



Raindrop Size Distributions Retrieved from Vertically Staring Coherent Doppler Lidar

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Abstract. The US Department of Energy's Atmospheric Radiation Measurement (ARM) program operates pulsed coherent Doppler lidars at all its fixed and mobile sites. These instruments provide accurate range- and time-resolved measurements of line-of-sight (radial) velocity and aerosol backscatter in the atmospheric boundary layer under clear-air conditions. Consequently, they have been used extensively to study winds and turbulence in the atmospheric boundary layer, while their ability to measure precipitation properties has received much less attention.

In this study, Doppler spectra from a vertically staring pulsed coherent Doppler lidar (XR+) are used to retrieve clear-air vertical velocities in the presence of precipitation, and raindrop size distributions (RSDs) across multiple convective precipitation events at ARMs Southern Great Plains (SGP) site. RSDs derived from the lidar's lowest valid height bin are compared to a nearby surface-based laser disdrometer. The disdrometer and lidar-derived RSDs show a high degree correlation, particularly under light to moderate wind speed conditions. For wind speed less than 2 ms⁻¹, the median RSD correlation was 0.94. As the wind speeds and rain rates increased the correlations exhibit more scatter such that the median correlation for all observed wind speeds was 0.88. The median percent difference in the modal diameters was found to be 3.4% with the lidar producing slightly higher estimates. Significantly better agreement is obtained when the disdrometer is used to calibrate the lidar's backscatter efficiency. In that case, median correlation coefficient for light winds increases to 0.96 and the median percent difference in the modal diameters decreases to -0.7%, with the lidar producing slightly lower modal diameter estimates than the disdrometer. The results of this study indicate that coherent Doppler lidars could be used operationally to obtain accurate height-resolved RSD retrievals. This would require careful data management given the large data volumes associated with the Doppler lidar spectra.

1 Introduction

Measurements of raindrop size distributions (RSDs) at the surface and aloft are crucial for understanding rain and cloud microphysical processes (Friedrich et al 2016) and for developing improved parameterizations in mesoscale and numerical weather prediction models (Zhang et al. 2006). In-situ instruments such as laser and high-speed video disdrometers provide accurate measurements of RSDs at the surface, while remote sensing techniques can provide height-resolved measurements with careful calibration. Vertically staring cloud radar systems such as pulsed Ka- and W-band (Kollias et al. 2016), or FM-



30 CW systems such as the Micro Rain Radar (MRR) (Klugmann et al. 1996) provide excellent sensitivity to small cloud droplets, drizzle and raindrops, but poor sensitivity to aerosol. Doppler lidars operating in the near-IR are sensitive to backscatter from aerosol as well as various hydrometeors. The lidar's sensitivity to aerosol backscatter enables accurate determination of the local air vertical velocity, and therefore the terminal fall speed of the raindrops. For moderate to heavy rains, the beam attenuation generally constrains vertical profiling to altitudes below 1 km when the precipitation fills the entire vertical column. However, regions of elevated precipitation, i.e. virga, can also be detected at higher altitudes with lidar.

Due to the sensitivity to aerosol backscatter Doppler lidars have traditionally been used for the study of winds and turbulence in the atmospheric boundary layer under clear-air conditions (Berg et al. 2017; Turner et al. 2018; Pichugina et al. 2023; Balmes et al. 2023), while their ability to measure precipitation properties has received much less attention. Doppler spectra from a vertically staring Doppler lidar under precipitation exhibit multi-modal structures due to backscatter from aerosol and raindrops. The aerosol mode can be easily identified from the local maxima, allowing for the retrieval of the aerosol (clear-air) velocity even when the precipitation signal is dominant. This is useful in combined lidar-radar RSD retrievals in which the lidar provides the clear-air vertical velocity for determination of the terminal fall speeds (Williams 2026). Additionally, RSDs could be estimated from the lidar spectra alone.

45 To date, there have been only a limited number of published studies exploring the ability of a coherent Doppler lidar measure RSDs. Aoki et al. (2016) was the first study demonstrating the ability of the coherent Doppler lidar to retrieve RSDs. They obtained reasonably good correlations (>0.80) with a surface-based disdrometer and observed that stratiform precipitation gave better results than convective precipitation events. Aoki et al. (2016) also used disdrometer measurements to essentially calibrate the backscatter efficiency. By contrast, Wei et al. (2021) computed the backscatter efficiency curve based on a combination of Mie scattering for small drops and a ray-tracing model for larger aspherical drops. They were able to demonstrate much better agreement with a surface-based disdrometer.

These previous studies established proof-of-concept. In this study, we apply a similar approach using raw spectra from a Lumibird XR+ Doppler lidar. A number of these systems are currently being operated by the US Department of Energy's (DOE) Atmospheric Radiation Measurement (ARM) program at its fixed and mobile sites (Mather and Voyles, 2013; Newsom and Krishnamurthy 2022), and there is interest among the research community to better exploit the information in the raw spectra from these systems. Thus, the goal of this study is to examine the characteristics of the spectra recorded by the XR+ systems under clear-air and rainy conditions, describe the processing step necessary to obtain the spectral signal-to-noise ratio (SNR), assess the accuracy with which RSDs can be estimated from the SNR, and address issues associated with routine collection and processing of raw data from the ARM XR+ systems. The accuracy is assessed by comparison with a collocated surface laser disdrometer. We examine the impact of two different empirical models relating raindrop terminal fall speed to equivalent drop diameter and show that small differences in the speed model can have a significant impact on the RSDs. We also that it's possible to achieve very good agreement by essentially calibrating the backscatter efficiency using the collocated disdrometer.



This paper is organized as follows: Section 2 describes the experiment site and the instruments used in this study, and section 3 describes processing of the raw data from the XR+. Section 4 describes the methods used to identify multiple local maxima in the SNR, and how that information is used to retrieve the aerosol velocity in the presence of precipitation. Section 5 describes the methods used to estimate uncalibrated drop size distributions from the SNR. In section 6, the lidar-derived RSDs are compared to measurements from a surface-based disdrometer, and section 7 discusses data management issues associated with routine collection of spectral data from the Doppler lidars.

2 Experiment Site

Measurements used in this study were conducted at ARM's Southern Great Plains (SGP) S4 site between 19 May and 5 July 2023. This site was equipped with several ground-based in situ and remote sensing instruments (Moriarty et al. 2025; Newsom et. al. 2025; Krishnamurthy et al. 2025. Specific instruments used in this study included one pulsed coherent Doppler lidar (Lumibird XR+, S/N 215), a pair of orthogonally mounted laser disdrometers (OTT Parsivel²), and a surface meteorological station that provided winds, temperature, pressure and humidity at a height of 2 mAGL. The surface meteorological station was located 30 m to the SSW of the lidar. Both the lidar and disdrometers were deployed on a platform mounted to the top of a modified shipping container, as indicated in Figure 1. The lidar was at a height of 3.7 m AGL, and the disdrometers were mounted at the top of short masts at a height of about 5 m AGL.

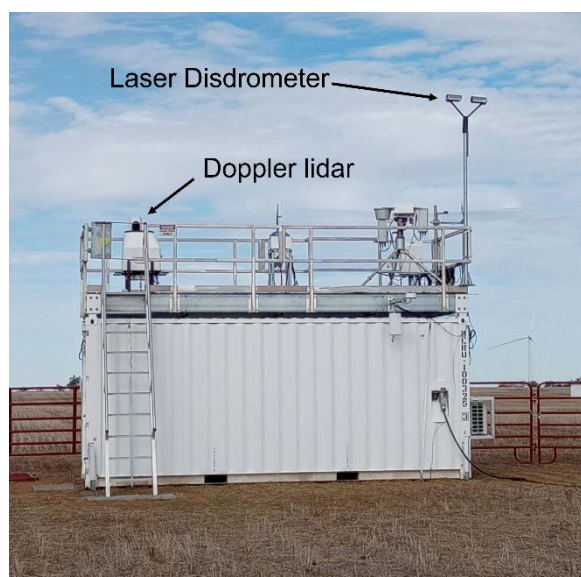


Figure 1. The ARM profiling module showing the locations of the Doppler lidar and laser disdrometers



The Parsivel² laser disdrometer measures raindrop size and speed from voltage changes as the raindrops traverse through a laser sheet. It outputs the number of drops detected within discrete speed and diameter bins and uses that information to compute the RSD and the rain rate (Tokay et al 2014; Zhang, et al 2001, 2020; Saha and Testik 2023). Both disdrometers were configured to generate output using 15-sec averaging intervals. The speed and diameter grids are each 32 elements in length, and the bin sizes increase as the values increase. As a result, RSDs from the disdrometer are more coarsely resolved than the spectra from the lidar.

The two disdrometers were mounted such that one system was aligned north-south, and the other was aligned east-west, as determined by the directions of their laser sheets. As a result, the east-west-aligned system will experience minimal obscuration and optimal sensitivity when the winds are out of the north or south (Chinchella et al. 2025). Thus, the measurements from each disdrometer were combined into a single dataset using wind direction measurements from the surface meteorological station. For winds out of the east (45° to 135°) or west (225° to 315°), the north-south-aligned disdrometer data was used, otherwise data from the other system was used.

The XR+ lidar used in the study employs a sampling rate of 50MHz. Thus, each I&Q sample is separated by 20 ns or 3 m. The total acquisition time is 80 μs per pulse, which is equivalent to 12 km. The total number of samples acquired for each pulse is 4000. Relevant specifications for the XR+ are shown in Table 1. For this study, the pulse integration time was set to 1 s, and the range gate size was 60 m. As a result, there are 20 I&Q samples per range gate. To minimize the vertical distance between the lidar and disdrometer sample volumes we used a range bin centered at 110 m above the lidar. This was just high enough to completely avoid the lidar's dead zone.

Table 1. XR+ Doppler Lidar specifications and configurations used in this study. The pulse integration time and the range resolution are configurable whereas the other parameters are fixed.

pulse repetition frequency	10 kHz
pulse length	~200 ns
pulse energy	<100 μJ
wavelength	1.55 μm
sampling frequency	50 MHz
velocity range	±19.4 ms ⁻¹
range (velocity) resolution	60 m (1.935 ms ⁻¹)
pulse integration time	1 s

3 Lidar Doppler Spectra

3.1 Raw Data



110 The XR+ lidars store their raw spectral data in the form of ungated autocovariance functions (ACFs) of the complex I&Q signal (Newsom and Krishnamurthy 2022). Raw data in this form enables flexible placement and sizing of the range gates in post-processing, but results in rather large data files. The ACFs for a single profile averaged over the pulse integration time can be expressed as

$$\sigma_{jk} = \overline{f_j f_{j+k}^*}, \quad (1)$$

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where

$$f_j = I_j + iQ_j \quad (2)$$

120 is the baseband-shifted return signal for a single pulse consisting of in-phase (I) and quadrature (Q) components, j is the sample index, and k is the lag index. The total number of samples acquired for each pulse is 4000, and the ACFs are approximated using 20 lags.

There is in general a small change in frequency or chirp in the outgoing pulse. This causes distortion in the Doppler power spectra, which can result in biased radial velocity measurements (Drobinski and Flamant, 1998; Bühl et al 2012). The chirp is a consistent feature of the transmitter, so the manufacturer provides a factory-determined, range-independent chirp correction file for each XR+ system. The chirp-corrected ACF is given by

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$$g_{jk} = C_k \sigma_{jk}, \quad (3)$$

where C_k is the chirp correction, and g_{jk} is the chirp-corrected ACF.

130 Range gating is achieved by averaging the equation (3) over a subset of sample indices, j , corresponding to a prescribed range bin. The pulse-averaged, chirp-corrected, range-gated ACF for n^{th} gate is given by

$$\bar{g}_{nk} = \sum_{j=n-\frac{m}{2}}^{n+\frac{m}{2}} g_{jk} \quad (4)$$



135 where m is the number of I&Q samples per range gate. For a typical 60 m range gate using a sampling rate of 50MHz the value of m is 20.

The power spectrum for the n^{th} gate is given by the discrete Fourier transform of $\bar{g}_{nk}$, i.e.

$$G_{nk} = \sum_{\ell \geq 0} \bar{g}_{n\ell} e^{ik\ell/2\pi} + \sum_{\ell < 0} \bar{g}_{n\ell} e^{ik\ell/2\pi}. \quad (5)$$

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Equation (5) involves a summation over negative and positive lags. Negative lags are not stored in the raw output. Instead, they are obtained using the Hermitian property of the complex autocovariance function, i.e.

$$\bar{g}_{n,-\ell} = \bar{g}_{n\ell}^*. \quad (6)$$

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As a result, equation (5) simplifies to

$$G_{nk} = 2\text{Re} \left[\sum_{\ell > 0} \bar{g}_{n\ell} e^{ik\ell/2\pi} \right] \quad (7)$$

150 The frequencies corresponding to the index k in equation (7) are given by

$$f_k = \frac{f_s}{N_{FFT}} \left(k - \frac{N_{FFT}}{2} \right) \text{ for } k = 0..N_{FFT} - 1 \quad (9)$$

where f_s is the sampling rate (50MHz) and N_{FFT} is the number of points in the Fast Fourier Transform (FFT).

155 Normally, Doppler power spectra are represented as functions of velocity rather than frequency. The relationship between radial velocity, v_k , and Doppler frequency, f_k , is given

$$v_k = -\frac{\lambda f_k}{2} \quad (10)$$



160 where λ is the wavelength (1548 nm). The negative sign is necessary because negative Doppler shifts are caused by scatterers moving away from the lidar, which correspond to positive radial velocities by definition. The velocities are bounded such that $|v_k| \leq v_{Nyquist}/2$, where $v_{Nyquist} = \frac{\lambda f_s}{2}$ is the Nyquist velocity. For $\lambda = 1548$ nm and $f_s = 50$ MHz, $v_{Nyquist} = 38.7$ ms⁻¹. Since this range is split between positive and negative frequencies the actual measurement range is $|v_k| \leq 19.4$ ms⁻¹.

165 In practice, the ACFs are zero padded-out to a length of 1024 prior to the application of a Fast Fourier Transform (FFT). The number of FFT points is configurable, but 1024 is recommended by the manufacturer. Since the ACFs are only defined out to 20 lags, there is a considerable amount of zero padding, which artificially increases the spectral resolution. The true velocity resolution is $v_{Nyquist}$ divided by the number samples per gate, which for a 60m gate (i.e. 20 samples) is 1.9 ms⁻¹. The spacing between samples in the FFT output is $v_{Nyquist}/N_{FFT}$, where N_{FFT} is the number of FFT points. For N_{FFT}
170 =1024, the spacing is 0.038 ms⁻¹.

In addition to chirp, instrumental effects can cause systematic variation in the noise floor or background, resulting in distortion of the uncorrected Doppler spectra. The noise floor is affected by environmental conditions and generally changes slowly over time. The XR+ systems are set up to automatically acquire background data at the top of every hour by staring downward at the top of the lidar enclosure, thereby blocking the beam. The background ACFs are range-gated and chirp-
175 corrected in the same manner as the atmospheric measurements. They are then used to compute the noise-corrected Doppler spectra taken during the subsequent hour.

The pulse-averaged, chirp- and noise-corrected Doppler power spectrum at range gate n and frequency index k is given by

$$SNR_{nk} = \frac{G_{nk}}{H_{nk}} - 1 \quad (8)$$

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where H_{nk} is the power spectrum of the background noise.

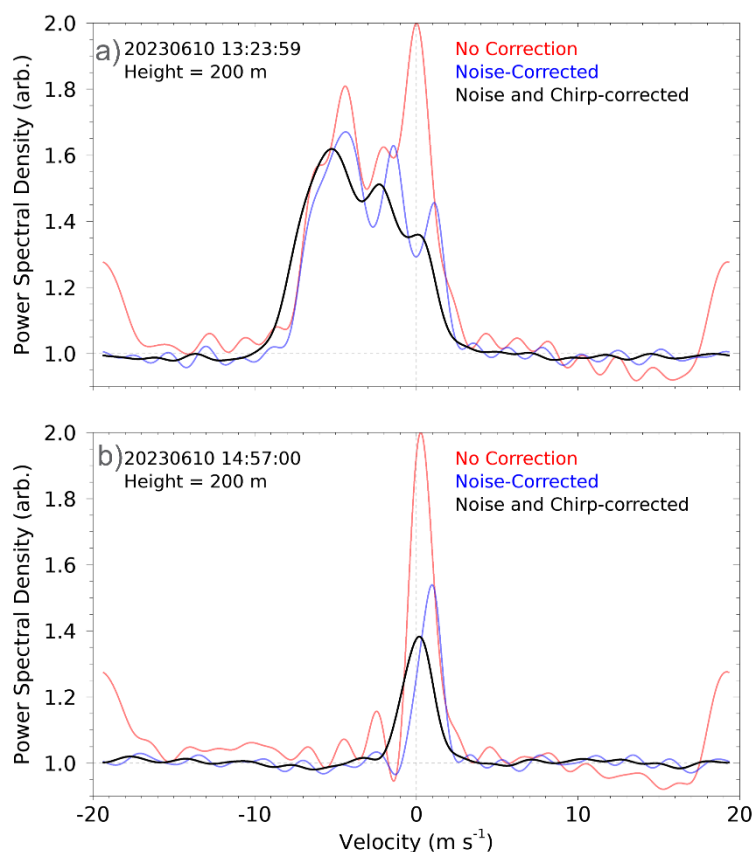


Figure 2. Examples of uncorrected (red), background-corrected (blue) and background- and chirp-correction power spectra (black) during a) a precipitation event at SGP S4 on 10 June 2023, and b) under clear-sky conditions (same site and day).

Figure 2 shows the effects of the chirp- and background-corrections on the final Doppler spectrum under rainy (Fig 2a) and clear-air (Fig 2b) conditions. The uncorrected spectra (red) have been scaled for comparison purposes. The blue curves show the effects of normalizing the red curves by the background spectra. This removes considerable distortion and flattens out the noise floor in the noise-corrected results (blue). The chirp-correction shifts the location of the maximum, reduces spectral leakage effects, and removes some of the asymmetry in the spectrum, resulting in a more Gaussian shape (black). This is evident in the noise- and chirp-corrected clear-air spectrum of Fig 2b. For lidar systems with short pulses (i.e. the XR+) using short integration times, the shape of the aerosol spectrum is largely determined by the pulse, with very little sensitivity to turbulence (Manami et al 2025).

3.2 Multi-Mode Estimation

For the XR+ lidars, the reported radial velocities are obtained from the global maxima of the (background- and chirp-corrected) Doppler spectra. During periods of precipitation, the global maxima can be due to either precipitation or aerosol,



depending on which scatterer caused the largest signal. This ambiguity, which complicates the interpretation of radial velocity data during periods of precipitation, could be resolved if the velocity estimator reported the locations of the most prominent local maxima in the spectrum, in addition to the global maximum.

In this study, we employ a simple multi-mode estimation technique to determine the presence of precipitation and estimate the aerosol (i.e. clear-air) contribution to the total SNR. The method, which is illustrated in Fig 3, locates the largest three peaks in the Doppler spectrum. The SNRs and velocities corresponding to local maxima are estimated by computing the first derivative of the SNR with respect to velocity and locating all zero-crossings with negative second derivatives where the SNR exceeds a predefined threshold. If the maximum SNR exceeds one then the threshold is set to 10% of the maximum SNR, otherwise the threshold is set to 0.1. These limits help to reduce false detections in both the weak and strong signal regimes. The example shown in Fig 3 has three local maxima that satisfy the above conditions. In this case, the primary mode is the aerosol mode, and the secondary and tertiary modes are caused by precipitation.

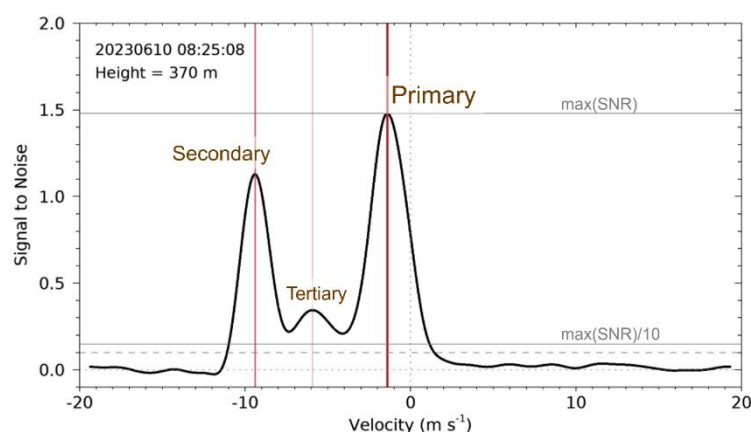


Figure 3. An example of the multi-modal estimation method using data collected during a precipitation event at SGP S4 on 10 June 2023. The algorithm locates points with zero first derivatives, negative second derivatives and SNRs above threshold. The threshold is determined from the larger of $\max(\text{SNR})/10$ or 0.1.

The multi-mode detection algorithm reports the velocities and SNRs corresponding to the largest three modes. These are referred to as the primary, secondary and tertiary modes in order from largest to smallest SNR. The locations of each local maxima are refined by locating the maximum value of a second-order polynomial that is fitted to the three samples nearest the local maximum. Missing values are reported if no modes are found that satisfy the detection criteria.

The multi-mode detection scheme allows for identification of the aerosol velocity under rainy conditions since the aerosol velocity will always be greater than the precipitation velocity, given the radial velocity sign convention (positive away).

Figure 4 shows time-height cross sections of the primary, secondary, tertiary and aerosol modes during a rain event at SGP S4 on 10 June 2023. The primary mode (Figure 4a) exhibits the characteristic “mode-hopping” behavior that occurs as the global maximum shifts from the aerosol mode to a precipitation mode and vice versa. As a result, the primary mode contains



a mix of aerosol and precipitation velocities depending the relative strength of the two modes. By contrast, velocities corresponding to the aerosol mode (Fig 4d) are relatively smoothly varying and do not show the same patchiness as the primary mode.

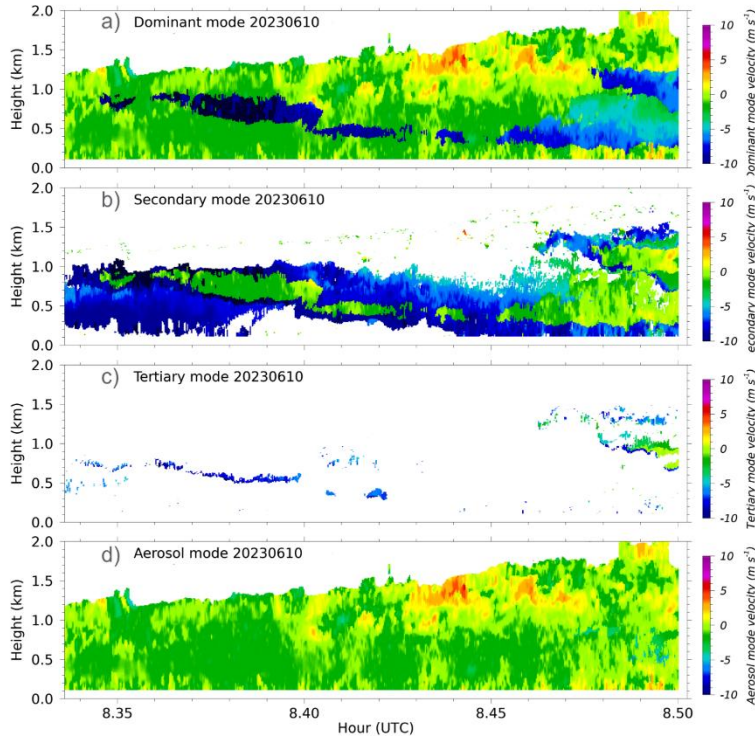


Figure 4. Example of the multimode detection scheme during a rain event on 10 June 2023 at SGP S4. The panels show a) the primary mode, b) the secondary mode, c) the tertiary mode, and d) the aerosol mode. The primary and aerosol modes have been filtered to reject data where the primary SNR is less than 0.05.

4 Rain Drop Size Distributions

The lidar equation can be expressed as

$$SNR(z, v) = c(z) \beta(z, v) T(z, v) / z^2 \quad (11)$$

where z is the distance from the lidar, v is the velocity, $c(z)$ is a factory-determined calibration curve, $\beta(z, v)$ is the volume backscatter, and $T(z, v)$ is the two-way transmission through the atmosphere. The primary scatterers are assumed to be aerosol and rain drops, so that

$$\beta(z, v) = \beta_a(z, v) + \beta_p(z, v). \quad (12)$$



where β_a and β_p are the backscatter coefficients due to aerosol and precipitation, respectively. Similarly, the SNR can be expressed as the sum of aerosol and precipitation contributions, i.e.

$$245 \quad SNR(z, v) = SNR_a(z, v) + SNR_p(z, v). \quad (13)$$

If we assume constant atmospheric extinction along the lidar beam over the 25MHz (38.7 ms⁻¹) passband, then at any given height z we have

$$250 \quad SNR_a(v) \propto \beta_a(v) \quad (14)$$

and

$$SNR_p(v) \propto \beta_p(v). \quad (15)$$

Equation (15) enables the retrieval of the uncalibrated drop size distributions if the precipitation SNR can be accurately
255 retrieved from the total SNR. There are a couple of different approaches that could be used to accomplish this task. A common approach in radar analysis is to assume a functional form the precipitation spectrum such as a gamma distribution, or other single- or multi-mode function (Brandes, et al. 2003; Brandes et al. 2004; Zhang et al. 2001; Träumner, et al. 2010; Pang et al., 2021; Atlas et al., 1973). The aerosol mode is difficult to detect with radar so the vertical velocity is often assumed to be zero, which can introduce significant bias (Kobayashi et al. 2005; Williams et al. 2016). The method used in
260 this study takes advantage of the strength and consistent shape of the aerosol signal in the lidar Doppler spectra.

Figure 5 illustrates the method used in this study to separate the precipitation spectrum from the total SNR. First, the multi-mode detection algorithm is used to identify the aerosol velocity, v_a , i.e. the mode with the highest velocity. The Doppler spectrum is then shifted to align the peak of the aerosol mode with zero velocity such that

$$265 \quad u = v - v_a. \quad (16)$$

Transforming the velocity in this way gives the Doppler spectrum in a frame of reference moving with the local vertical velocity. As a result, u represents the terminal fall speed in the shifted spectra. The volume backscatter coefficient due to precipitation can then be expressed as a function of the terminal fall speed, i.e.

$$270 \quad \beta_p(u) \propto SNR_p(v - v_a). \quad (17)$$

Second, a least squares approach is used to fit a modified Gaussian function to the shifted spectrum using points within ± 1 ms^{-1} . The fitting function takes the following form:

$$SNR_a^{fit}(u) = \exp(a + bu + cu^2), \quad (18)$$

where a , b and c are the fit parameters. The process of fitting the aerosol mode is key to separating the precipitation spectrum from the total Doppler spectrum. To minimize potential bias from the precipitation portion of the total spectrum, the fit range is limited to ± 1 ms^{-1} . Figure 5 shows that equation (18) provides an accurate fit to aerosol mode despite the limited range over which the fit is performed.

The precipitation spectrum is estimated by essentially subtracting equation (18) from the total SNR. To prevent unphysical values the subtraction is conditional such that

$$SNR_p(u) = SNR(u) - SNR_a^{fit}(u) \text{ for } SNR > SNR_a^{fit}$$

and

$$SNR_p(u) = 0 \text{ for } SNR_a^{fit} > SNR, \text{ or } u > 0 \text{ ms}^{-1}, \text{ or } u < -15 \text{ ms}^{-1}.$$

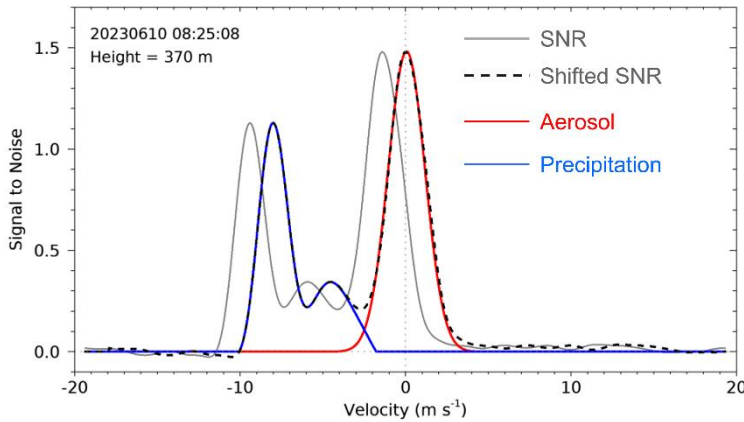


Figure 5. Example of the method used to separate the precipitation spectrum from the total SNR. The SNR is first shifted in velocity to align the aerosol peak with zero velocity (dashed). A modified Gaussian function is then used to fit the aerosol contribution (red). These results are derived from 1-sec raw data. This example was taken from the SGP S4 Doppler lidar at 08:25:08 UTC on 10 June 2023.

4.2 Broadening

The observed precipitation spectrum, $SNR_p(u)$, can be represented as the convolution of the system point spread function (PSF) with the true precipitation spectrum. The PSF includes effects that cause broadening the of the Doppler spectrum,



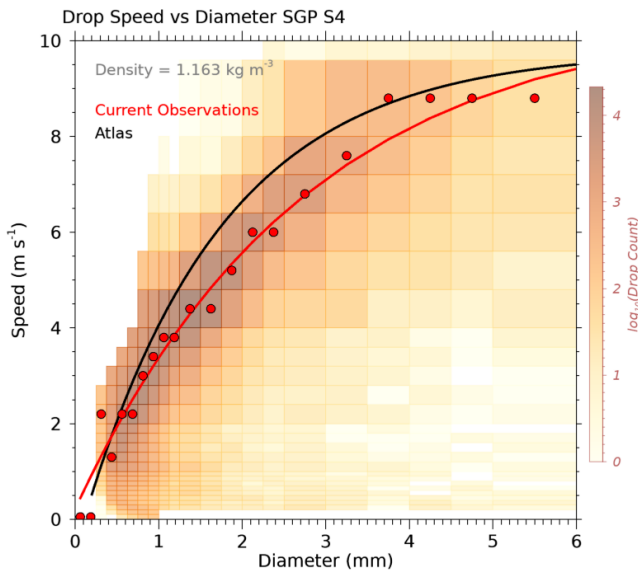
such as turbulence and the window function. In radar wind profiler studies, several researchers use the normalized aerosol spectrum, when detectable, as an approximation to the system PSF (Williams et al. 2016; Aoki et al. 2016; Wei et. al 2021).
 300 Deconvolution methods (Lucy 1974) are then applied to estimate the true precipitation spectrum. In this study, we tested various deconvolution methods but none gave satisfactory results. In this study, the Doppler spectra used in this study were obtained using a short 1-sec averaging time. This short averaging time reduces the smearing of the aerosol and precipitation spectra due to turbulence. As a result, no broadening corrections were applied in this study.

305 4.1 Speed Model

It is necessary to re-express the precipitation spectrum as function of drop diameter, D . This is done using well established empirical relationships between terminal drop velocity to diameter (Beard 1976). A form that is commonly used in radar analysis is given by (Atlas et. al, 1973).

$$310 \quad u(D) = -(a_o + b_o e^{c_o D}) \left(\frac{\rho_o}{\rho} \right)^{0.4}. \quad (20)$$

where ρ is the air density, ρ_o is the reference air density, D is the effective drop diameter in mm, and a_o , b_o , and c_o are the fit parameters at the reference air density. The factor $(\rho_o/\rho)^{0.4}$ accounts for deviations from the reference density.



315 **Figure 6.** Drop counts observed by the disdrometer for all precipitation events from 19 May to 9 July 2023. The black is the curve is the Atlas speed model, and the red curve is referred to as the current speed model. The current speed model represents the best fit to the modal speed estimates.



Figure 6 shows the accumulated drop counts from the disdrometer at SGP S4 between 19 May and 5 July 2023. These results were computed using air densities that were within $\pm 1\%$ of the median surface air density over that period, which was measured to be 1.165 kg m^{-3} . The red dots in Fig 6 represent the peaks of the speed distributions for each diameter bin, and the red curve is the best fit of equation (20) to those values. By contrast, the black curve in Fig 6 represents equation (20) with the same fit parameters used by Atlas et al. (1973) and in numerous previous studies (Wei, et al 2019; Pang, et al., 2021). The disdrometer's speed estimates are generally lower than those predicted by the Atlas model curve. For example, at a diameter of 1.5 mm the Atlas model predicts a drop speed that is roughly 20% larger than the current observations indicate.

In this study, results using two different speed models are compared to the disdrometer observations. Table 2 lists the fit parameters used in equation (20) for the two speed models. The Atlas model uses the original fit parameters from Atlas et al. (1973), as indicated by the black curve in Fig 6. The current model corresponds to the best fit to the current disdrometer observations, as indicated by the red curve in Figure 6.

Table 2. Fit parameters for the drop speed models used in this study.

	$a_o \text{ (m s}^{-1}\text{)}$	$b_o \text{ (m s}^{-1}\text{)}$	$c_o \text{ (mm}^{-1}\text{)}$	$\rho_o \text{ (kg m}^{-3}\text{)}$
Atlas Model	9.65	-10.3	-0.6	1.194
Current Model	10.62	-10.4	-0.4	1.163

Using equation (20) to re-express the precipitation spectrum in terms of diameter results in irregular spacing of the diameter axis. Thus, the precipitation spectrum is resampled to a uniform diameter grid using linear interpolation. Additionally, air density estimates require simultaneous height-resolved measurements of temperature and pressure, i.e. radiosonde measurements. For this study, we extrapolate surface measurements to the lidar's height bin using the US Standard Atmosphere model. This provides a good approximation for first few hundred meters of the atmosphere. In any event, attenuation generally limits the maximum range of the lidar to roughly 1 km or less during most precipitation events observed at the surface.

Estimates of the drop size distribution are obtained from

$$\beta_p(D) = N_D(D) \left. \frac{\partial \sigma}{\partial \Omega} \right|_{\pi}. \quad (21)$$

where $N_D(D)$ is drop size distribution, and $\partial \sigma / \partial \Omega|_{\pi}$ is the differential backscatter cross section for a rain drop. If the cross section can be accurately computed from scattering theory, then $N_D(D)$ can be estimated from



$$N_D(D) \propto SNR_p(u(D)) \left/ \frac{d\sigma}{d\Omega} \right|_{\pi}. \quad (22)$$

350 Alternatively, the disdrometer observations could be used to estimate the backscatter cross section using a combination of lidar and disdrometer data, i.e.

$$\left. \frac{d\sigma}{d\Omega} \right|_{\pi} \propto SNR_p(u(D)) / N_D^{ld}(D) \quad (23)$$

355 where $N_D^{ld}(D)$ is the observed drop size distribution from the laser disdrometer. This assumes that the lidar and disdrometer sample the same volumes. In this study, there is a 100 m vertical separation in the sample volumes, so the difference in drop statistics are expected to be small under most light to moderate wind conditions.

4.3 Differential Backscatter Cross Section

360 Accurate RSD retrievals depend critically on accurate estimation of the differential backscatter cross section in equation (22). Optical scattering computations are made more difficult by the fact that the drop shape transitions from spherical to “oblate-like” as the drop size grows. As the drop size increases beyond about 1 mm, the drops become slightly oblate. At larger sizes the bottom surface begins to flatten out (Beard and Chuang 1987). Mie theory (Bohren and Huffman 2008) provides general solutions to the scattering of electromagnetic waves from a homogenous sphere at all size parameters.

365 However, the theory does not handle the nonspherical geometries of drop larger than ~1.0 mm. For larger non-spherical drops ray tracing models are required to compute scattering cross sections.

This study uses the backscatter efficiency curve in Figure 2 of Wang et al 2026. That result uses the Mie solution for small drop diameters and the geometric optics approximation (Ren et al 2011; Onofri et al. 2015) for diameters greater than 1 mm. The scattering calculations for water drops were done at a wavelength of 1.55 nm using the drop-shape model of Beard and

370 Chuang (1987). Figure 7 shows a comparison between the differential backscatter cross section for spherical drops (blue) versus drops that transition from spherical to oblate-like as the diameter increases (red). For larger drops the blue curve increases as the square of the diameter, as expected. The red curve diverges from the blue curve at about 1mm, and the difference increases above that. For this study, the red curve in Fig 7 is used to model the differential backscatter cross section.

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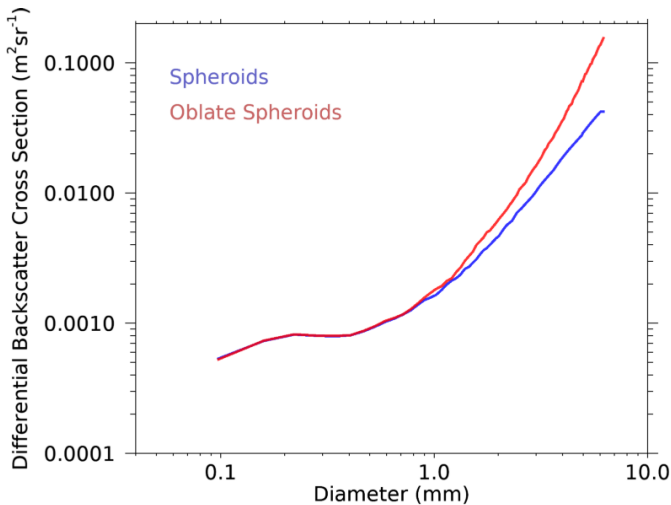


Figure 7.The differential backscatter cross sections, $\partial\sigma/\partial\Omega|_{\pi}$, for liquid rain drops that are perfect spheres (blue) and for drops that transition from spheres to oblate spheroids at higher fall speeds (red).

Table 3 lists specific precipitation events at SGP S4 that were analyzed for this study. This includes roughly 25 precipitation events ranging from 19 May through 9 July 2023 for which data from the lidar and both disdrometers were available. We note that one of the disdrometers was not operating for about 2 weeks in mid- to late-June 2023, so that period has been excluded from the analysis.

Table 3. Dates and times of precipitation events that were analyzed in this study. The second column lists specific hours during which precipitation was measured by both the lidar and the surface disdrometers.

Date	Hours (UTC)
19 May 2023	7-13, 17, 22
23 May 2023	16, 18, 19
24 May 2023	10-11
25 May 2023	19
28 May 2023	18
1 June 2023	20
10 June 2023	10-13
13 June 2023	9
27 June 2023	13
1 July 2023	7
3 July 2023	15, 18, 19
5 July 2023	13,14,18,22



6 July 2023	13, 14, 15
7 July 2023	11, 12, 13, 19
8 July 2023	3
9 July 2023	6, 7, 8, 9, 10

5.1 1-sec Lidar SNR and RSD Profiles

Representative examples of 1-sec SNR profiles and the corresponding RSD retrievals are shown in Figures 8 and 9. Figure 8 shows an example during a period of light rain at 10:21 UTC on 19 May, and Figure 9 shows the profiles during a period with much heavier rain at 06:26 UTC on 9 July 2023. In both cases the RSD retrievals were successful up to cloud base. At cloud base, the return signal is dominated by scattering from the cloud droplets, which makes it difficult to detect the precipitation signal.

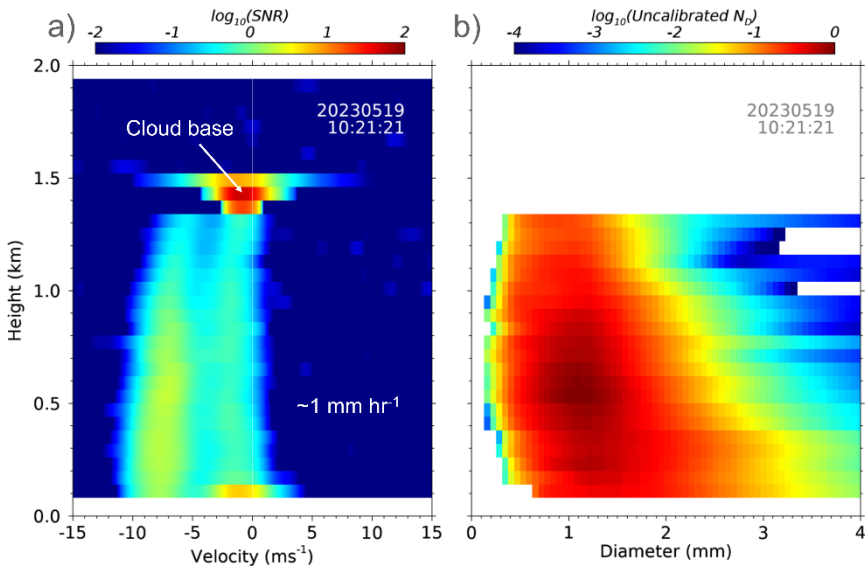


Figure 8. One-second profiles of a) SNR and b) uncalibrated RSD at 10:21:21 UTC on 19 May 2023 during a period when the surface disdrometers indicated a (15-sec) rain rate of $\sim 1 \text{ mm hr}^{-1}$. One-second profiles of a) SNR and b) uncalibrated RSD during a light rain event ($\sim 1 \text{ mm hr}^{-1}$) at SGP S4 on 19 May 2023. Panel a) indicates the signal from the cloud base. The uncalibrated RSD profile has been normalized by its maximum value for display purposes.

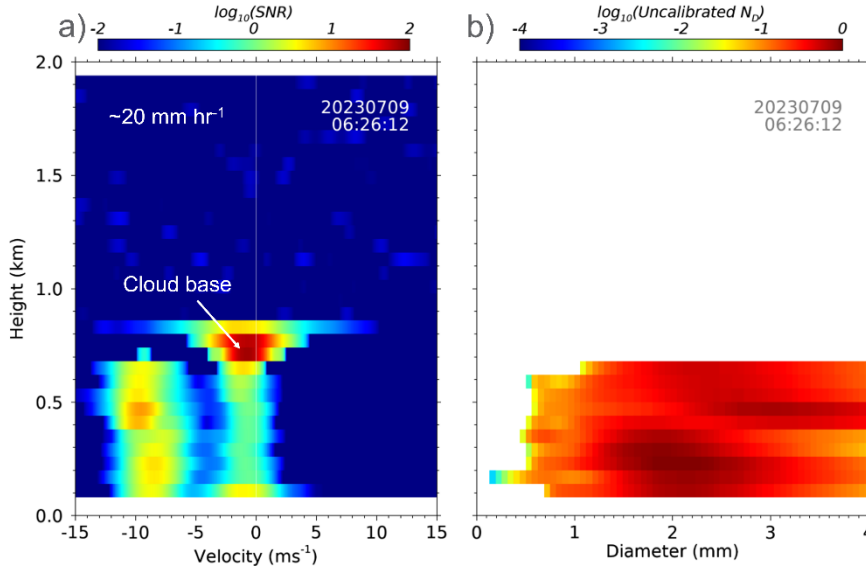


Figure 9. One-second profiles of a) SNR and b) uncalibrated RSD at 06:26:12 UTC on 9 July 2023 during a period when the surface disdrometers indicated a (15-sec) rain rate of $\sim 20 \text{ mm hr}^{-1}$. Panel a) indicates the signal from the cloud base. The uncalibrated RSD profile has been normalized by its maximum value for display purposes.

5.2 Lidar-Disdrometer Comparison

To compare the surface disdrometer data to the lidar RSD retrievals the results from both were averaged (or accumulated) over a common 5-minute time grid. Raw disdrometer measurement were initially recorded using a 15 s averaging period, and the lidar RSD retrievals were performed using a 1-sec pulse integration time. The short averaging period for the disdrometers resulted in low count rates so averaging helped to improve the statistics. For the lidar results, we note that it is crucial to average the 1-sec RSDs rather than averaging the SNR prior to retrieving the RSD. Averaging the SNR first would cause significant broadening of the aerosol and precipitation spectra.

Representative examples of 5-minute RSDs retrieved from the lidar and from the disdrometers are shown in Figure 10. These results have been filtered to exclude periods with drop counts below 100, and periods with fewer than 10 (1-sec) lidar RSDs. To enable comparison with the disdrometers, the continuous lidar RSDs were averaged over the discrete diameter bins of the disdrometers, as indicated by the horizontal error bars in Fig 10. The uncalibrated lidar results were scaled to fit the average disdrometer observations using a least squares approach. This scaling parameter is given by

$$\alpha = \sum_i \bar{N}_{Di}^{ld} \bar{N}_{Di}^{dl} / \sum_i (\bar{N}_{Di}^{dl})^2, \quad (24)$$

where $\bar{N}_{Di}^{ld}$ is the disdrometer RSD and $\bar{N}_{Di}^{dl}$ is the bin-averaged uncalibrated lidar DSD. The scaled lidar DSD is then given by



$$N_D(D) = \alpha N_D^{dl}(D). \quad (25)$$

The panels in Figures 10 are ordered by increasing rain rates as observed by the disdrometers. Panels a through c show typical results at rain rates below 3 mm hr⁻¹, panels d through f show typical results for rain rates between 4 and 8 mm hr⁻¹, and panels d through f show results for the largest rain rates that were observed, from 16 to nearly about 46 mm hr⁻¹. Drop size distributions using the Atlas (blue) and current (red) speed models are shown in Fig 10 together with the results from the disdrometer (black). Both speed models produce distributions that are generally well correlated with the shape of the observed disdrometer RSDs except at the highest rain rates (> 20 mm hr⁻¹). At very high rain rates the lidar tends to produce distributions with much broader tails compared to the disdrometer. The Altas speed model (blue) gives better overall agreement with the disdrometer, while the current speed model often produces larger estimates for diameters greater than about 1.2 mm.

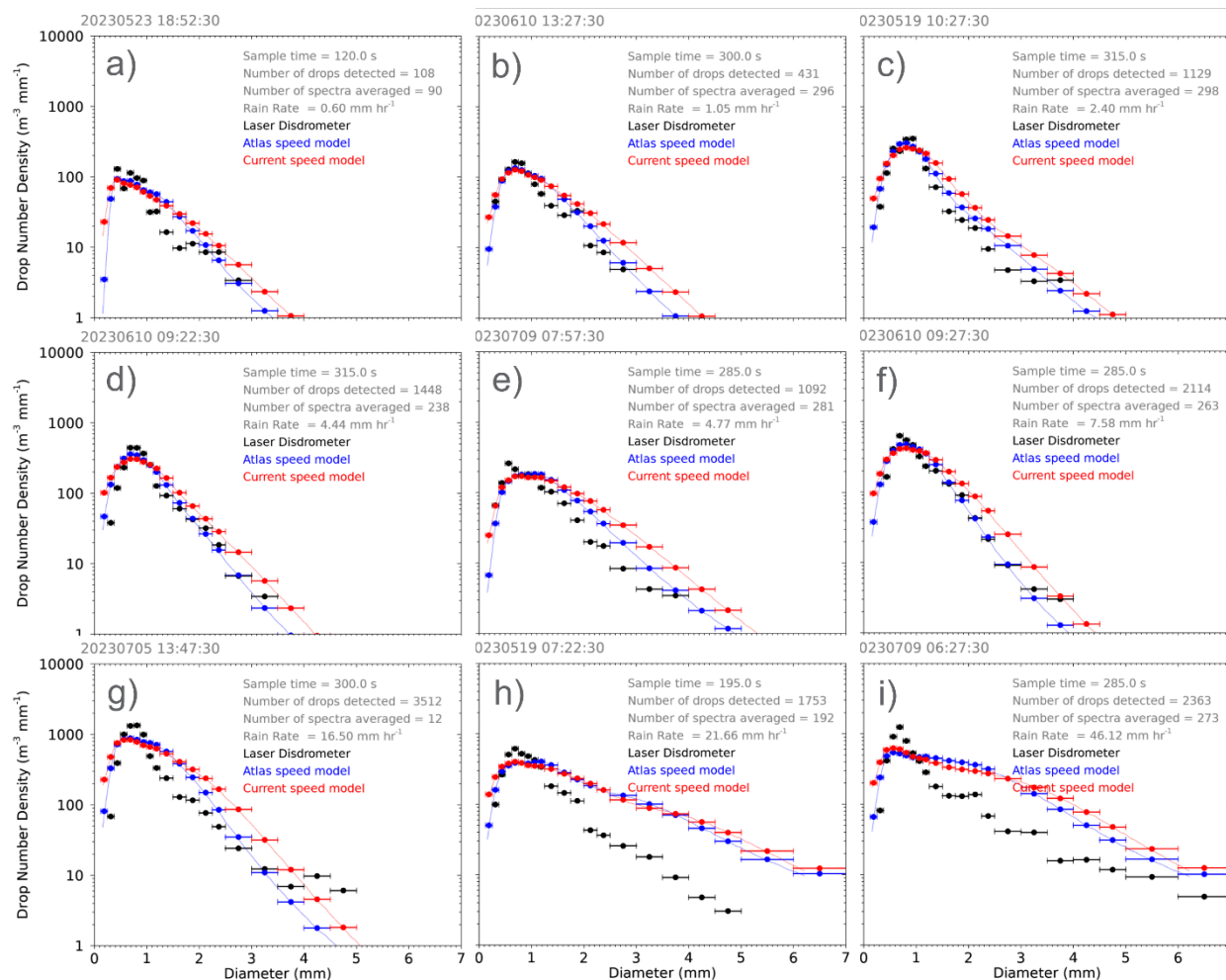
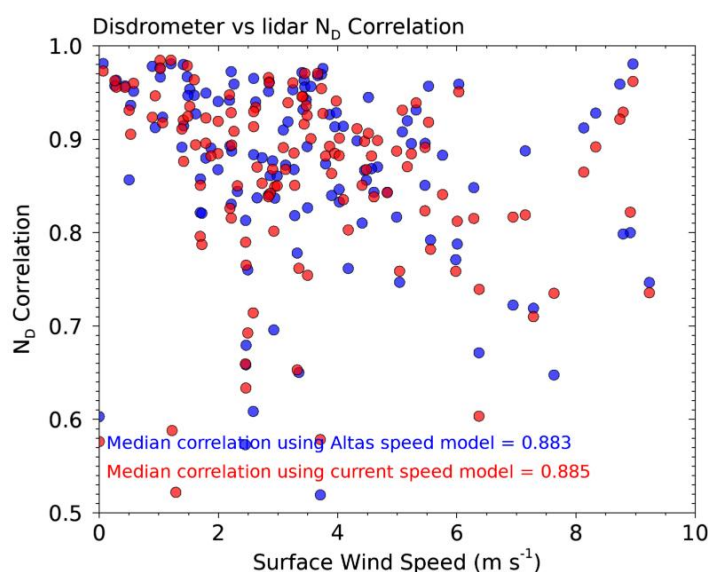


Figure 10. Representative examples of RSDs from the ground-based disdrometer (black) and retrieved from the lidar using the Atlas speed model (blue), and the current speed model (red). The continuous solid curves represent scaled results from the lidar. The horizontal error bars indicate the widths of the diameter bins used by the disdrometer. Red- and blue-filled circles represent averages of the continuous curve over the disdrometer's diameter bins. The panels are ordered by increasing rain rates as observed by the disdrometers.

To assess the accuracy of the result we examine differences and linear correlation coefficients between the lidar and disdrometer RSDs, as well as differences and linear correlation coefficients between the modes of the distributions. Figure 10 shows that for light to moderate rain rates, the disdrometer's higher diameter bins often contain zero when the lidar indicates non-zero values. These bins are treated as missing values when computing statistical comparisons between the lidar and disdrometer.



445 **Figure 11. Linear correlation coefficients between the lidar and the disdrometer RSDs as a function of surface wind speed as observed by the surface met station.**

Figure 11 shows the linear correlation coefficient between the lidar and disdrometer DSDs as a function of wind speed, where each dot represents one 5-minute period. The results for the Atlas speed are shown in blue, and the results for the
 450 current speed model are shown in red. Both speed models produced similar correlations, and both results show a tendency for the correlations to degrade with increasing windspeed. The median correlation for all wind speeds was about 0.88, but for winds less than 2 ms⁻¹, the median correlation was 0.96. The decrease in correlation with wind speed could be caused by wind-induced bias in the disdrometer (Friedrich et al. 2013; Testik and Pei 2017; Saha and Testik 2023) or by non-collocation between the lidar and disdrometer sample volumes.

455 Figure 12 show comparisons between drop diameter estimates from the lidar and the disdrometer, with the comparison between modal diameters shown in red and the comparison between mean diameters shown in blue. Estimating the peak of the distribution from the lidar spectra is simpler with the lidar spectra given its finer resolution. The coarseness of the disdrometer bins adds uncertainty to the determination of the peak. In this study, the peak of the distribution was estimated by fitting a second-order polynomial to the highest bin and the two bins on each side. The diameter corresponding to the
 460 maximum of curve fit was taken to be the mode. The same process was applied to finding the peak of the lidar distribution although it had much less impact due to the finer resolution of the lidar distribution. Figure 12 shows that both the Atlas and current speed models produce modal diameter estimates that are strongly clustered with no clear linear trend. Again, the Atlas speed model performs slightly better with a median percent difference of +3%, as opposed to +7% for the current speed model.



465 The mean diameters for both speed models show a stronger linear trend than the modal diameters. However, the values diverge from the one-to-one line with increasing diameter, particularly above about 1.2 mm. The result for the current speed model (Fig 9a) shows a larger offset than the Atlas model (Fig 11b). The Altas speed model performs slightly better with a median percent difference of +14%, as opposed to +22.5% for the current speed model. Both models produce larger mean diameter estimates than the disdrometer because the disdrometer RSDs often contain zero counts in bins where the lidar showed non-zero values. As a result, integration of the lidar RSDs produce larger mean drop diameters and larger number densities.

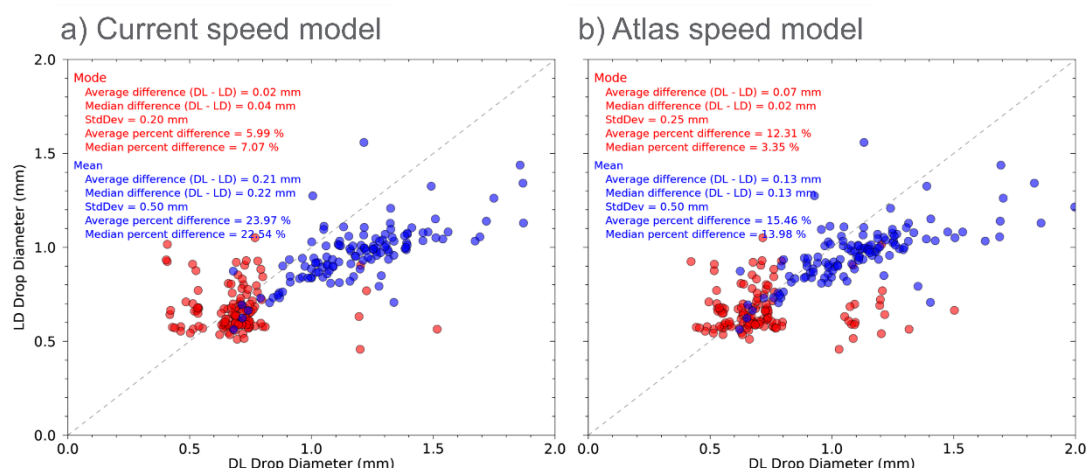


Figure 12. Disdrometer versus lidar drop diameter estimate for mode (red) and mean (blue).

475 A comparison of drop number densities computed from the disdrometer and the scaled-lidar RSDs are shown in Figure 13. The results from both speed models show a very distinct linear trend that is offset from the one-to-one line with the scatter increasing with increasing number densities. Number densities based on the Atlas model show slight better overall agreement with the disdrometer with a median percent difference of 13% and a slope of 0.76, as opposed to a median percent difference of 25% and a slope of 0.73 for the current speed model.

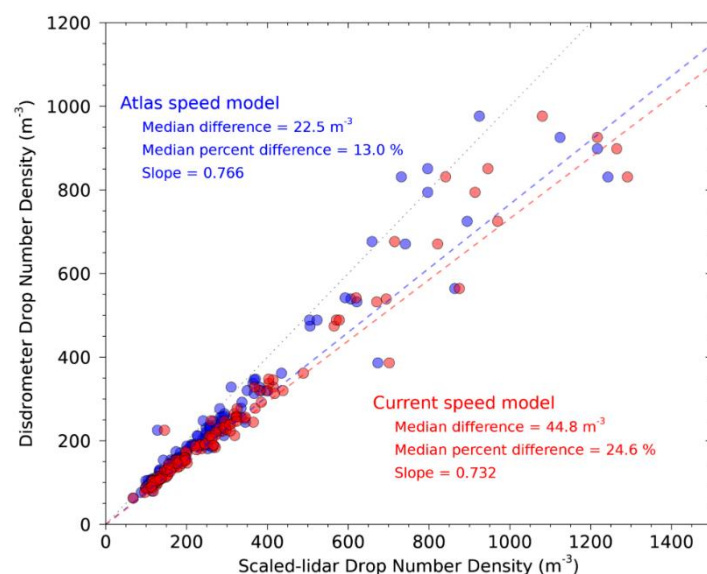
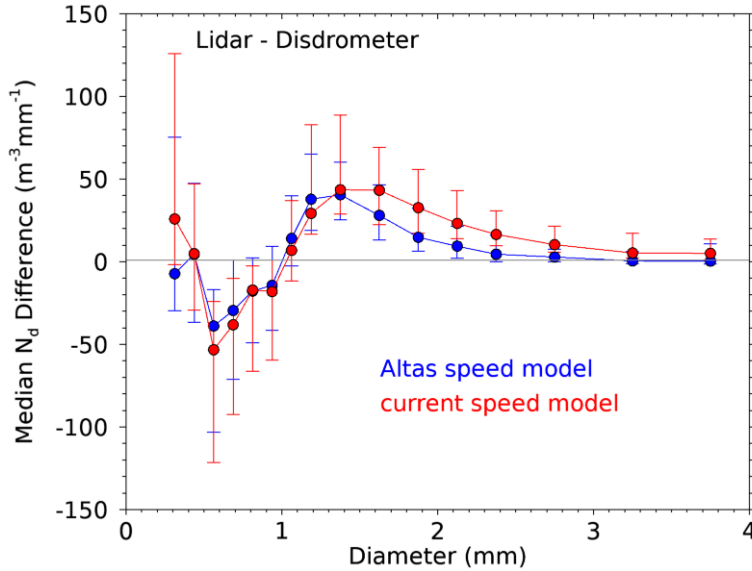


Figure 13. Disdrometer versus scaled-DL drop number densities.

Figure 14 shows the median difference between the scaled-lidar and disdrometer DSDs. Both speed models show the same
485 general variation. Relative to the disdrometer, there is a tendency for the lidar to underestimate the distribution for diameters
between 0.4 to 1 mm and overestimate the distribution between 1 and 2 mm. The Atlas speed model produces results that are
in closer agreement with the observed distributions from the disdrometer.



490 **Figure 14. Median difference between the scaled-lidar and disdrometer DSDs. Error bars indicate the range of the 25th to 75th percentiles. Results using the Atlas speed model are shown in red, and results for the current speed model are shown in blue.**

Results described above show that the choice of speed model has a significant effect on the results. The current speed model provided a better fit to the disdrometer measurements than the Atlas model, which generally predicted higher drop speeds. However, the Atlas model produced better overall agreement between the lidar and disdrometer RSDs. This suggests that the
 495 disdrometer speed measurements are biased low. Several other studies have also indicated low speed biases in the Parsvel2 (OTT) (Saha and Testik 2023; Yuan et al., 2025; Tokay et al. 2010, 2014; Zhang et al. 2020).

Although the Atlas speed model performs best, Fig 14 shows that there are still significant differences. These differences will not go away by tweaking the speed model to any reasonable degree. Additional sources of error might include bias in
 the computed differential backscatter cross section, or significant variation in the extinction across the passband. Both effects
 500 could cause distortion of the RSDs.

5.3 Empirical Differential Backscatter Cross Section

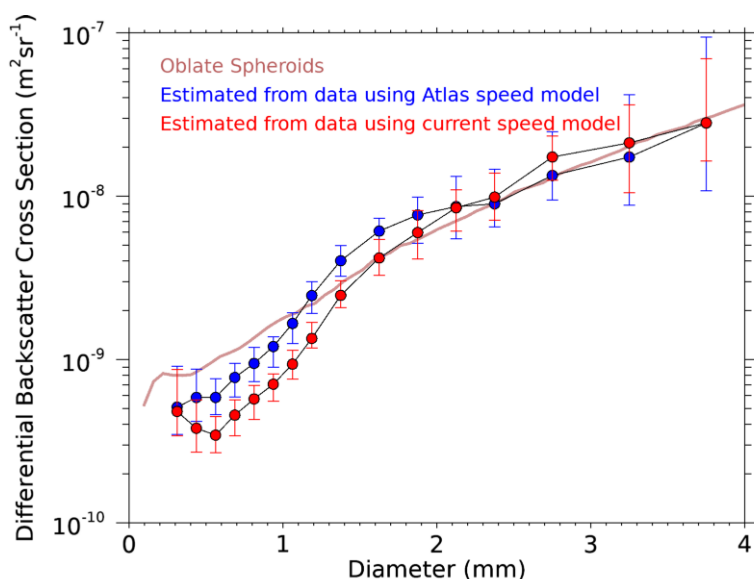
As mentioned earlier it is possible to infer the differential backscatter cross from the data. If the disdrometer observations are
 505 regarded as truth they can be used to estimate the differential backscatter cross section. From equation (21) we have

$$\left. \frac{d\sigma}{d\Omega} \right|_{\pi} \propto SNR_p(u(D)) / \bar{N}_D^{ld}(D). \quad (26)$$

The median value of the right-hand-side of equation (26) was computed for each diameter using all precipitation data collected during the events listed in Table 3. Figure 15 shows the result of this calculation overplotted with the calculated backscatter cross sections used in this study. For display purposes, the uncalibrated empirical cross sections in Fig 15 have



510 been scaled such that their integrated values equal the integrated value of the disdrometer curve. The results for both speed models show significant dips near 0.5 mm. This dip is particularly pronounced for the current model. While the current speed model appears to track the calculated result at larger diameters, the Atlas model has a smaller overall deviation.



515 **Figure 15.** Estimates of the differential backscatter cross section obtained from equation (26) using results from Atlas speed model (blue) and the current speed model (red). Also shown is the computed cross section in brown from Wang et al. (2026).

The agreement between the lidar and disdrometer improves significantly when the calculated cross section is replaced with the empirical cross sections shown in Fig 15. This is not unexpected since this approach essentially uses the disdrometer to force agreement in both the amplitude and shape of the lidar RSDs, and is similar to the approach taken by Akoi et al. (2016). As a result, it compensates for deficiencies in the speed and/or scattering models or for broadening effects. Nevertheless, this approach provides a practical means of calibrating the lidar RSDs if the calibrations remain stable. Figure 16 shows the median difference between the scaled-lidar and disdrometer RSDs using the empirically-derived differential backscatter cross sections of Figure 15. Comparing Fig 16 to Fig 14 shows a dramatic reduction in the median RSD bias when the empirical cross section is used to estimate the RSDs.

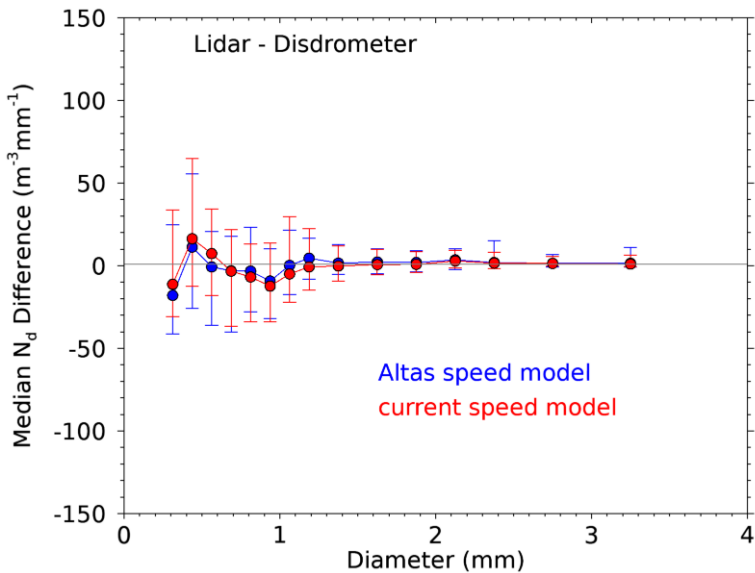


Figure 16. Same as Figure 14 except the lidar result is calculated using the empirical differential backscatter cross sections shown in Figure 15. Results using the Atlas and current speed models are shown blue and red, respectively.

Table 4 summarizes the statistical comparison between the disdrometer and the lidar using the two different speed models and the two different backscatter cross sections. Lidar RSDs that were computed using the empirical cross sections give significantly better agreement with the disdrometer than those using the calculated cross section. Both speed models result in similar RSD correlations for a given cross section. The current speed model with the empirical cross section resulted in the largest RSD correlation (0.95) and smallest bias ($-1.1 \text{ m}^{-3} \text{ mm}^{-1}$) and standard deviation ($27.9 \text{ m}^{-3} \text{ mm}^{-1}$). However, the Atlas speed with the empirical cross section gave the smallest modal diameter difference (-0.7%).

Table 4. Comparison between lidar and disdrometer drop statistics using different speed models and backscatter cross sections. The calculated cross section is shown as the red curve in Fig 7. The empirical cross sections for each speed model are shown in Fig 15.

	Current speed model + calculated cross section	Atlas speed model + calculated cross section	Current speed model + Empirical cross section	Atlas speed model + Empirical cross section
N_D correlation	0.89	0.88	0.95	0.94
Median N_D bias ($\text{m}^{-3} \text{ mm}^{-1}$)	5.5	3.2	-1.1	-1.3



Median N_D standard deviation ($\text{m}^{-3} \text{mm}^{-1}$)	43.4	40.7	27.9	28.1
percent difference in modal diameters	7.1	3.4	-4.7	-0.7
percent difference in mean diameters	22.5	14.0	1.5	2.9
percent difference in number densities	24.6	13.0	0.7	0.8
Number density slope	0.73	0.77	0.93	0.87

540 6 Raw Data Reduction

Currently, ARM collects raw data from the Doppler lidars only upon request due to the large data volumes. For 50 MHz XR+ systems such as those currently used in ARM, operating with a typical pulse averaging time of 1 s, the raw data volume is approximately 5 Gb hr^{-1} . During times when these data are being collected, they are archived in their original format according to standard ARM protocol. The original vendor-formatted data are converted to ARM standard NetCDF files, and
 545 those data are archived as well. Given the replication and the large file sizes, data storage and management is an issue.

With some simple on-site processing, the quantity of raw data transmitted to the ARM Data Center (ADC) could be reduced considerably. First, most of the usable precipitation-affected spectra are found well below 4km. Saving only data below 4 km reduces the data volume by 75%. Second, raw data from lidar are output as double precision floating point values whereas single precision is more than sufficient to retain all necessary information. Conversion to single-precision values reduces the
 550 data volume by 50%. Third, range-gating the ungated autocovariance data reduces the size considerably (but removes the ability to reprocess to different gate sizes). For a range-gate size of 60 m, the data volume is reduced by 95%. Combining these steps reduces the raw data volume from about 5Gb hr^{-1} to roughly 8 Mb hr^{-1} for a typical pulse averaging time of 1 s and a 60 m gate size. This could be further reduced by saving only precipitation-affected profiles. For example, saving profiles with at least one multi-modal spectra below the maximum height would preserve the two-dimensional (time-height)
 555 structure of the output data.

7 Conclusions

In this study, we showed that the lidar Doppler spectra provide unambiguous detection of both the raindrop fall speeds and the aerosol (i.e. clear-air) velocity within the same sample volume enabling the estimation of the aerosol mode in the
 560 presence. The aerosol mode is well approximated using a modified-Gaussian function. This enables separation of the precipitation contribution from the total Doppler spectrum.

Lidar-derived RSDs were compared with a collocated surface laser disdrometer using data collected from ARM's SGP S4 site between 19 May and 9 July 2023. Lidar RSD retrievals were performed using two different drop speed models. The standard Atlas model performed better than one based on current observations from the surface disdrometer, suggesting that
 565 the disdrometer drop speed estimates are biased low. Regardless of the speed model, systematic diameter-dependent biases were observed. These biases were reduced considerably by using an empirical estimate of the differential backscatter cross



section, as opposed to the calculated cross section. The empirical estimate was derived from the median value of equation (26) over roughly 25 precipitation events spanning a period of about 2 months. This provides a practical method of calibrating the lidar RSDs. Additionally, the results of this study demonstrate the stability of that calibration over a period of at least 2 months.

The current approach to separating the aerosol contribution from the total Doppler spectrum requires fitting a modified Gaussian function using data near the peak of the aerosol distribution (within $\pm 1 \text{ ms}^{-1}$). This method performs well when there is sufficient separation between the aerosol and precipitation velocities. However, under very light rain or drizzle conditions the precipitation and aerosol contributions overlap to such an extent that there is only a single detectable maximum in the Doppler spectrum. In that case, the current multi-mode method would return only a single velocity value, and that value would be assumed to be associated with the aerosol motion, when in fact it is a mix of the two contributions. Thus, more robust methods are needed to handle light rain and drizzle situations. We are currently exploring the use of machine learning methods to improve the detection of the aerosol mode and retrieval the precipitation spectrum.

Lastly, the XR+ systems, with their flat exit windows, were optimized for scanning, but not necessarily for vertical precipitation measurements. The pooling of water on the exit window surface adds additional attenuation that could be avoided with the use of a tilted exit window to better shed rain water.

Code and data availability

Raw Doppler lidar data used in this study are freely available through the ARM website at <https://www.arm.gov/>. The datastream name is “sgpdlacfS4.a0”. The disdrometer and surface meteorological station data are freely available through the US Department of Energy’s Wind Data Hub at <https://wdh.energy.gov/home>. For the disdrometer data, search for “awaken/sa1.ld.z01” and “awaken/sa1.ld.z02”. For the meteorological station data search for “awaken/sa1.met.z01.” Codes used for processing and analysing data are available upon request.

Author contributions

RN lead the data processing and analysis of the lidar spectral data, as well as the writing of the manuscript with significant input from RK. RK procured and deployed the disdrometers and helped to design the experimental set up at the site. RK also lead the procurement of the XR+ Doppler lidar used in this study.



595 Competing interests

The authors declare that they have no competing interests.

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