Effect of disdrometer sampling area and time on the precision of precipitation rate measurement

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Abstract. Due to the discretized nature of rain, the measurement of a continuous precipitation rate by disdrometers is subject to statistical sampling errors. Here, Monte Carlo simulations are employed to obtain the precision of rain detection and rate as a function of disdrometer collection area and compared with World Meteorological Organization guidelines for a one-minute sample interval and 95% probability. To meet these requirements, simulations suggest that measurements of light rain with rain rates $R \leq 0.50$ mm h^{-1} require a collection area of at least 6 cm $\times$ 6 cm, and for $R > 1$ mm h^{-1}, the minimum collection area is 10 cm $\times$ 10 cm. For $R = 0.01$ mm h^{-1}, a collection area of 2 cm $\times$ 2 cm is sufficient to detect a single drop. Simulations are compared with field measurements using a new hotplate device, the Differential Emissivity Imaging Disdrometer. The field results suggest an even larger plate may be required to meet the stated accuracy, although for reasons that remain to be determined.

1 Introduction

Ground-based precipitation sensors are commonly used to validate larger scale precipitation measurement systems including satellite (TRMM), WSR-88D radar measurements (Kummerow et al., 2000; Fulton et al., 1998), and numerical weather prediction models (Colle et al., 2005) aimed at hydrology, agriculture, transportation, and recreation applications (WMO, 2018; Estévez et al., 2011; Campbell and Langevin, 1995; Brun et al., 1992). The ability of an automated weather station to detect the presence of even very light precipitation can be crucial for weather forecasting in remote locations where a human observer is not available to verify the presence of rainfall (Horel et al., 2002; Miller and Barth, 2003). Light rain or drizzle can severely impede road safety (Andrey and Yagar, 1993; Andrey and Mills, 2003; Bergel-Hayat et al., 2013; Theofilatos and Yannis, 2014).

Disdrometers measure particle drop size distributions and provide calculated precipitation rate from the integrated mass flux. Among available disdrometers are the mechanical Joss Waldvogel (JW) disdrometer (Joss and Waldvogel, 1967), laser or optical sensors such as the OTT Parsivel2 (Tokay et al., 2013; Bartholomew, 2014), and video disdrometers such as the 2DVD (Kruger and Krajewski, 2002; Thurai et al., 2011; Brandes et al., 2007).

Among other instrument-specific considerations, disdrometer accuracy depends on sampling area and time interval (Gultepe, 2008). Joss and Waldvogel (1969) defined a sample size as the product of an area and a sample time. Under the assumption that raindrop size follows a negative exponential distribution, to measure a precipitation rate of $R = 1$ mm h^{-1} to a precision

of 10% within 95% confidence bounds, the required sample size is 1.5 m² s, corresponding to a cross-sectional sampling area of $A = 250$ cm² for a nominal 60 s collection interval.

The World Meteorological Organization (WMO) recommends that a disdrometer measure precipitation intensities between 0.02 and 2,000 mm h^{-1} with an output averaging time of one-minute (WMO, 2018). Measurement uncertainty is defined as
30   "the uncertainty of the reported value with respect to the true value and indicates the interval in which the true value lies within a stated probability" specified to be 95%. For liquid precipitation intensity, the uncertainty requirements for rates of 0.2 to 2 mm h^{-1} are ± 0.1 mm h^{-1}, and for precipitation rates > 2 mm h^{-1} they are 5% (see Table 2). For < 0.2 mm h^{-1}, the requirement is only detection.

Most commercial instruments do not reach such strict standards. Table 1 provides the reported uncertainties for several
35   precipitation instruments. The instrumentation used by ASOS weather stations located at major airports utilizes a Heated Tipping Bucket (HTB) for precipitation accumulation and a Light Emitting Diode Weather Identifier (LEDWI) for precipitation type and intensity. The LEDWI uses signal power return to determine the drop size distribution of rain or snow, then classifies the precipitation intensity based on the size distribution (Nadolski, 1998). A significant limitation of the ASOS system is that it cannot discriminate drizzle from light rain, and it qualitatively expresses small amounts as a trace (Wade, 2003; Nadolski,
40   1998).

Vaisala manufactures a range of optical precipitation sensors that detect and categorize precipitation from the forward scattering of a light beam, including the PWD12, PWD22, PWD52, and FD71P. The PWD12 detects rain, snow, unknown precipitation, drizzle, fog, and haze. The PWD22 has the same resolution and accuracy as the PWD12, but it also detects freezing drizzle, freezing rain, and ice pellets (Vaisala, 2019b). The PWD52 has an increased observation range of 50 km, compared to
45   20 km for the PWD 22 (Vaisala, 2018a). All three PWD instruments have a precipitation intensity resolution of 0.05 mm h^{-1} for a 10-minute sampling interval at 10% uncertainty (Vaisala, 2019b). The PWD22 is included with tactical weather instrumentation intended for U.S. military and aviation operations (TACMET) and reports precipitation type in WMO METAR code format (Vaisala, 2018b). The FD71P has a higher stated sampling frequency and resolution than the PWD instruments of 0.01 mm h^{-1} with 2.2% uncertainty in a 5-second measurement cycle (Vaisala, 2019a), although there has yet to be independent
50   scientific evaluation of the device.

Hotplate disdrometers offer an alternative with the advantage of requiring fewer assumptions as mass is inferred from the energy required for evaporation. The Yankee Environmental Systems TPS-3100 determines liquid water precipitation rate of rain or snow by taking the power difference between an upward and a downward-facing hot plate as a measure of the latent heat energy required to evaporate precipitation (Rasmussen et al., 2010). The technology is currently marketed as the
55   Pond Engineering Laboratories K63 Hotplate Total Precipitation Gauge (Pond Engineering, 2020). The hotplate is 5 inches in diameter, or 126.7 cm², which is equivalent to a square with a width of 11.26 cm. It measures precipitation rate with a resolution of 0.10±0.5 mm h^{-1} and can detect the onset of light snow within one minute (Yankee Environmental Systems, 2011; Pond Engineering, 2020).

A newer hotplate disdrometer, yet to be commercialized, is the Differential Emissivity Imaging Disdrometer (DEID) de-
60   veloped at the University of Utah. By assuming conservation of energy during heat transfer from a square plate to a melting

Table 1. Precipitation measurement instrument specifications

Model	Type	Resolution [mm h^{-1}]	Uncertainty	Time [s]	Meets WMO Requirement
Vaisala PWD12/22/52	Optical	0.05	10%	600	N
Vaisala FD71P	Optical	0.01	2.2%	5	Y
ASOS HTB	Tipping Bucket	0.25	0.5 mm or 4%*	60	N
ASOS LEDWI	Optical	0.25	> 4 mm h^{-1}	60	N
YES TPS-3100 / Pond K63	Hotplate	0.10	0.5 mm h^{-1}	60	N
WMO		0.10	0.1 mm h^{-1} or 5%*	60	

*Whichever is greater

hydrometeor, the mass of individual precipitation particles is obtained. To determine particle size during evaporation, a thermal camera is directed at a heated aluminum sheet. Since aluminum is a thermal reflector (thermal emissivity $\epsilon \approx 0.03$), whereas water is not ($\epsilon \approx 0.96$), particles are seen as white regions on a black background. From the measured cross-sectional surface area, temperature, and evaporation time of each hydrometeor, the effective diameter and volume, and mass of each particle can be calculated with high precision (Singh et al., Pending).

The work here was originally motivated by a desire to minimize DEID power and maximize measurement precision, although the calculations are applicable more generally to other disdrometers such as those described. We employ a Monte Carlo approach (Liu et al., 2012, 2018; Jameson and Kostinski, 1999, 2001a, 2002) to stochastically generate raindrops based on canonical size distributions aimed at determining the minimum required disdrometer collection area and sampling frequency for precise measurement of precipitation rates between 0.01 and 10 mm h^{-1}. We consider the precipitation rate uncertainty relative to WMO standards. Inherent precipitation measurement uncertainties associated with the instrument mechanism are not addressed here. Where (Joss and Waldvogel, 1969) approached the problem analytically by assuming the interarrival times of droplets up to 6 mm in diameter are distributed according to a Poisson distribution, here we approach the problem numerically by employing a Monte Carlo approach. In principle, the results should converge, although the Monte Carlo approach also facilitates the calculation here of the time required to measure the "first drop" in a precipitation event.

2 DEID principle

A piece of polyimide tape with $\epsilon \approx 0.95$ is placed on the side of the sampling area as a reference for the differential emissivity calculation and determination of the camera's pixel resolution. For the study described here, the DEID's aluminum plate had an area of 15.24 cm × 15.24 cm. Polyimide tape applied to the surface restricted the collection area to $A \approx 7$ cm × 5 cm, equivalent to a square width of $W = 5.8$ cm. Thermal camera imagery with a sampling frequency between 2 and 60 Hz was used to determine the cross-sectional surface area, temperature, and evaporation time of each hydrometeor (Singh et al., Pending).

From these parameters, individual hydrometeor mass is calculated from conservation of energy, whereby the heat gained by the hydrometeor is equal to the heat lost by the hotplate when evaporating water through

$$c_p \Delta T \int dm + L_{eqv} \int dm = \int_0^t \frac{K}{H} A(t)(T_p - T_w(t)) dt \qquad (1)$$

85   where c_p is the specific heat capacity of water at constant pressure, ΔT is the difference in temperature between 0 and time, t, m is the mass of the hydrometeor, and L_{eqv} is the equivalent latent heat required for the conversion of the hydrometeor to gas. For liquid precipitation $L_{eqv} = L_v$ where L_v is the latent heat of vaporization of water. K is the thermal conductivity of the plate, H is hotplate thickness, $A(t)$ is the area of the water droplet at time t, T_p is the temperature of the hotplate, and $T_w(t)$ is the temperature of the water at time t.

90   Equation (1) simplifies to

$$\int dm = K_d \int_0^t A(t)(T_p - T_w(t)) dt$$

where the constant K_d is determined experimentally.

The precipitation rate R_{DEID} is calculated from the total mass of hydrometeors evaporated on the hotplate during a given sample time interval. For each frame of the hotplate captured by the thermal camera,

$$95 \quad R_{DEID} = \frac{\beta f_s K_d A_{evap} I_{mean}}{\rho_w A_{hot}} \qquad (2)$$

where $\beta = 3.6 \times 10^6$ mm s mm^{-1} h^{-1}, f_s is the camera resolution in frames per second, A_{evap} is the total area of water on the sampling area, I_{mean} is the pixel intensity related to the temperature difference between the plate and water through $T_p - T_w(t) \approx (255 - I_{mean})/256 \times T_p$, ρ_w is the density of water (1000 kg m^{-3}), and A_{hot} is the hotplate area in units of meters squared.

100   3   Monte Carlo simulations

3.1   Size distribution generation

For a range of collection areas A and time intervals Δt, a rain drop distribution is generated stochastically and compared with the assumed rate R. Initially, we adopt a Marshall-Palmer (Marshall and Palmer, 1948) drop size distribution

$$n(D) = n_0 e^{-\Lambda D} \qquad (3)$$

where n_0 = 8000 m^{-3} mm^{-1} and $\Lambda = 4.1R^{-0.21}$ mm^{-1}. D ranges between 0 and D_{max} in linear bins evenly spaced by ΔD. We establish D_{max} = 6 mm to account for the expected breakup of large raindrops (Villermaux and Bossa, 2009) and ΔD = 0.25 mm for 50 bins. The value of ΔD is arbitrary but was chosen to approximate the spatial measurement resolution of the prototype DEID. For an assumed value of R, the array of drops is stochastically generated according to Eq. (3) where $N_{MP} = \sum n(D)\Delta D$ is the total number of drops generated from each bin. Each drop in the bin is assigned a diameter of $D_{mean} = D + \Delta D/2$. For each value of D_{mean}, the fall speed is

$$v = aD_{mean}^b \tag{4}$$

where the coefficient a and the exponent b are determined for the Stokes regime for $D_{mean} \leq 0.08$ mm, the intermediate regime for 0.08 mm $\leq D_{mean}$ < 1.2 mm. and the turbulent regime for $D_{mean} \geq 1.2$ mm following Lamb and Verlinde (2011). The maximum value of v is used to determine the sample volume of the generated Marshall-Palmer distribution of drops $v_{max}A\Delta t$ m^3.

The calculated size distribution of drops incident on the collection area during sampling time Δt is then

$$N(D)_{coll} = n(D)Av\Delta t \tag{5}$$

with units of inverse millimeter. The total calculated number of drops N_{coll} incident on the collection area is a summation of Eq. (5) over the range 0 to D_{max}.

Note that the size distribution for $N(D)_{coll}$ does not converge to $N(D)_{MP}$ for long sampling times because smaller drops fall slowly. Rather, as will be discussed, the distribution more closely resembles a gamma distribution (Ulbrich and Atlas, 1984). Nevertheless, the contribution of small drops to ground-based measurements of precipitation tends to be small as they are comparatively less massive. Also, precipitation particles form primarily from droplet collisions in the updrafts within clouds, and so must attain the size that they fall sufficiently fast to leave cloud base and fall to the ground where they can be sampled by ground-based instruments (Garrett, 2019).

3.2 Calculated precipitation rate

N_{coll} drops are randomly sampled assuming a Marshall-Palmer distribution. From the drops that impact the collection area, the calculated precipitation rate R_{calc} is (cf. Lane et al., 2009)

$$R_{calc} = \alpha\frac{\pi}{6}\frac{\sum_{i=1}^{50} N_i D_i^3}{A\Delta t} \tag{6}$$

where α = 3.6/1000 m^2 s mm^{-1} h^{-1} and N_i is the number of drops with diameter D_i with i corresponding to bin number. 100 simulations of R_{calc} are performed for each value of equivalent sampling area width $W = \sqrt{A}$, each evenly spaced by

1 cm. The 95th and 5th percentile bounds of R_{calc} are specified as the upper and lower bounds of sampling uncertainty $(R_{calc}/R - 1)$.

3.3 First and Hundredth Drop

135 To determine the sampling time required to detect the onset of precipitation, 100 simulations were performed for $R = 0.01$, 0.1, and 1 mm h^{-1} and for 100 evenly spaced width bins W between 1 cm and 20 cm. For each width bin, the number size distribution (Fig. 3a) was calculated from $n(D)$ for a 1 m^3 volume directly above the collection area with height $h = 1/A$. A sample of drops is generated from Eq. (5), where $\Delta t = h/v$ is maximized for the value of v corresponds with the smallest droplet diameter. Small drops may contribute negligibly to the precipitation rate but be the first detected, so the value of $n(D)$

140 is taken from a gamma distribution rather than the exponential in Eq. (3).

$$n(D) = n_0 D^\mu e^{-\Lambda D} \tag{7}$$

So that small particles with D < 1 mm are not over-represented (Ulbrich and Atlas, 1984), the drop size distribution is modified by the shape parameter μ. The drop distribution is generated according to Eq. (5) and each drop is assigned a random height Δz above the collection area within a distance h above the plate. The time elapsed for the plate to detect a drop is

145 $t_p = \Delta z/v$. The shortest of these times is the first drop detection time t_1 (Fig. 3).

Following the collection approach taken by Marshall et al. (1947), reproduction of a Marshall-Palmer size distribution is assumed to require collection of 100 drops. The time elapsed for the calculated incidence of 100 drops is t_{100} (Fig. 3). If fewer than 100 drops were obtained in N_{coll}, a new sample of drops is obtained from Eq. (5) with an increased value of Δt.

4 Results

150 ### 4.1 Monte Carlo simulations

The sampling uncertainty in the precipitation rate is illustrated in Fig. 1. Precipitation rates of $R = 0.02$, 0.20, and 2.00 mm h^{-1} were analyzed for a standard sampling time of 60 seconds. Collection areas smaller than approximately 6 cm $\times$ 6 cm meet WMO standards for $R \leq 0.50$ mm h^{-1}, but a collection area of over 10 cm $\times$ 10 cm is required for $R > 1$ mm h^{-1}.

To illustrate the relationship between accuracy and sampling time, Fig. 2 compares $R = 0.10$, 1.00, and 10.00 mm h^{-1}

155 with sampling times of 10 seconds, 5 minutes, and 10 minutes. For heavy rain rates of 10 mm h^{-1}, for a time interval of 5 minutes, a disdrometer width of 4 cm yields measured rain rates with a precision of $\pm 5\%$ error for 95% of the measurements. The intersection between 95th and 5th percentile bounds and WMO accuracy criteria occurs at larger collection areas as R increases.

First drop simulation results are shown in Fig. 3. Three simulations were performed using three values of μ, where $\mu = 0$

160 represents the Marshall-Palmer exponential distribution and closely represents the distributions generated by the uncertainty simulations. Following (Ulbrich and Atlas, 1984), DEID measurements show values of μ between 1 and 2 best represent the
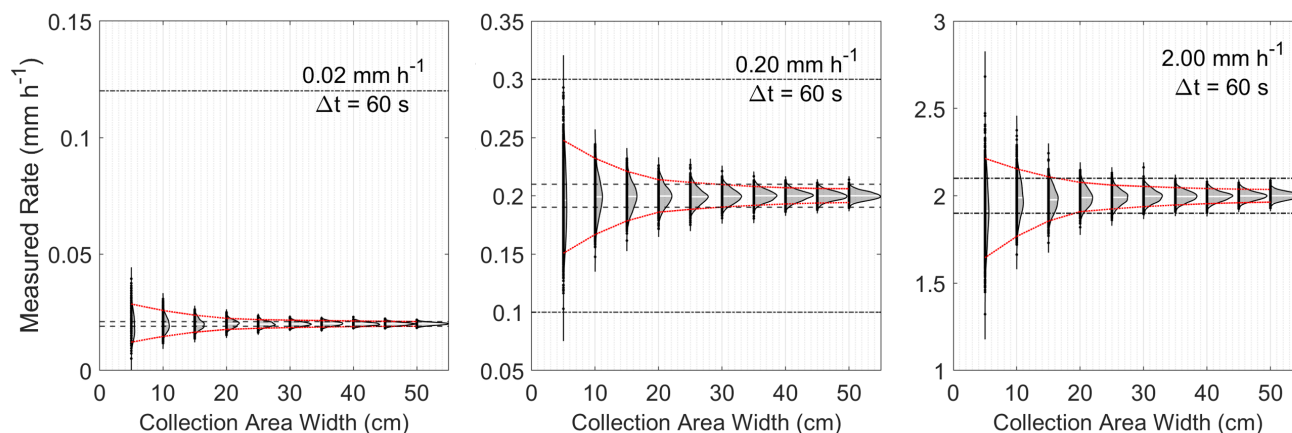
Figure 1. Precipitation rate R_{calc} calculated 1000 times for each W with a uniformly distributed random selection of particle sizes from a Marshall-Palmer distribution with diameters up to 6 mm for Δt = 60 s. Vertical curves represent a PDF of calculated R_{calc} with the widths scaled according to the widest curve. 95th and 5th percentile bounds are smoothed and shown in red, dotted lines. WMO standards ($\pm 5\%$ (dashed) and ± 0.1 mm h^{-1} (dot-dashed)) are shown as horizontal lines. The intersection of these lines indicates the required square disdrometer sampling width to determine R according to WMO standards.

distribution of drops that arrive on the hotplate (Fig. 4b and 5b). Monte Carlo calculations of the size distribution N_{coll} are shown in Fig. 3. For $\mu = 2$, few of the smallest drops with D < 1 mm are incident on the collection area. A square collection width of 2 cm $\times$ 2 cm is sufficient to detect the onset of light precipitation with a rate of R = 0.01 mm h^{-1} within one minute.

Table 2. Minimum collection area required to meet WMO precision criteria for various precipitation rates and time intervals evaluated within one centimeter intervals

Rate (mm h^{-1})	WMO Precision	Δ t = 10 s	Δ t = 60 s	Δ t = 300 s	Δ t = 600 s
		Width (cm)			
0.01	First Drop (μ=2)	5	**2**	< 1	< 1
0.10	First Drop (μ=2)	<1	**1**	<1	<1
0.20	± 0.1 mm h^{-1}	6	**1**	1	<1
0.50	± 0.1 mm h^{-1}	14	**6**	3	3
1.00	± 0.1 mm h^{-1}	25	**13**	5	4
2.00	± 0.1 mm h^{-1} & $\pm 5\%$	40	**29**	8	5
10.00	$\pm 5\%$	30	**15**	6	4
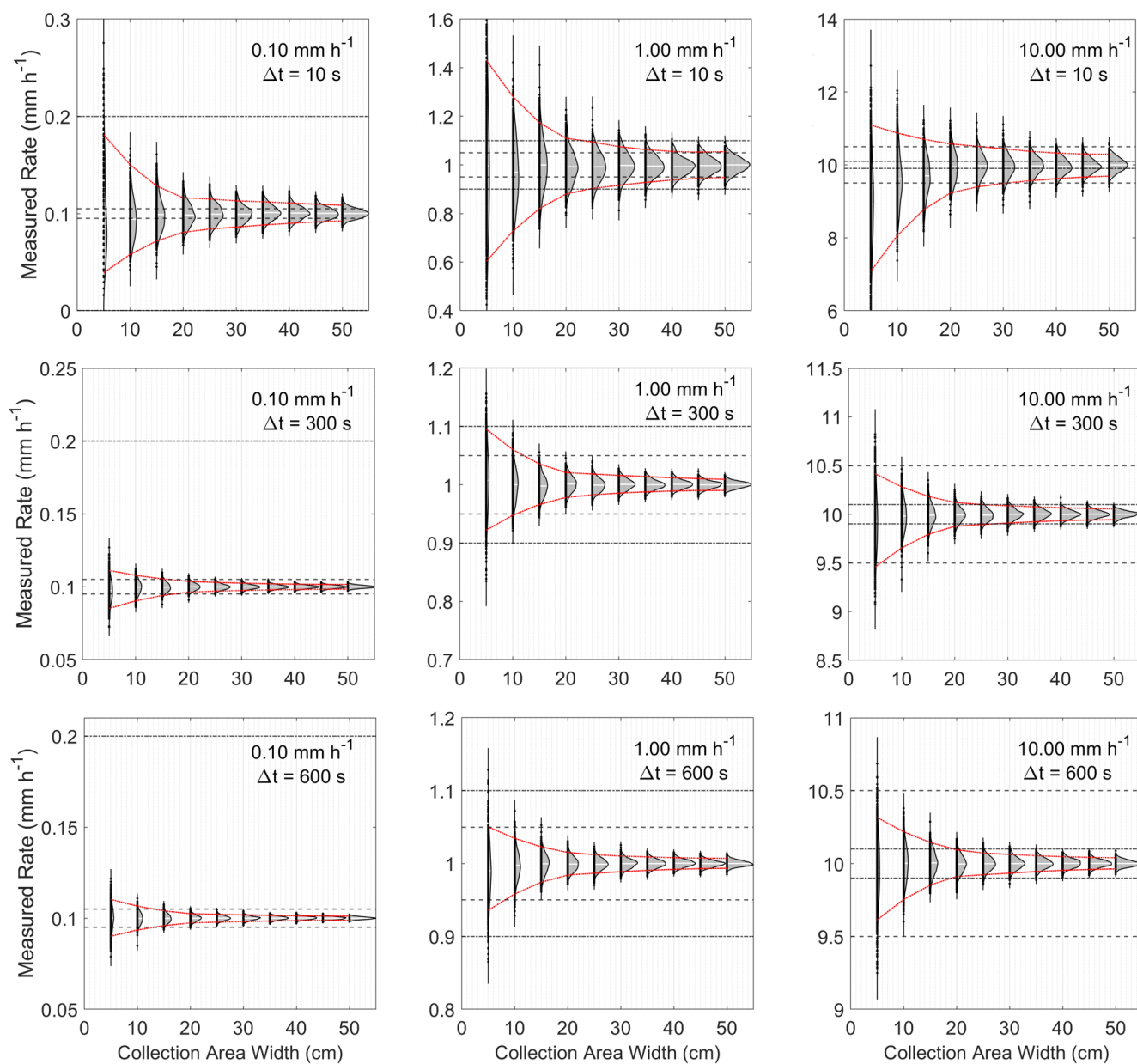
Figure 2. Comparison of $R = 0.10$, 1.00, and 10.00 mm h^{-1} for $\Delta t = 10$ s, 5 minutes, and 10 minutes.
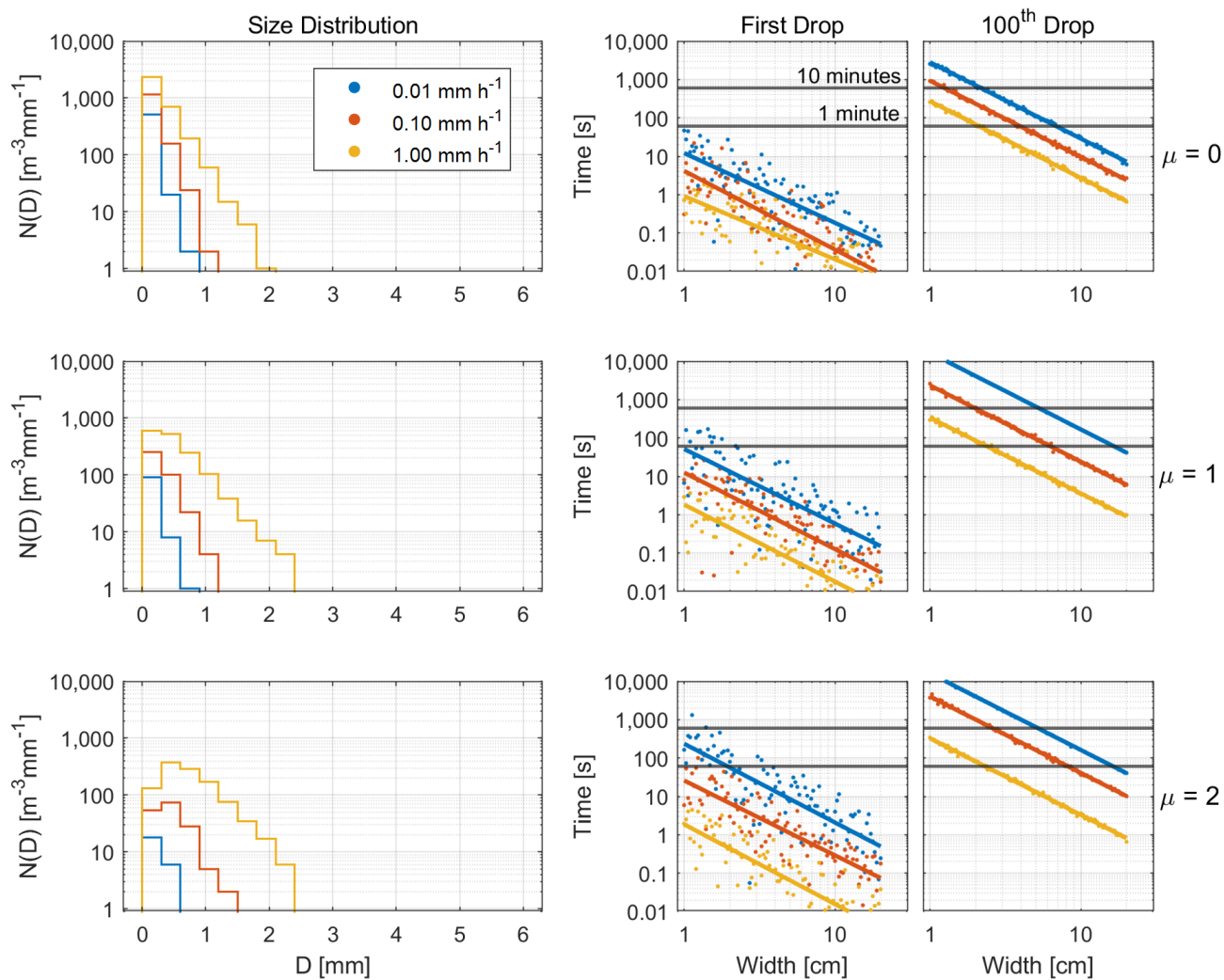
Figure 3. Generated size distributions (left) First Drop Simulation (middle), and 100th Drop Simulation (right) for $\mu = 0$, 1, and 2 (top, middle, and bottom).

4.2 Application to DEID measurements

During a field campaign that took place at the University of Utah between April 2019 and March 2020, the DEID recorded the mass and density of individual hydrometeors, along with the one-minute-averaged precipitation rate R_{DEID}. DEID particle mass distributions for two contrasting one-minute samples of moderate (R_{DEID} = 4.2 mm h^{-1}) and light (R_{DEID} = 0.1 mm h^{-1}) rain are shown in Fig. 4 and 5. These disdrometer data are used here in place of an assumed size distribution to calculate R_{calc} (Eq. 6) in 100 iterations, each taken from data randomly sampled over time interval segments of Δt = 10, 20, 30, 40, and 50 s (Fig. 4c and 5c) and plate area segments of W = 1, 2, 3, 4, and 5 cm (Fig. 4d and 5d). Segments of Δt include all particles within the DEID collection area and segments in W encompass the entire 60 second time interval. In a three dimensional space of plate cross-sectional area and sampling time, the associated number concentration of drops for each case is shown in Fig. 4a-b and Fig. 5a-b.

The version of the DEID used in this study had a maximum collection area width of W = 5.8 cm. For light rain, the statistical uncertainty bounds at 95% confidence converge to within ± 0.1 mm h^{-1} of the DEID 1-minute measured rate for a plate collection area width of $W \sim 3$ cm. This value is larger than that suggested by the Monte Carlo calculation shown in Table 2, although for reasons that are unclear. One possibility is that the raindrop interarrival time and spacing were non-Poissonian (Jameson and Kostinski, 2001b) as implicitly supposed using a Monte Carlo approach. For the moderate rain case, the WMO precision requirement is $\pm 5\%$ (dashed lines). The derived minimum required hotplate width to meet WMO requirements is larger than 10 cm, larger than the plate used. That is, the size of plate used was insufficient for the measurement of rain this intense.

(a)

(b)

(c)

(d)
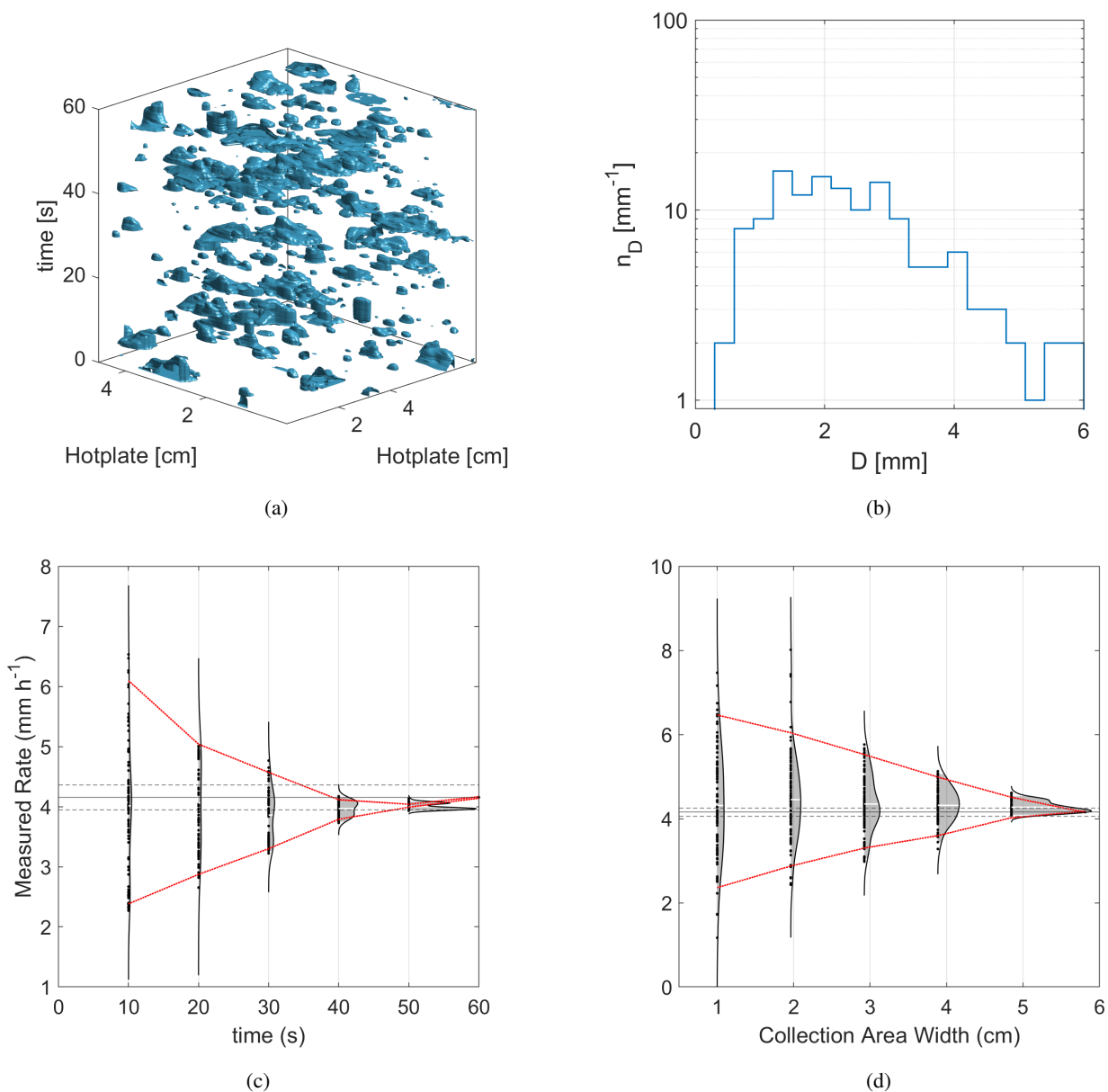
Figure 4. Recalculation of R_{calc} (Eq. 6) from 1000 uniformly distributed, randomly sampled iterations of a 1-minute DEID data set from March 8, 2020 at 1443 MST with rain rate R_{DEID} = 4.2 mm h^{-1} (a). R_{calc} was recalculated using uniformly distributed random segments of time (c) and hotplate width (d). As $t \rightarrow 60$ and $W \rightarrow W_{DEID}$, R_{calc} approaches R_{DEID}.
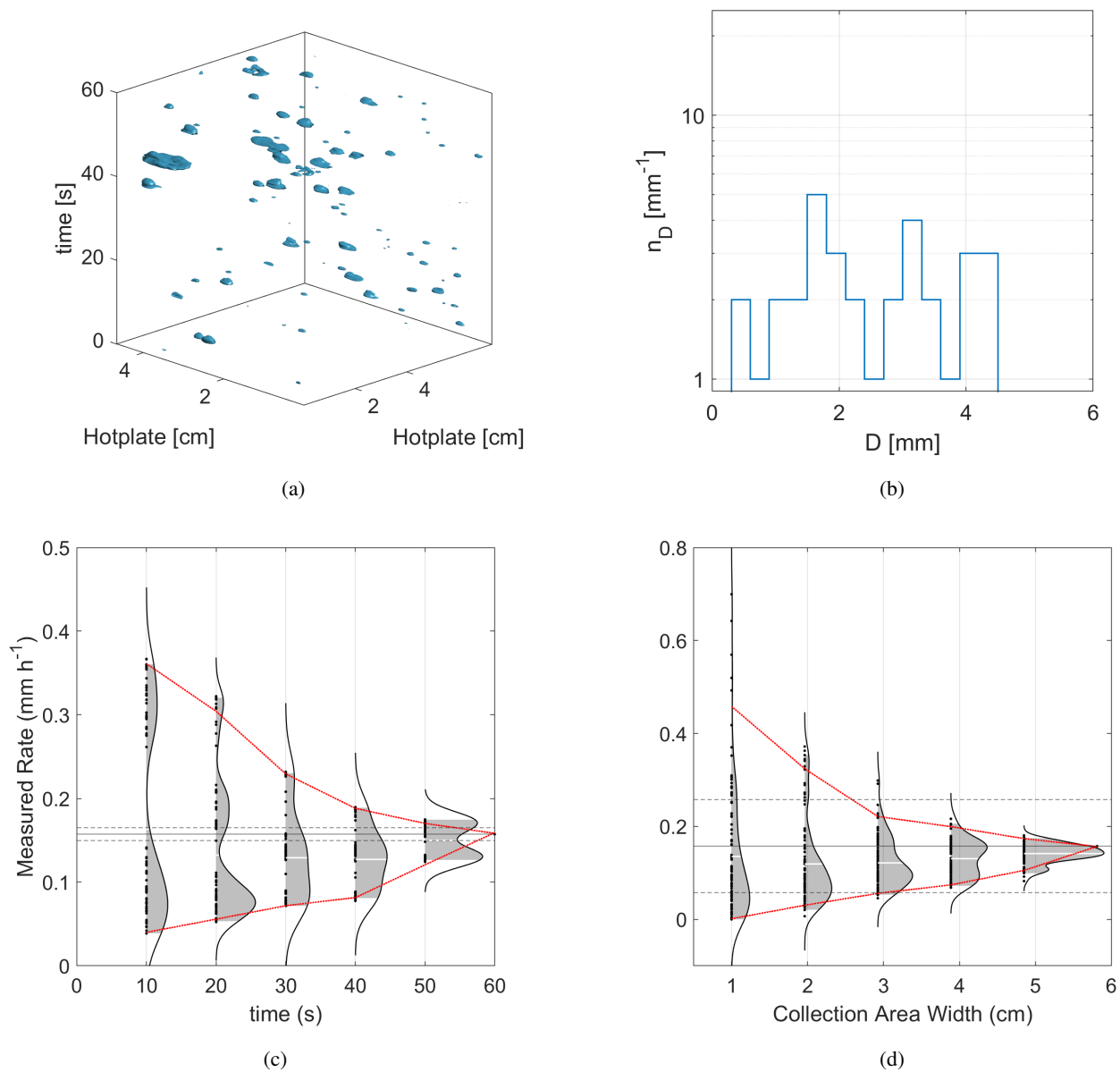
Figure 5. Recalculation of R_{calc} from 1000 iterations of a 1-minute DEID data set from March 8, 2020 at 1514 MST with rain rate R_{DEID} = 0.1 mm h^{-1} (a). R_{calc} was calculated using uniformly distributed random segments of time (c) and hotplate width (d). As $t \rightarrow 60$ and $W \rightarrow W_{DEID}$, R_{calc} approaches R_{DEID}.

5 Conclusions

A Monte Carlo approach was used to determine the minimum required cross-sectional collection area for a disdrometer to
measure a given precipitation rate with a WMO target precision at 95% probability for a one-minute collection period. Intrinsic
instrument uncertainties were not considered, only those associated with statistical sampling errors associated with the raindrop
size distribution. Following these criteria, a square collection area of 6 cm $\times$ 6 cm is sufficient to detect the onset of light rain
with $R \le 0.50$ mm h^{-1}.

For $R > 1$ mm h^{-1}, a sample area of over 10 cm $\times$ 10 cm is required, although a smaller collection area may achieve the
required accuracy by increasing the sampling time. For example, in five minutes, a 4 cm $\times$ 4 cm collection area can measure
10 mm h^{-1} precipitation rates to within the WMO required precision 95% of the time. A collection area as small as 2 cm $\times$ 2
cm may detect the onset of light drizzle with $R = 0.01$ mm h^{-1} within one minute, even in instances where small particles in
the drop size distribution fall too slowly to intercept the collection area.

Theoretical results obtained from Monte Carlo simulations were compared with observed field measurements from a new
precipitation sensor, the Differential Emissivity Imaging Disdrometer, for both light and moderate rain. Randomly selected
segments of decreasing sampling time and area from the DEID were used to recalculate the precipitation rate. The results
suggest a larger plate may be required than those indicated by the Monte Carlo simulations, although it is not yet known why.

Competing interests. TJG is co-owner of Particle Flux Analytics, Inc. which is commercializing the DEID.

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