly related to the quantization inherent to the instrument, which is caused by the discrete volume of its buckets. This strong quantization results in numerous identical values, explaining the identical 110% uncertainty values at short time steps and low $R$ values (quantile estimates are affected by a lot of identical values in the sample). For example, the resolution of a rain-rate measurement corresponding to one tip of 0.1 mm is 6 mm h$^{-1}$ for a temporal resolution of 60 s. For temporal resolution about 15 min, the sampling uncertainty affecting PARSIVEL and TB rain gauge is similar. For time steps about 30 min or larger, TB rain gauge measurements are affected by a smaller sampling uncertainty than PARSIVEL ones. For instance, at a temporal resolution of 24 h (not shown in Fig. 13), $\sigma_{w(R)}$ for PARSIVEL (8%) is about four times higher than the one for TB rain gauges (2%).

f. Sampling uncertainty associated with radar reflectivity estimates expressed in dBZ

The map of sampling uncertainty according to the different $Z_h$ classes and temporal resolutions is presented in Fig. 15, and the corresponding values of $\sigma_{w(Z_h)}$ are provided in Table B4 in appendix B. For $Z_h$ below 40 dBZ, $\sigma_{w(Z_h)}$ is below 14% for all the investigated temporal resolutions. For $Z_h$ above 40 dBZ, the relative sampling uncertainty is between 3% and 17%. For time steps about 300 s or larger, $\sigma_{w(Z_h)}$ is below 7% for X band independently of $Z_h$ values (see Table B4 in appendix B). The relative sampling uncertainty associated with $Z_h$ estimates is globally decreasing for increasing time steps as well as for increasing $Z_h$ values up to about 30 dBZ. For $Z_h$ values higher than 30 dBZ, $\sigma_{w(Z_h)}$ increases up to 17%.

Figure 16 presents the median of the number of drops measured over the 15 months as well as the mean diameter as a function of $Z_h$ classes at a temporal resolution of 60 s. Similarly to $R$, small $Z_h$ values are affected by a larger relative sampling uncertainty because of the lower number of drops measured by the instrument for low $Z_h$ values (see Fig. 16). When averaging over longer time steps, the number of drops measured by the
instrument is increasing (see Table 1). Hence, the relative sampling uncertainty is less sensitive to a few missed drops. Because $Z_h$ is a moment of higher order ($\sim 6$) than $R$ ($\sim 3.67$), it is more sensitive to the very limited number of big drops. The mean diameter according to each $Z_h$ class presented in Fig. 16 shows the presence of larger drops in higher $Z_h$ classes. Therefore, the increase of the sampling uncertainty for $Z_h$ values above 30 dBZ is due to the influence of a few missed big drops (which have low concentrations).

The pattern of relative sampling uncertainty, presented in Fig. 15 at X band, is very similar at C and S band, with $\sigma_{rel}(Z_h)$ ranging from 3(2)% to 20(12)% for C (S) band. All the values are provided in Table B4 in appendix B.

g. Sampling uncertainty associated with differential reflectivity estimates

Polarimetric capabilities have been shown to be of great added value for weather radar systems (e.g., Bringi and Chandrasekar 2001). As explained in section 4, the dataset considered in this paper corresponds to limited values of specific attenuation and specific differential phase (even at X band). The focus will therefore be on the differential reflectivity $Z_{dr}$. Figure 17 presents the relative sampling uncertainty as a function of $Z_{dr}$ classes and the temporal resolutions. The corresponding values are provided in Table B5 in appendix B. The relative sampling uncertainty associated with $Z_{dr}$ estimates is ranging from 8% to 50%. The value of $\sigma_{rel}(Z_{dr})$ is below 31% for $Z_{dr}$ below 0.5 dB independently of the temporal resolution. For time steps below 5 min and for $Z_{dr}$ higher than 1 dB, $\sigma_{rel}(Z_{dr})$ is above 38%.

Because the shape of the probability density function is better defined for larger samples, the relative sampling uncertainty on $Z_{dr}$ is decreasing with increasing time steps. The pattern of the relative sampling uncertainty as well as the range of $\sigma_{rel}(Z_{dr})$ values are clearly different from the ones presented for $R$ and $Z_h$. Contrary to $Z_h$, $\sigma_{rel}(Z_{dr})$ is strongly increasing for increasing $Z_{dr}$ classes. The median of the number of drops as well as the mean diameter as a function of $Z_{dr}$ classes are presented in Fig. 18 at a temporal resolution of 60 s. The increase of the mean diameter associated with the
decrease of the median of the number of drops for the higher \(Z_{dr}\) classes indicates that large \(Z_{dr}\) values are due to big oblate drops that have very low concentrations. Therefore, missing one or a few of these big drops has a strong impact on the uncertainty in the shape of the empirical probability density function and, therefore, on the uncertainty in \(Z_{dr}\). The values of \(s_r (D_0)\) at C and S band are also very similar (see Table B5 in appendix B).

5. Conclusions

The quantification of the variability of the DSD in time and space is of great interest for many environmental fields and, in particular, for precipitation estimation using remote sensing. A reliable quantification of the DSD variability must take into account the variability due to the sampling process of DSD measurement. To address this issue for PARSIVEL measurements, two collocated PARSIVELs as well as two TB rain gauges have been deployed in Lausanne, Switzerland. The experiment ran for 15 months. The difference between the values recorded by both instruments only depends on the sampling process. Using this large dataset, the relative sampling uncertainty associated with two quantities characterizing the DSD—namely the total concentration of drops \(N_t\) and the median-volume diameter \(D_0\)—is quantified as a function of the temporal resolution and their respective values. Similarly, the sampling uncertainty associated with the estimates of rain-rate \(R\), radar reflectivity \(Z_{hr}\), and differential reflectivity \(Z_{dr}\) (all weighted moments of the DSD) is quantified at different weather radar frequencies (X, C, and S band).

The relative sampling uncertainty associated with \(N_t\) estimates is below 25% and is globally decreasing with increasing \(N_t\) values and increasing time steps. The quantity \(D_0\) shows a different pattern of sampling uncertainty with higher values of \(s_r (D_0)\) for higher \(D_0\) values and shorter time steps, for which it can reach about 27%. On average, for \(D_0\) smaller than 1 mm, \(s_r (D_0)\) is below 8%. For \(R\) estimates, the relative sampling uncertainty associated with PARSIVEL is below
25%—contrary to TB rain gauges, for which \( \sigma_{R}^{2} \) can reach 110% at high temporal resolution (below 120 s). For both types of instruments, \( \sigma_{R}^{2} \) is decreasing for increasing time steps. For temporal resolution of about 30 min or above, TB rain gauge measurements are affected by a smaller sampling uncertainty than PARSIVEL ones for rain rates higher than 2 mm h\(^{-1}\).

At X, C, and S band, the sampling uncertainty associated with \( Z_{h} \) estimates (in dBZ) exhibits a similar pattern to \( R \). For \( Z_{h} \) values lower than 35 dBZ, \( \sigma_{Z(h)}^{2} \) is below 12% for time steps below 1 h. For \( Z_{h} \) values between 40 and 50 dBZ, \( \sigma_{Z(h)}^{2} \) is below 17%. Concerning \( Z_{dr} \), its estimates are affected by a larger sampling uncertainty ranging from 8% to about 50%. The increase of \( \sigma_{Z(h)}^{2} \) with \( Z_{dr} \) can be related to the strong influence of the very low concentration of big oblate raindrops in the estimation of \( Z_{dr} \). For time steps smaller than 5 min and \( Z_{dr} \) values below 0.75 dB, \( \sigma_{Z(h)}^{2} \) is smaller than 36%. For \( Z_{dr} \) values above 1 dB, the relative sampling uncertainty is between 16% and 50%.

The quantification of the sampling uncertainty affecting measurements from the PARSIVEL optical disdrometer is a crucial step to be able to accurately quantify the natural variability of the DSD from PARSIVEL measurements, in particular at small scales. Because the dataset is only representative of light-to-moderate rainfall in a temperate climate, the present analysis needs to be extended to heavy rain.

Acknowledgments. The authors acknowledge financial support from the Swiss National Science Foundation (Grant 200021-118057/1) as well as A. Studzinski for the deployment of the instruments.

APPENDIX A

Calculation of the Relative Sampling Uncertainty

Taking \( X = m_{S_{X}} = (1/k) \sum_{i \in S_{X}} (M + \omega_{i}) \) and \( Y = m_{n} = (1/n) \sum_{i=1}^{n} (M + \omega_{i}) \), according to Eq. (13) we have

\[
\sigma_{X_{S_{X}}}^{2} = \text{Var} \left( \frac{X}{Y} \right). \tag{A1}
\]

The variables \( X \) and \( Y \) being strictly positive and random, we have according to Stuart and Ord (1994, p. 351)

\[
\text{Var} \left( \frac{X}{Y} \right) = \frac{E^{2}(X) \text{Var}(X)}{E^{2}(Y)} - \frac{2 \text{Cov}(X, Y)}{E(X)E(Y)} + \frac{\text{Var}(Y)}{E^{2}(Y)} + O(n^{-1}), \tag{A2}
\]

with \( n \), the number of samples (time steps) considered in the class of interest \( (n_{X} \geq 30) \). All collocated sensors are supposed to sample the same population of DSDs:

\[
E(X) = E \left[ \frac{1}{k} \sum_{i \in S_{X}} (M + \omega_{i}) \right] = E \left[ \frac{1}{k} \sum_{i \in S_{X}} M \right] + E \left[ \frac{1}{k} \sum_{i \in S_{X}} \omega_{i} \right]. \tag{A3}
\]

The sampling error \( \omega_{i} \) is assumed to be a Gaussian white noise; consequently

\[
E(\omega_{i}) = 0 \quad \forall i \in n, \quad \text{and} \quad \text{Cov}(\omega_{i}, \omega_{j}) = 0 \quad \forall i \neq j. \tag{A4}
\]

Therefore we have

\[
E(X) = E(Y) = E(M). \tag{A6}
\]

Assuming in addition that \( M \) and \( \omega \) are not correlated within the classes of the considered quantity related the DSD \( \text{Cov}(M, \omega) = 0 \) and that the sampling uncertainty has a similar distribution for all sensors \( \sigma_{\omega} = \sigma_{R} = \sigma_{\omega} \forall i, j \), we have:

\[
\text{Var}(X) = \text{Var}(m_{n}) = \sigma_{M}^{2} + \frac{1}{k} \sigma_{\omega}^{2}, \tag{A7}
\]

\[
\text{Var}(Y) = \text{Var}(m_{n}) = \sigma_{M}^{2} + \frac{1}{n} \sigma_{\omega}^{2}, \quad \text{and} \tag{A8}
\]

\[
\text{Cov}(Y) = \text{Var}(m_{n}) = \sigma_{M}^{2} + \frac{1}{n} \sigma_{\omega}^{2}. \tag{A9}
\]

Substituting Eqs. (A6), (A7), (A8), and (A9) in Eq. (A2), the variance of \( e_{S_{X}} \) is approximated as

\[
\text{Var}(e_{S_{X}}) \simeq \frac{\sigma_{\omega}^{2}}{E^{2}(M)} \left( \frac{1}{k} - \frac{1}{n} \right). \tag{A10}
\]

Then, the relative sampling uncertainty \( \sigma_{\omega}^{2} \) can be calculated from \( \sigma_{e_{S_{X}}}^{2} \):

\[
\sigma_{\omega}^{2} \simeq \frac{\sigma_{\omega}^{2}}{E(M)} \simeq \sigma_{e_{S_{X}}} \sqrt{n/k}, \tag{A11}
\]
APPENDIX B

Experimental Values of $\sigma_0^r$ as a Function of the Temporal Resolution and the Variable Intensity Classes

### TABLE B1. Relative sampling uncertainty associated with $N_t$ estimates.

<table>
<thead>
<tr>
<th>Classes (m$^{-3}$)</th>
<th>$\Delta t$ (s)</th>
<th>20</th>
<th>60</th>
<th>120</th>
<th>180</th>
<th>240</th>
<th>300</th>
<th>600</th>
<th>900</th>
<th>1800</th>
<th>2700</th>
<th>3600</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0, 50)</td>
<td>0.25</td>
<td>0.17</td>
<td>0.13</td>
<td>0.12</td>
<td>0.11</td>
<td>0.09</td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
<td>0.05</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>(50, 100)</td>
<td>0.22</td>
<td>0.14</td>
<td>0.11</td>
<td>0.09</td>
<td>0.08</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.05</td>
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<td>(100, 200)</td>
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<td>0.11</td>
<td>0.09</td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.06</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>(200, 400)</td>
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<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
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<td>0.04</td>
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<td>0.04</td>
<td>0.04</td>
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<td>0.04</td>
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<tr>
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<td>0.05</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
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<td>0.04</td>
<td></td>
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<td></td>
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<tr>
<td>(800, 1000)</td>
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<td>0.05</td>
<td>0.05</td>
<td>0.04</td>
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<td></td>
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<tr>
<td>(1000, 1500)</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>(1500, 2000)</td>
<td>0.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

### TABLE B2. Relative sampling uncertainty associated with $D_0$ estimates.

<table>
<thead>
<tr>
<th>Classes (m$^{-3}$)</th>
<th>$\Delta t$ (s)</th>
<th>20</th>
<th>60</th>
<th>120</th>
<th>180</th>
<th>240</th>
<th>300</th>
<th>600</th>
<th>900</th>
<th>1800</th>
<th>2700</th>
<th>3600</th>
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<tbody>
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<td>(0.6, 0.7)</td>
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<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.7, 0.8)</td>
<td>0.06</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>(0.8, 0.9)</td>
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<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
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</tr>
<tr>
<td>(0.9, 1.0)</td>
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<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
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<td>0.04</td>
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</tr>
<tr>
<td>(1.0, 1.25)</td>
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<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
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<td>0.05</td>
<td>0.03</td>
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</tr>
<tr>
<td>(1.25, 1.5)</td>
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<td>0.07</td>
<td>0.06</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
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<tr>
<td>(1.5, 1.75)</td>
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<td>(1.75, 2.0)</td>
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<tr>
<td>(2.0, 2.25)</td>
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</table>

### TABLE B3. Relative sampling uncertainty associated with $R$ estimates.

<table>
<thead>
<tr>
<th>R classes (mm h$^{-1}$)</th>
<th>$\Delta t$ (s)</th>
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<th>60</th>
<th>120</th>
<th>180</th>
<th>240</th>
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<th>1800</th>
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<td>PARSIVEL</td>
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<td>0.12</td>
<td>0.11</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.09</td>
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<td></td>
<td>(2, 4)</td>
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<td>0.11</td>
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<td>0.10</td>
<td>0.09</td>
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<tr>
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<td>(6, 8)</td>
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<td>TB gauge</td>
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<td>1.10</td>
<td>1.10</td>
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<td>0.11</td>
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</tr>
<tr>
<td></td>
<td>(2, 4)</td>
<td>1.10</td>
<td>1.10</td>
<td>1.10</td>
<td>0.37</td>
<td>0.37</td>
<td>0.22</td>
<td>0.12</td>
<td>0.09</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(4, 6)</td>
<td>1.10</td>
<td>1.10</td>
<td>0.37</td>
<td>0.22</td>
<td>0.19</td>
<td>0.16</td>
<td>0.09</td>
<td>0.05</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6, 8)</td>
<td>1.10</td>
<td>0.37</td>
<td>0.22</td>
<td>0.16</td>
<td>0.14</td>
<td>0.11</td>
<td>0.07</td>
<td>0.05</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(8, 10)</td>
<td>1.10</td>
<td>0.37</td>
<td>0.22</td>
<td>0.17</td>
<td>0.10</td>
<td>0.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10, 15)</td>
<td>1.10</td>
<td>0.37</td>
<td>0.33</td>
<td>0.28</td>
<td>0.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15, 20)</td>
<td>1.10</td>
<td>0.39</td>
<td></td>
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<td></td>
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<td></td>
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<tr>
<td></td>
<td>(20, 25)</td>
<td>0.74</td>
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<tr>
<td></td>
<td>(25, 30)</td>
<td>0.69</td>
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</tbody>
</table>
### Table B4. Relative sampling uncertainty associated with $Z_h$ estimates (dB Z) at X (9.4 GHz), C (5.6 GHz), and S band (2.8 GHz), respectively.

<table>
<thead>
<tr>
<th>Classes (dB Z)</th>
<th>X band</th>
<th>C band</th>
<th>S band</th>
</tr>
</thead>
<tbody>
<tr>
<td>(10, 15)</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>(15, 20)</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>(20, 25)</td>
<td>0.09</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>(25, 30)</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>(30, 35)</td>
<td>0.09</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>(35, 40)</td>
<td>0.14</td>
<td>0.14</td>
<td>0.14</td>
</tr>
<tr>
<td>(40, 45)</td>
<td>0.17</td>
<td>0.17</td>
<td>0.17</td>
</tr>
<tr>
<td>(45, 50)</td>
<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
</tr>
</tbody>
</table>

### Table B5. Relative sampling uncertainty associated with $Z_{dr}$ estimates (dB) at X (9.4 GHz), C (5.6 GHz), and S band (2.8 GHz), respectively.

<table>
<thead>
<tr>
<th>Classes (dB Z)</th>
<th>X band</th>
<th>C band</th>
<th>S band</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.1, 0.2)</td>
<td>0.16</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>(0.2, 0.3)</td>
<td>0.22</td>
<td>0.22</td>
<td>0.22</td>
</tr>
<tr>
<td>(0.3, 0.4)</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>(0.4, 0.5)</td>
<td>0.31</td>
<td>0.31</td>
<td>0.31</td>
</tr>
<tr>
<td>(0.5, 0.75)</td>
<td>0.36</td>
<td>0.36</td>
<td>0.36</td>
</tr>
<tr>
<td>(0.75, 1.0)</td>
<td>0.41</td>
<td>0.41</td>
<td>0.41</td>
</tr>
<tr>
<td>(1.0, 1.5)</td>
<td>0.47</td>
<td>0.47</td>
<td>0.47</td>
</tr>
<tr>
<td>(1.5, 2.0)</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
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<tr>
<td>(2.0, 3.0)</td>
<td>0.49</td>
<td>0.49</td>
<td>0.49</td>
</tr>
</tbody>
</table>

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REFERENCES


