



# OBJECTIVE CHARACTERIZATION OF RAIN MICROPHYSICS

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Gyuwon Lee and Ziad Haddad



# Motivation

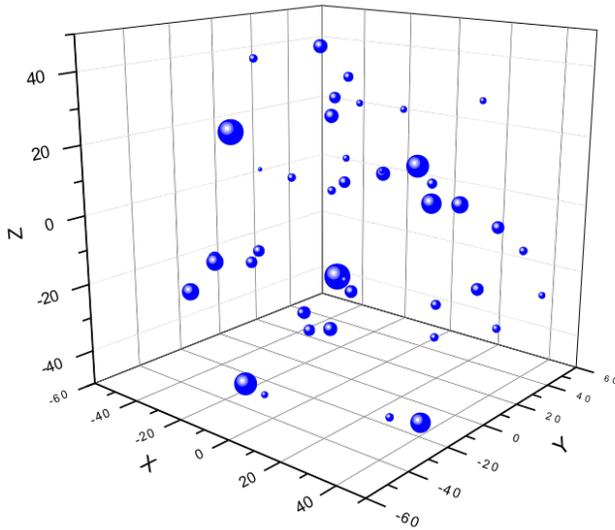
**GCMs, RCMs, CRMs and NWP  
models diagnose/prognose**

$$\frac{\partial N_T}{\partial t} \quad \frac{\partial q_h}{\partial t}$$

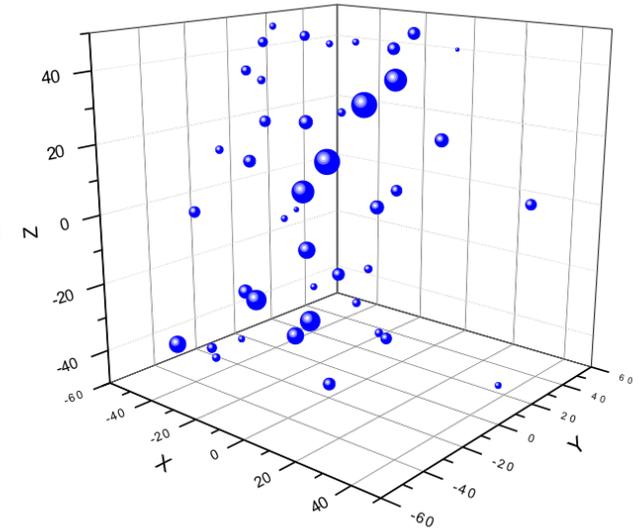
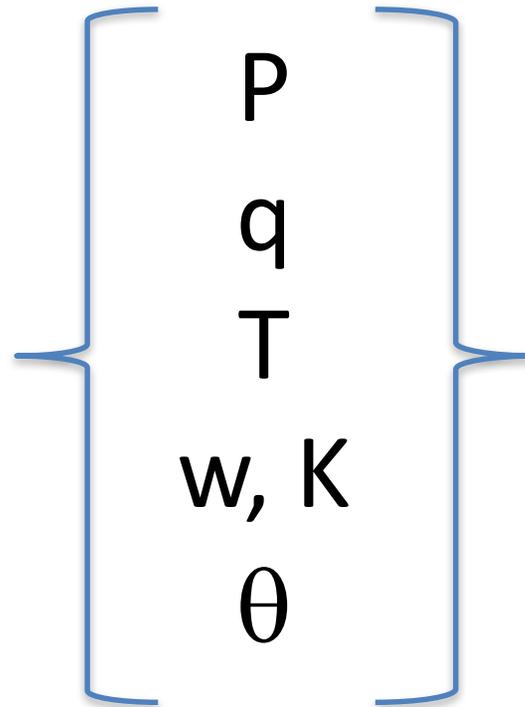
So it is important to retrieve these quantities independently to develop, calibrate, tune, verify and validate those models



# microphysics (mp)

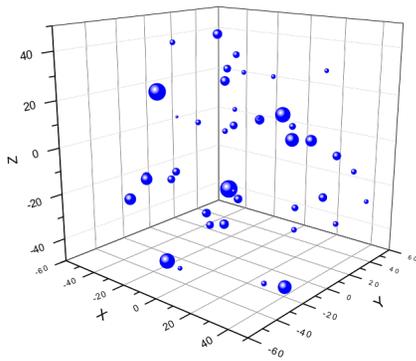


$t_1$



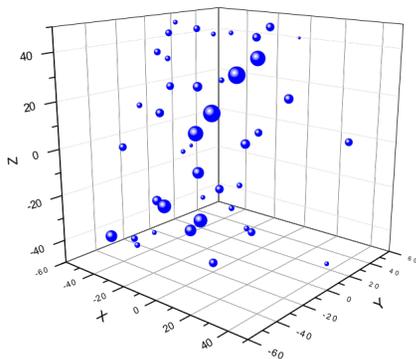
$t_2$

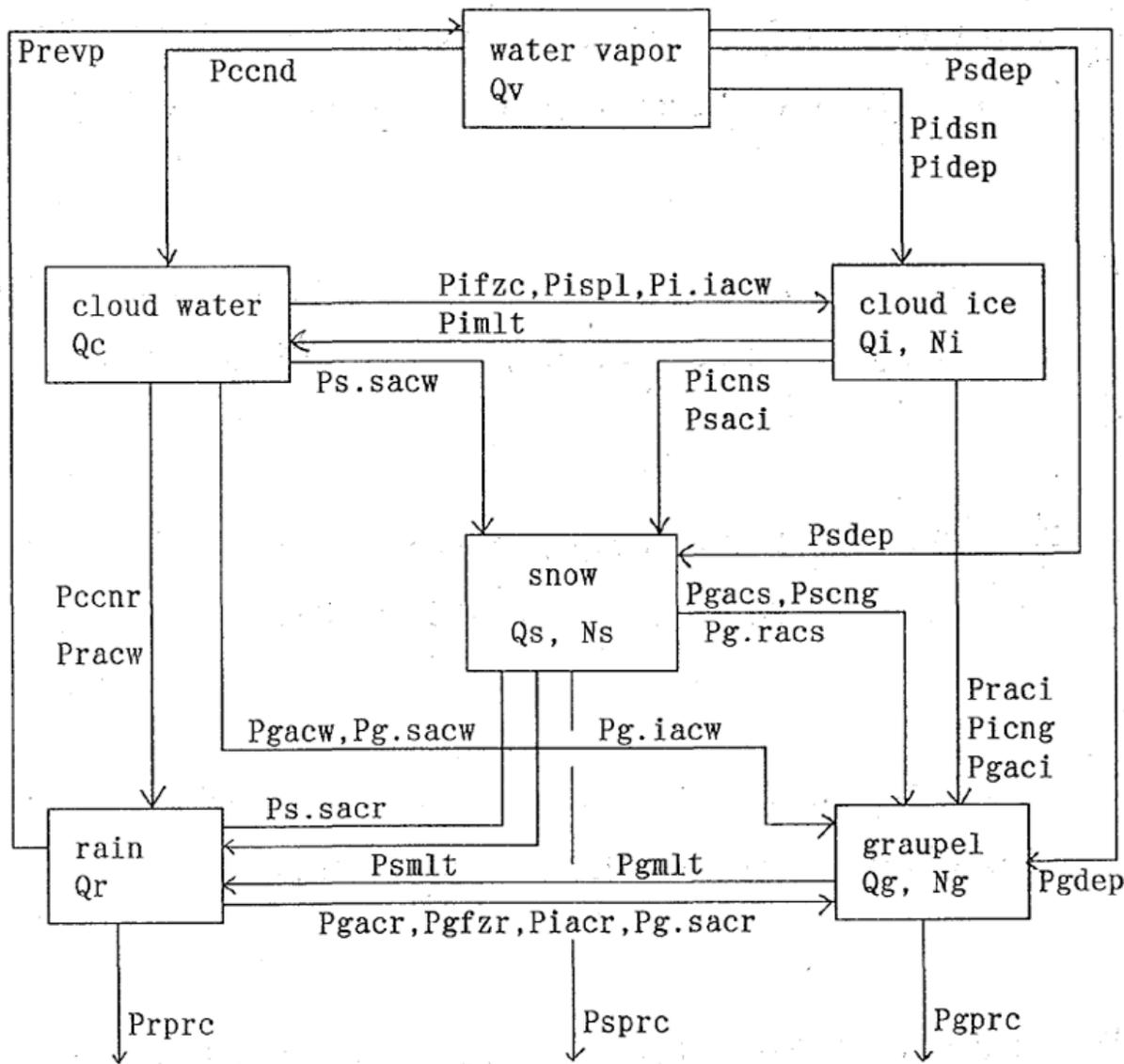
# for instance, in practice, in the P3 mp



$$N = \int_0^{\infty} N'(D) dD = \int_0^{\infty} N_0 D^{\mu} e^{-\lambda D} dD \quad \text{and}$$

$$q = \int_0^{\infty} m(D) N'(D) dD = \int_0^{\infty} m(D) N_0 D^{\mu} e^{-\lambda D} dD$$





Ikawa&Saito 1991



# Rain aggregation

PRaggR		$(\partial\{N_R, q_R\}/\partial t)_{RaggR}$	1/41
Pictorial representation			Assumptions
Effects on N and gamma pdf	$N_V =$ $m_V =$ $S_V =$ $N_R \downarrow$ $m_R \uparrow$ $S_R \downarrow$ $N_S =$ $m_S =$ $S_S =$ $N_I =$ $m_I =$ $S_I =$ $N_G =$ $m_G =$ $S_G =$	Beheng (1994) $(\partial N_R / \partial t)_{aggRR} = -8.0 \cdot 10^3 \cdot N_R \cdot q_R$ $(\partial q_R / \partial t)_{aggRR} = 0$  <pre> ..... ! SELF-COLLECTION OF RAIN DROPS ! FROM BEHENG(1994) ! FROM NUMERICAL SIMULATION OF THE STOCHASTIC COLLECTION EQUATION ! AS DESCRIBED ABOVE FOR AUTOCONVERSION        IF (QR3D(K).GE.1.E-8) THEN ! include breakup add 10/09/09           dum1=300.e-6           if (1./lamr(k).lt.dum1) then               dum=1.           else if (1./lamr(k).ge.dum1) then               dum=2.-exp(2300.*(1./lamr(k)-dum1))           end if           NRAGG(K) = -8.*NR3D(K)*QR3D(K)*RH0(K)           NRAGG(K) = -5.78*dum*NR3D(K)*QR3D(K)*RH0(K)       END IF                     </pre>	Parameterizations

Francisco J. Tapiador's precipitation microphysics 2014





# Accretion of rain water by snow

PRacs
 $(\partial\{N_R, Q_R\}/\partial t)_{Racs}$ 
3/41

Pictorial representation		Assumptions															
Effects on N and gamma pdf	<table style="width: 100%; border-collapse: collapse;"> <tr> <td style="padding: 5px;"><math>N_V =</math></td> <td style="padding: 5px;"><math>m_V =</math></td> <td style="padding: 5px;"><math>S_V =</math></td> </tr> <tr> <td style="padding: 5px;"><math>N_R =</math></td> <td style="padding: 5px;"><math>m_R \uparrow</math></td> <td style="padding: 5px;"><math>S_R \uparrow</math></td> </tr> <tr> <td style="padding: 5px;"><math>N_S \downarrow</math></td> <td style="padding: 5px;"><math>m_S ?</math></td> <td style="padding: 5px;"><math>S_S ?</math></td> </tr> <tr> <td style="padding: 5px;"><math>N_I =</math></td> <td style="padding: 5px;"><math>m_I =</math></td> <td style="padding: 5px;"><math>S_I =</math></td> </tr> <tr> <td style="padding: 5px;"><math>N_G =</math></td> <td style="padding: 5px;"><math>m_G =</math></td> <td style="padding: 5px;"><math>S_G =</math></td> </tr> </table>	$N_V =$	$m_V =$	$S_V =$	$N_R =$	$m_R \uparrow$	$S_R \uparrow$	$N_S \downarrow$	$m_S ?$	$S_S ?$	$N_I =$	$m_I =$	$S_I =$	$N_G =$	$m_G =$	$S_G =$	Parameterizations
$N_V =$	$m_V =$	$S_V =$															
$N_R =$	$m_R \uparrow$	$S_R \uparrow$															
$N_S \downarrow$	$m_S ?$	$S_S ?$															
$N_I =$	$m_I =$	$S_I =$															
$N_G =$	$m_G =$	$S_G =$															
		Morrison's mp, based on <a href="#">Ikawa and Saito (1991)</a>															

Francisco J. Tapiador's precipitation microphysics 2014



# At the end, the evolution is linked with the initial DSD model

$$\partial N_h / \partial t$$

$$\partial q_h / \partial t$$

Drop number



Drop number +  
Shape of the RDSD





# RDSD models

## The $N_0$ model

$$n(D) = N_0 D^\mu \exp(-\Lambda D)$$

[ $N_0$  model]



# $N_0$ model - issues

$$n(D) = N_0 D^\mu \exp(-\Lambda D)$$

[ $N_0$  model]

- Such expression is not a PDF
- $N_0$  has units of  $m^{-4-\mu}$
- Parameters are not independent



# $N_0$ model - issues

$$n(D) = N_0 D^\mu \exp(-\Lambda D)$$

$$N_0 = \textcircled{N_T} \frac{\Lambda^{\mu+1}}{\Gamma(\mu+1)}$$



# $N_0$ model - issues

$$n(D) = N_0 D^\mu \exp(-\Lambda D)$$

$$N_0 = N_T \frac{\Lambda^{\mu+1}}{\Gamma(\mu+1)}$$



# $N_0$ model - issues

$$n(D) = N_0 D^\mu \exp(-\Lambda D)$$

- Not only mathematically ill-defined
- Also disconnected from mp modeling



# $N_w$ , normalized model

$$n(D) = N_w f_N(\mu) \left(\frac{D}{D_m}\right)^\mu \exp\left[-(4 + \mu)\frac{D}{D_m}\right]$$

$$f_N(\mu) = \frac{6}{4^4} \frac{(4 + \mu)^{\mu + 4}}{\Gamma(\mu + 4)}$$



# $N_w$ model - issues

$$N_w = \frac{4^4}{\pi \rho_w} \left( \frac{10^3 W}{D_m^4} \right)$$



# $N_w$ model - issues

$$N_w = \frac{4^4}{\pi \rho_w} \left( \frac{10^3 W}{D_m^4} \right) \quad N_w = k \frac{W}{D_m^4}$$

$$W = \frac{\pi \rho_w 10^{-6}}{6} \int_{D_{min}}^{D_{max}} D^3 n(D) dD \quad D_m = \frac{\int_{D_{min}}^{D_{max}} n(D) D^4 dD}{\int_{D_{min}}^{D_{max}} n(D) D^3 dD}$$

- Parameters are also intrinsically dependent
- Also disconnected from mp modeling



# Alternative: $N_T$ -based RDSDs

$$n(D) = N_T \cdot p(D)$$

Drop number

Shape of the RDSD

$p(D)$  is a proper PDF: (and we need a PDF

because we are doing statistics)



# There is even a general form for the DSD as an (infinite) sum of exponentials:

$$n(D) = N_T \cdot p(D) = N_T \cdot \frac{\exp(-\lambda_0 - \lambda_1 f_1(D) - \lambda_2 f_2(D) - \dots - \lambda_z f_z(D))}{Z}$$

$f_i$  can be any functions

for instance, central or raw moments



# Alternative: $N_T$ -based RDSDs

**Maxent DSD**  $\left\{ \begin{array}{l} E[D] = \int_{Dmin}^{Dmax} D p(D) dD \\ E[D^2] = \int_{Dmin}^{Dmax} D^2 p(D) dD \end{array} \right.$

$$n(D) = N_T \cdot p(D) = N_T \cdot \frac{\exp(-\lambda_0 - \lambda_1 D - \lambda_2 D^2)}{\sum_D \exp(-\lambda_0 - \lambda_1 D - \lambda_2 D^2)}$$



# Alternative: $N_T$ -based RDSDs

**Maxent  
gamma  
DSD**

$$\left\{ \begin{array}{l} E[D] = \int_{Dmin}^{Dmax} D p(D) dD \\ E[\log(D)] = \int_{Dmin}^{Dmax} \log(D) p(D) dD \end{array} \right.$$

$$n(D) = N_T \cdot p(D) = N_T \cdot \frac{\exp(-\lambda_0 - \lambda_1 D - \lambda_2 \log(D))}{\sum_D \exp(-\lambda_0 - \lambda_1 D - \lambda_2 \log(D))}$$



# Alternative: $N_T$ -based RDSDs

$$n(D) = N_T \cdot \Lambda^{\mu+1} D^\mu \frac{e^{-\Lambda D}}{\Gamma(\mu + 1)}$$

[Maxent-Gamma model]



$$Z = k_1 N_T \Lambda^{-6} \frac{\gamma(\mu + 7, D_{\max} \Lambda) - \gamma(\mu + 7, D_{\min} \Lambda)}{\Gamma(\mu + 1)}$$

$$W = k_2 N_T \Lambda^{-3} \frac{\gamma(\mu + 4, D_{\max} \Lambda) - \gamma(\mu + 4, D_{\min} \Lambda)}{\Gamma(\mu + 1)}$$

$$R = k_3 v_1 N_T \Lambda^{-(3+v_2)} \frac{\gamma(\mu + 4 + v_2, D_{\max} \Lambda) - \gamma(\mu + 4 + v_2, D_{\min} \Lambda)}{\Gamma(\mu + 1)}$$

$$D_m = \Lambda^{-1} \frac{\gamma(\mu + 5, D_{\max} \Lambda) - \gamma(\mu + 5, D_{\min} \Lambda)}{\gamma(\mu + 4, D_{\max} \Lambda) - \gamma(\mu + 4, D_{\min} \Lambda)}, \text{ does not}$$

depend on  $N_T$

$$\sigma_m^2 = \Lambda^{-2} \frac{\gamma(\mu + 6, D_{\max} \Lambda) - \gamma(\mu + 6, D_{\min} \Lambda)}{\gamma(\mu + 4, D_{\max} \Lambda) - \gamma(\mu + 4, D_{\min} \Lambda)} - \left[ \frac{\gamma(\mu + 5, D_{\max} \Lambda) - \gamma(\mu + 5, D_{\min} \Lambda)}{\gamma(\mu + 4, D_{\max} \Lambda) - \gamma(\mu + 4, D_{\min} \Lambda)} \right]^2, \text{ does not}$$

depend on  $N_T$

# The proof of the pudding



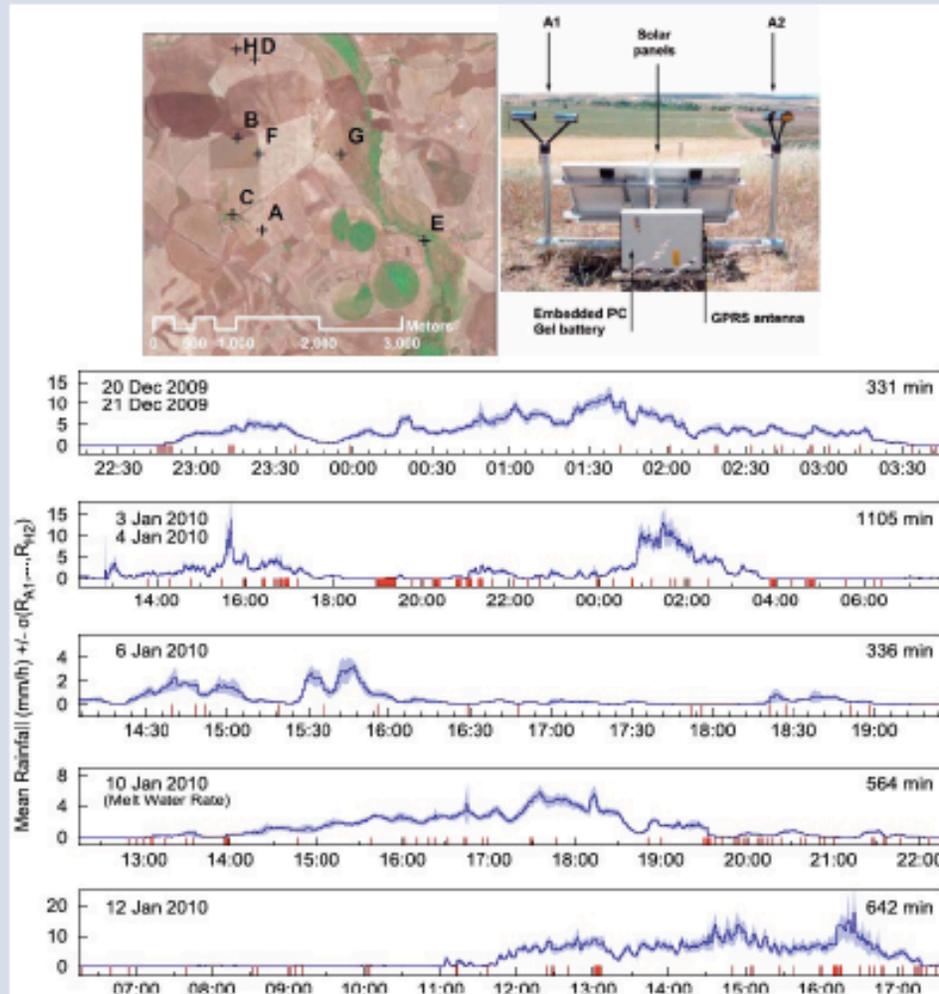


# UCLM database



# Experimental setup 1

## Medium-scale variability



In 2010, we used 16 Parsivel disdrometers (in a dual setup to ensure consistency) to analyze the spatial variability of the RDSD within a DPR-size pixel.

The experiments were made in central Spain, which has a semiarid climate with moderate rain rates, and thus within Parsivels' known limitations.

As described in the paper below, we found a consistent pattern of DSD variability with distance, and a noticeable spread in the  $a$  and  $b$  parameters of the Z/R relationship within the same episode.



# Experimental setup 2

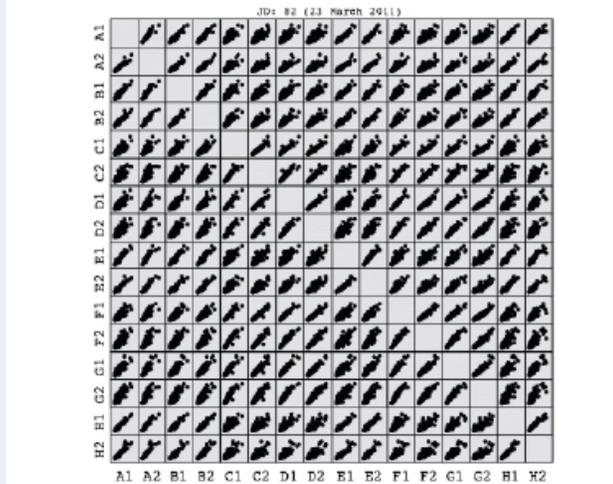
## Small-scale variability



In 2011, we located 16(+2) Parsivels to analyze the consistency of the instruments, the spatial variability of the RSD at decimeter scale, and to cross-compare the new Parsivel<sup>2</sup> instruments.

The experiments were made in Toledo, and included a sonic anemometer.

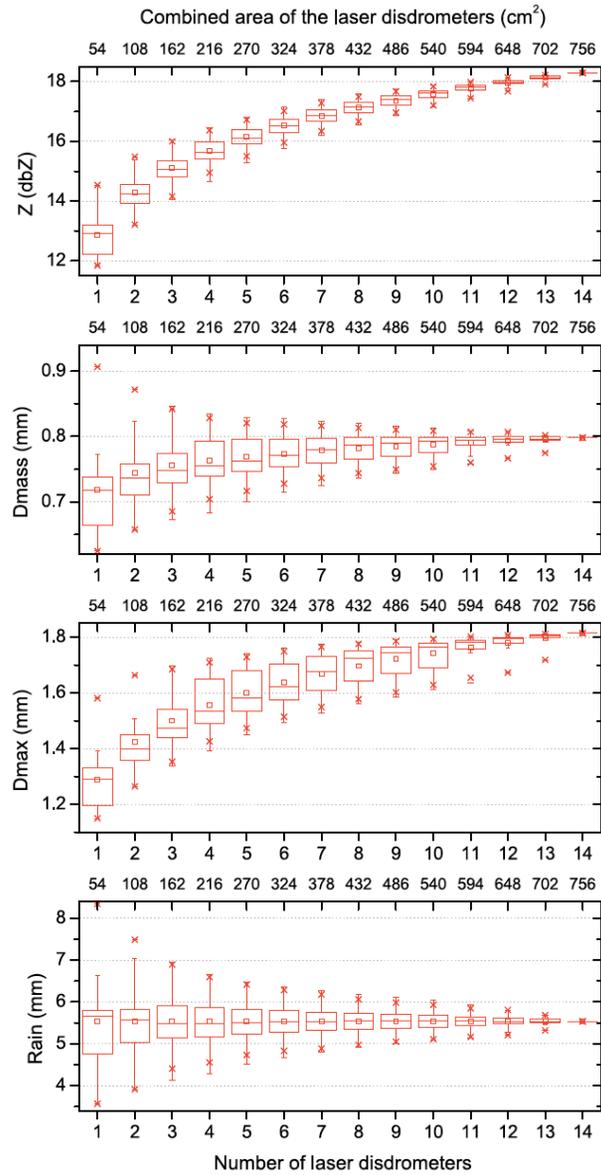
We found that the Parsivels provided consistent estimates of the RSD for moderate rainfall rates such as those found in Toledo.



Tapiador, F.J., Turk, J., Petersen, W., Hou, A.Y., García-Ortega, E., Machado, L.A.T, Angelis, C.F., Salio, P., Kidd, C., Huffman, G.J. and de Castro, M. 2011. Global Precipitation Measurement: Methods, Datasets and Applications. *Atmospheric Research*, accepted October 2011

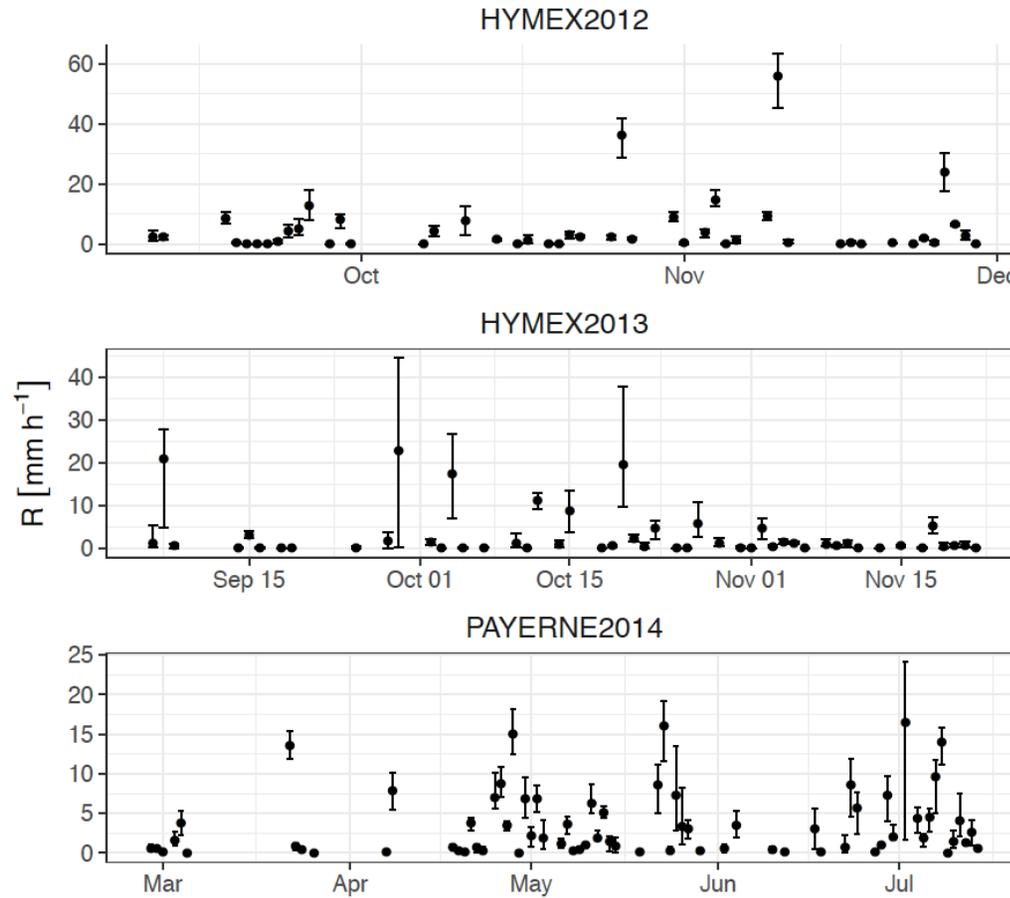


# Experimental setup 2





# EPFL database





# Calculations from disdrometer data

	Variable	Equation	Notes
$N_T$	Total drop concentration [ $m^{-3}$ ]	$N_T = \int_{D_{min}}^{D_{max}} n(D) dD$	$n(D)$ is the number of drops of diameter $D \pm dD/2$
$N_0$	Gamma PSD intercept [ $mm^{-1}mm^{-3}$ ]	$n(D) = N_0 D^\mu \exp(-AD)$ [N <sub>0</sub> model]	For the $N_0$ model, this corresponds to Gamma parameters fitted to each DSD using the method and (modified) R code of Johnson et al. 2014, which allows for truncated and classed DSDs.
$\Lambda$	Gamma PSD slope parameter [ $mm^{-1}$ ]		
$\mu$	Gamma PSD shape parameter [-]		
		$n(D) = N_T \cdot \Lambda^{\mu+1} D^\mu \frac{e^{-\Lambda D}}{\Gamma(\mu+1)}$ [Maxent-Gamma model]	For the other models, cfr. Sections 3.1 and 3.2.
$E[D]$	First raw moment of the PDF	$E[D] = \int_{D_{min}}^{D_{max}} D p(D) dD$	Mean of the PDF
$E[D^2]$	Second raw moment of the PDF	$E[D^2] = \int_{D_{min}}^{D_{max}} D^2 p(D) dD$	
$E[\log(D)]$	First raw moment of the PDF	$E[\log(D)] = \int_{D_{min}}^{D_{max}} \log(D) p(D) dD$	Logarithmic mean of the PDF
$W$	Total water content [mm]	$W = \frac{\pi \rho_w 10^{-6}}{6} \int_{D_{min}}^{D_{max}} D^3 n(D) dD$	Converted to mm from $g m^{-3}$ , assuming that the water content collects over an area of one $m^2$ . $\rho_w [g m^{-3}]$ is water density.
$F_{N(\mu)}$	Normalised PSD shape factor [-]	$F_{N(\mu)} = \frac{6}{4^4} \frac{(4 + \mu)^{\mu+4}}{\Gamma(\mu + 4)}$	Calculated using a value of $\mu$ fitted to each DSD using the technique of Johnson et al. 2014 for the gamma model, modified such that the slope was always given by $(\mu + 4)/D_m$ .
$N_w$	Normalised PSD intercept [ $mm^{-1} mm^{-3}$ ]	$N_w = \frac{4^4}{\pi \rho_w} \left( \frac{10^3 W}{D_m^4} \right)$	
$D_m$	Mass-weighted mean drop diameter [mm]	$D_m = \frac{\int_{D_{min}}^{D_{max}} D^4 n(D) dD}{\int_{D_{min}}^{D_{max}} D^3 n(D) dD}$	
$Z$	Radar reflectivity [ $mm^4 m^{-3}$ ]	$Z = \frac{10^6 \lambda^4}{\pi^5  K ^2} \int_{D_{min}}^{D_{max}} \sigma_b(D) n(D) dD$	$\sigma_b(D) [cm^2]$ is the back-scattering cross-section of a raindrop of equivolume diameter $D$ (in horizontal or vertical polarization). $ K ^2$ is the dielectric factor of water. $\lambda$ is the radar wavelength [cm].
$K_{DP}$	Specific differential phase shift [deg $km^{-1}$ ]	$K_{DP} = \left( \frac{180}{\lambda} \right) 10^{-1} CW (1 - r_m)$	



# Three competing models

**$N_0$**

$[N_0, \Lambda, \mu]$

**MaxEnt  
Gamma**

$[N_T, E[D], E[\log(D)]]$

**MaxEnt**

$[N_T, E[D], E[D^2]]$



# Parameter estimation

**$N_0$**

$[N_0, \Lambda, \mu]$

Numerical,  
Maximum Likelihood  
(MLE)

**MaxEnt  
Gamma**

$[N_T, E[D], E[\log(D)]]$

**MaxEnt**

$[N_T, E[D], E[D^2]]$



# Parameter estimation

## $N_0$

$$[N_0, \Lambda, \mu]$$

Numerical,  
Maximum Likelihood  
(MLE)

## MaxEnt Gamma

$$[N_T, E[D], E[\log(D)]]$$

$$\hat{\Lambda} = (\hat{\mu} + 1)/E[D]$$

$$\hat{\mu} = \frac{1 \pm \sqrt{1 + \frac{4}{3}c}}{4c} - 1; c \neq 0$$

$$c \equiv \log(E[D]) - E[\log D]$$

## MaxEnt

$$[N_T, E[D], E[D^2]]$$



# Parameter estimation

## $N_0$

$$[N_0, \Lambda, \mu]$$

Numerical,  
Maximum Likelihood  
(MLE)

## MaxEnt Gamma

$$[N_T, E[D], E[\log(D)]]$$

$$\hat{\Lambda} = (\hat{\mu} + 1)/E[D]$$

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$$c \equiv \log(E[D]) - E[\log D]$$

## MaxEnt

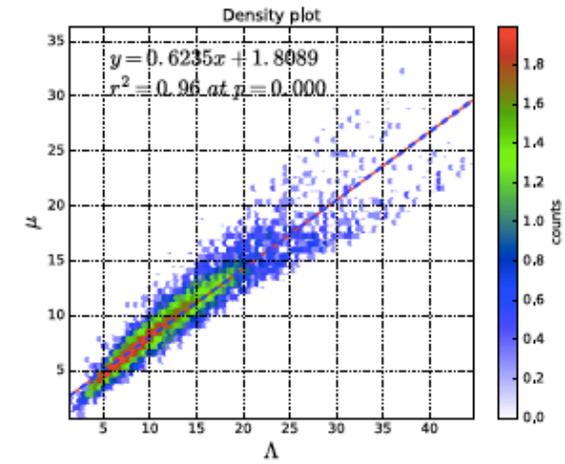
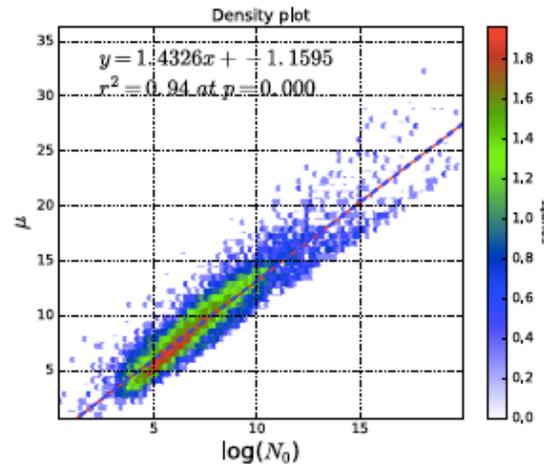
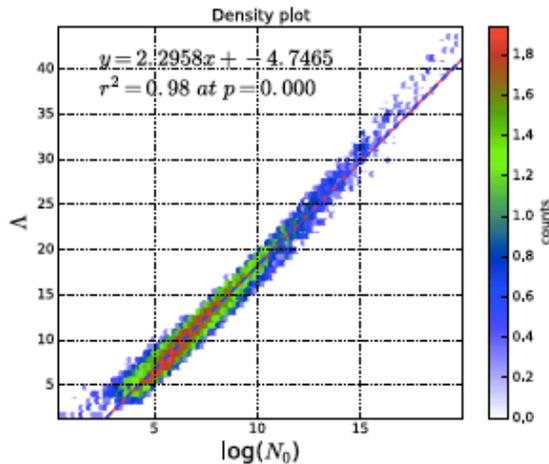
$$[N_T, E[D], E[D^2]]$$

Numerical,  
Newton-Raphson approach



# Parameters independence

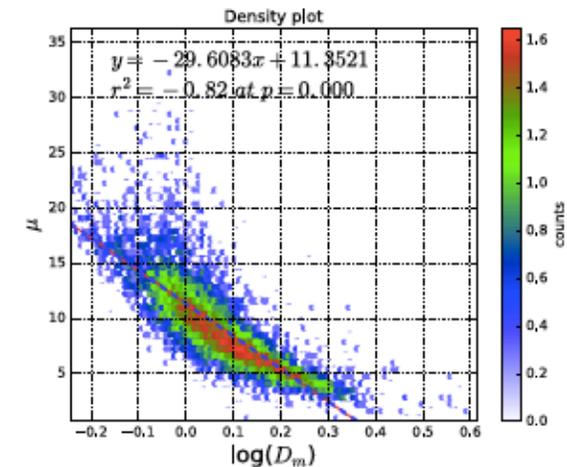
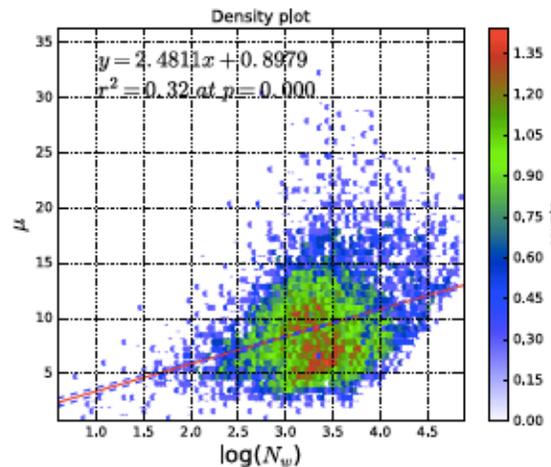
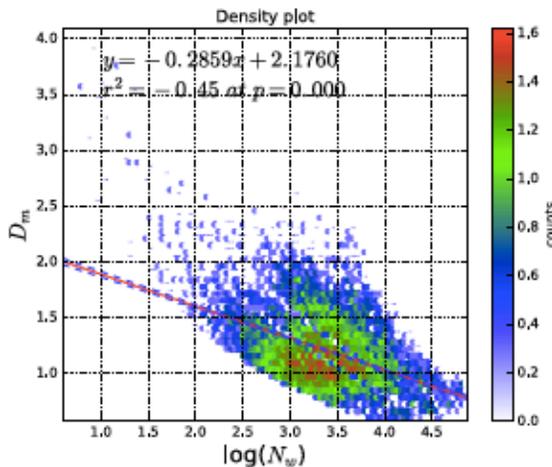
$N_0, \Lambda, \mu$  ( $N_0$  based)



- Number concentration and shape are mathematically related
- Data confirm that indeed are empirically correlated

# Parameters independence

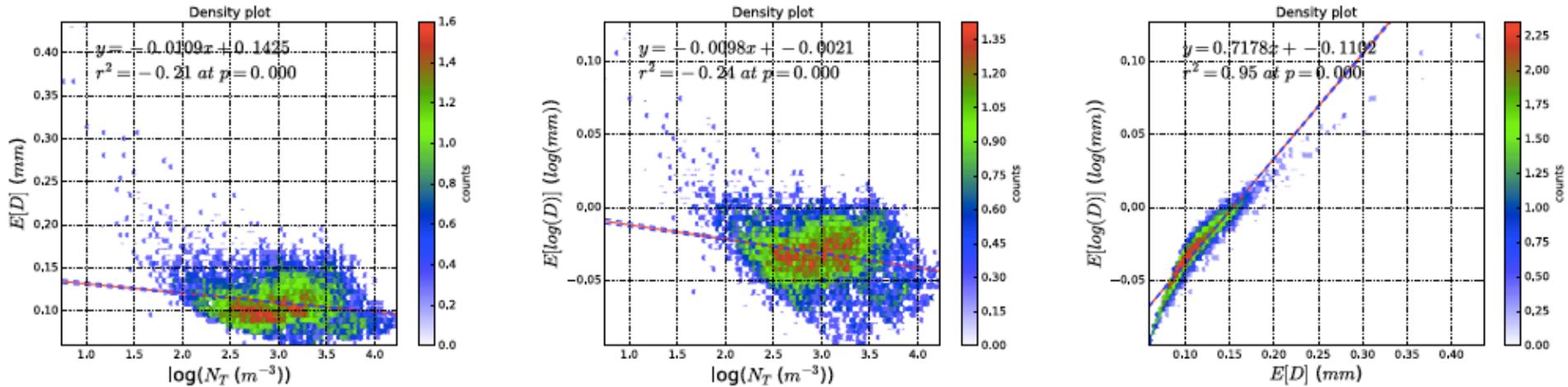
$N_w, D_m, \mu$  ( $N_w$  based)



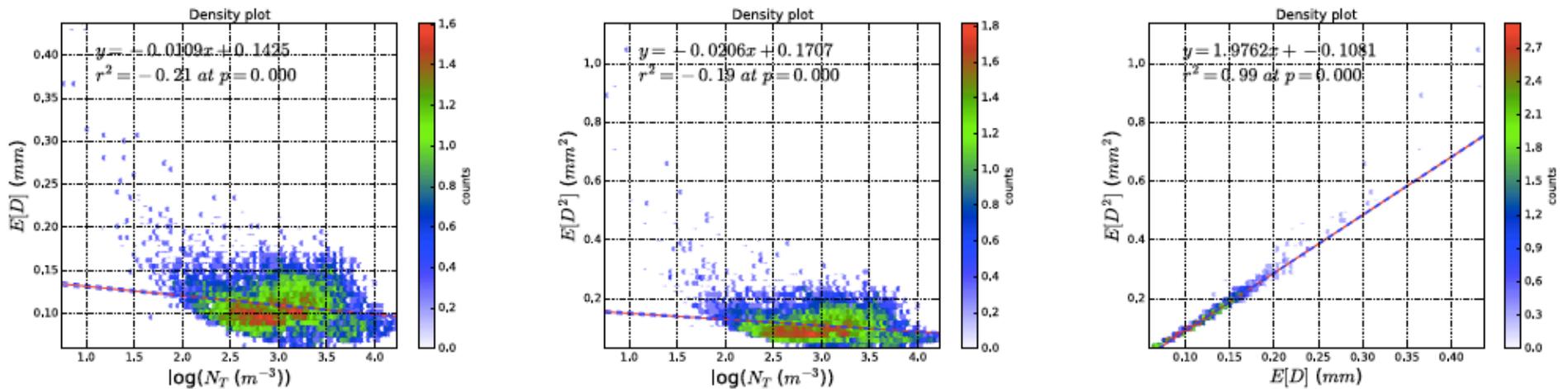
- Number concentration and shape are inherently related
- Data confirms that



## $N_T, E[D], E[\log(D)]$ (Maxent-Gamma)



## $N_T, E[D], E[D^2]$ (Maxent)





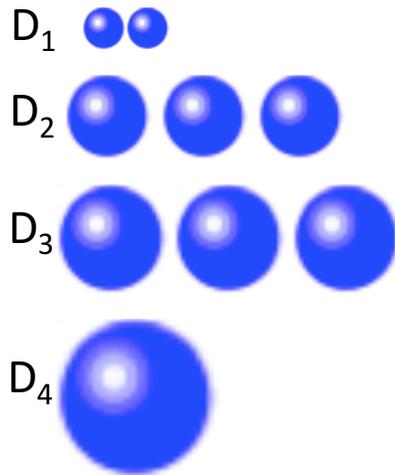
# But such dependence is sensible for rainfall!

- Number of drops does not depend on drop size probabilities!
- If the shape moves to the right (increase in mean diameter  $m$ ), then the PDF widens
- We can reduce the number of parameters, but in the shape side only



# RDSD #1

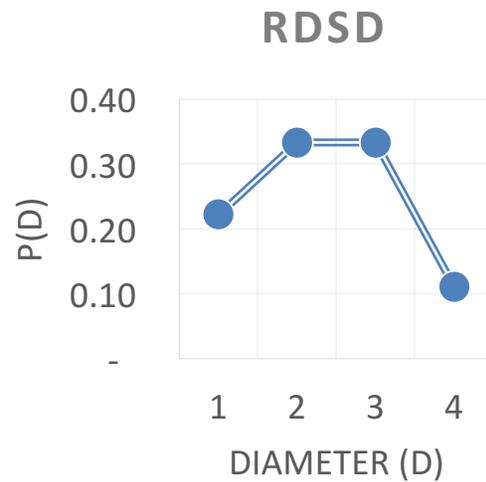
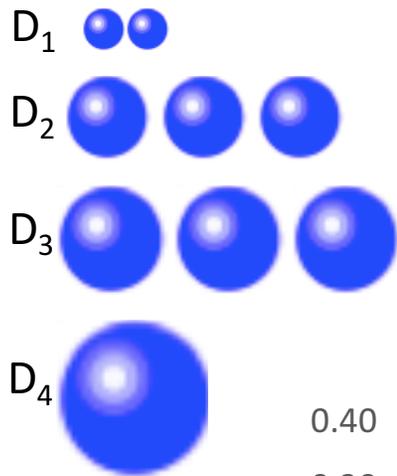
$$N_T=9$$





# RDSD #1

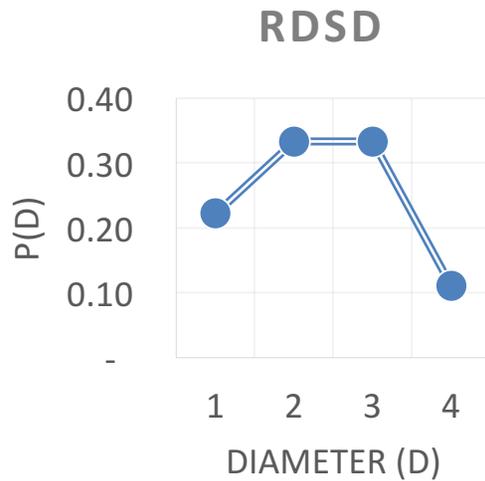
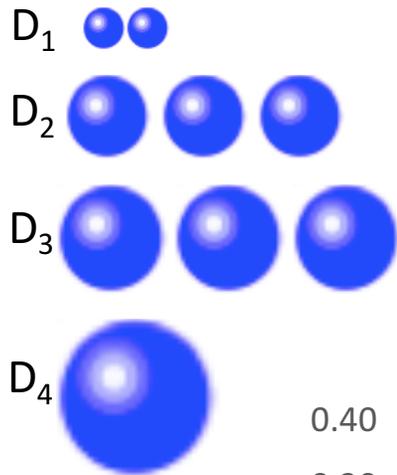
$$N_T=9$$





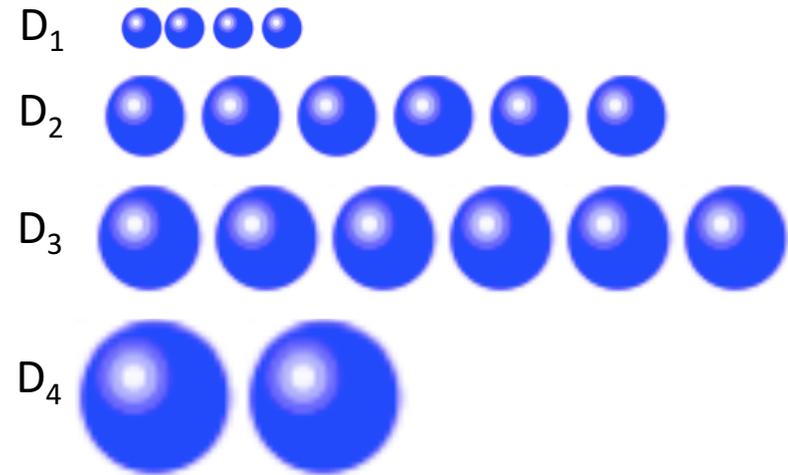
# RDSD #1

$N_T=9$



# RDSD #2

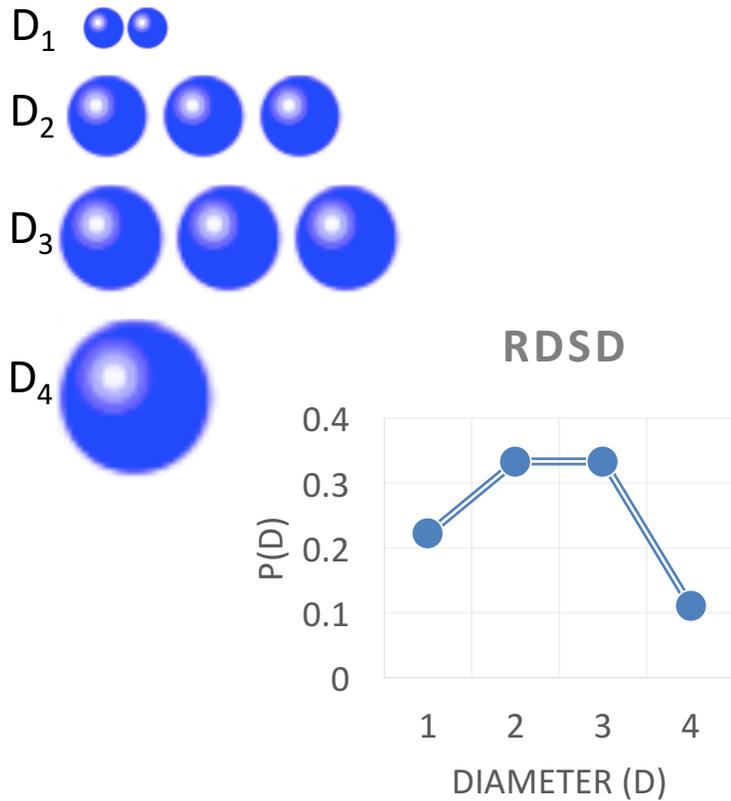
$N_T=18$





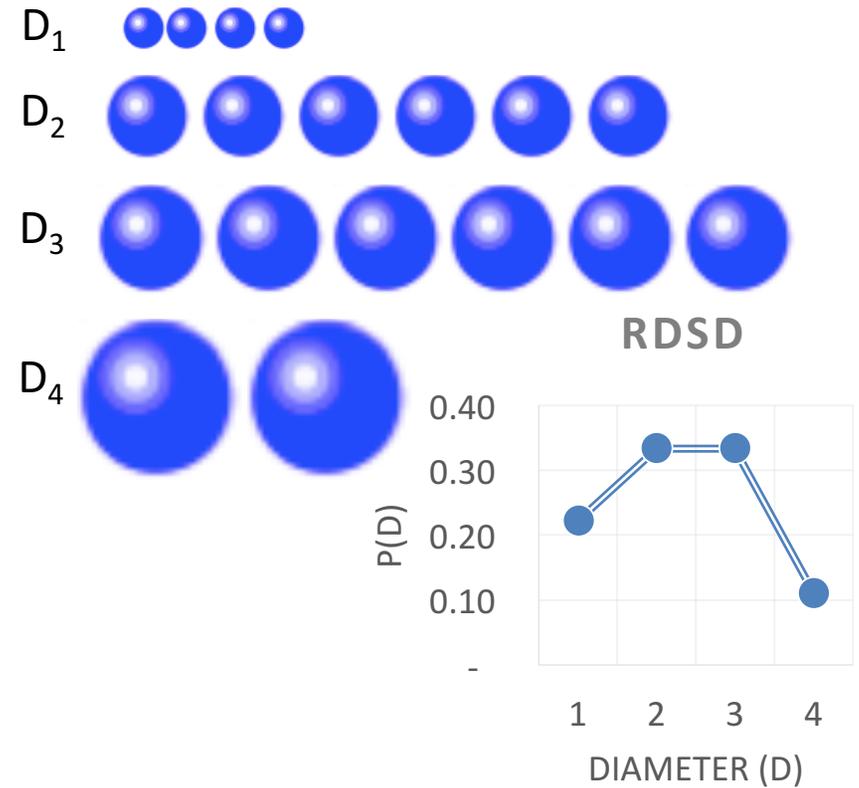
# RDSD #1

$N_T=9$



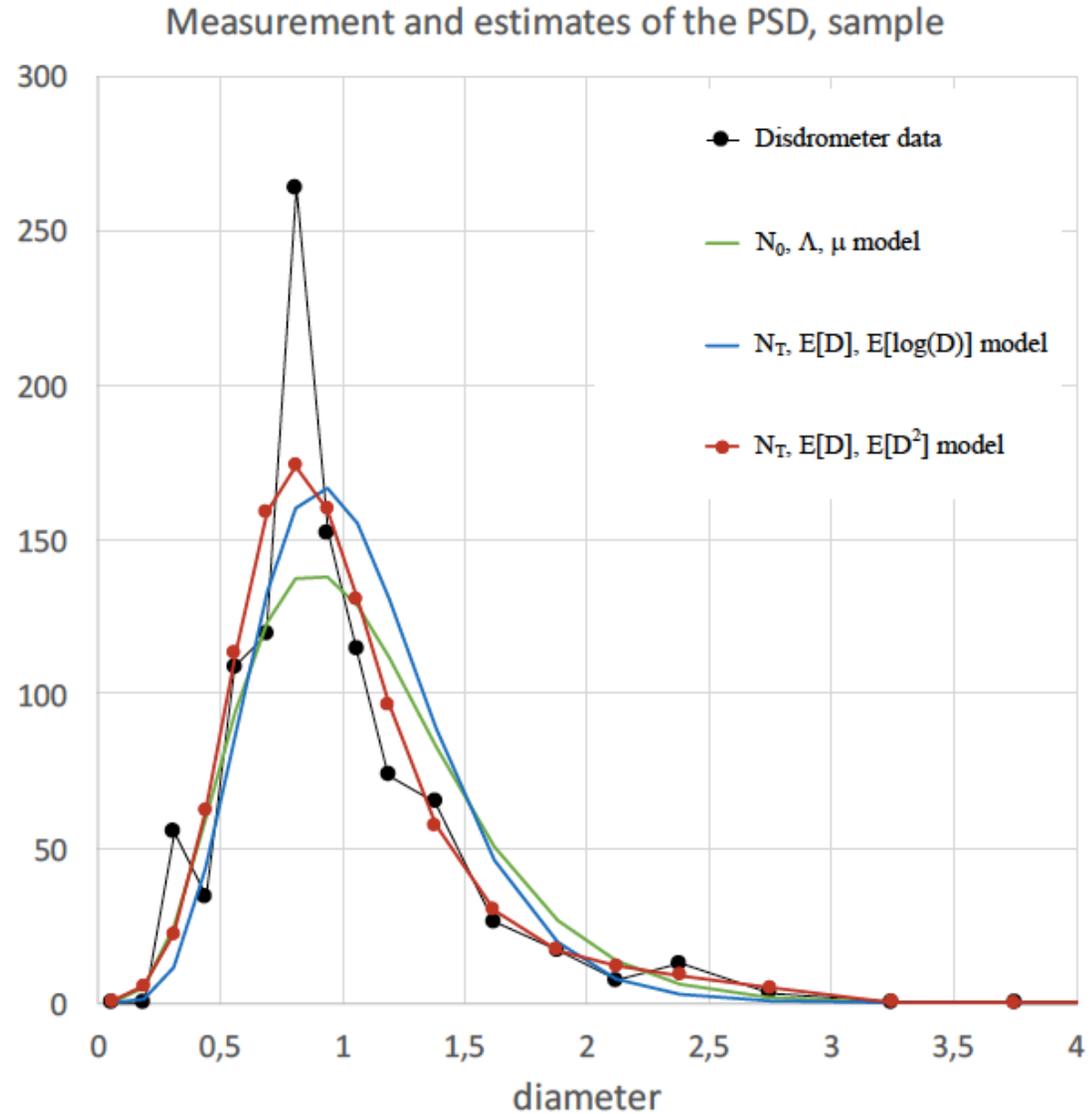
# RDSD #2

$N_T=18$



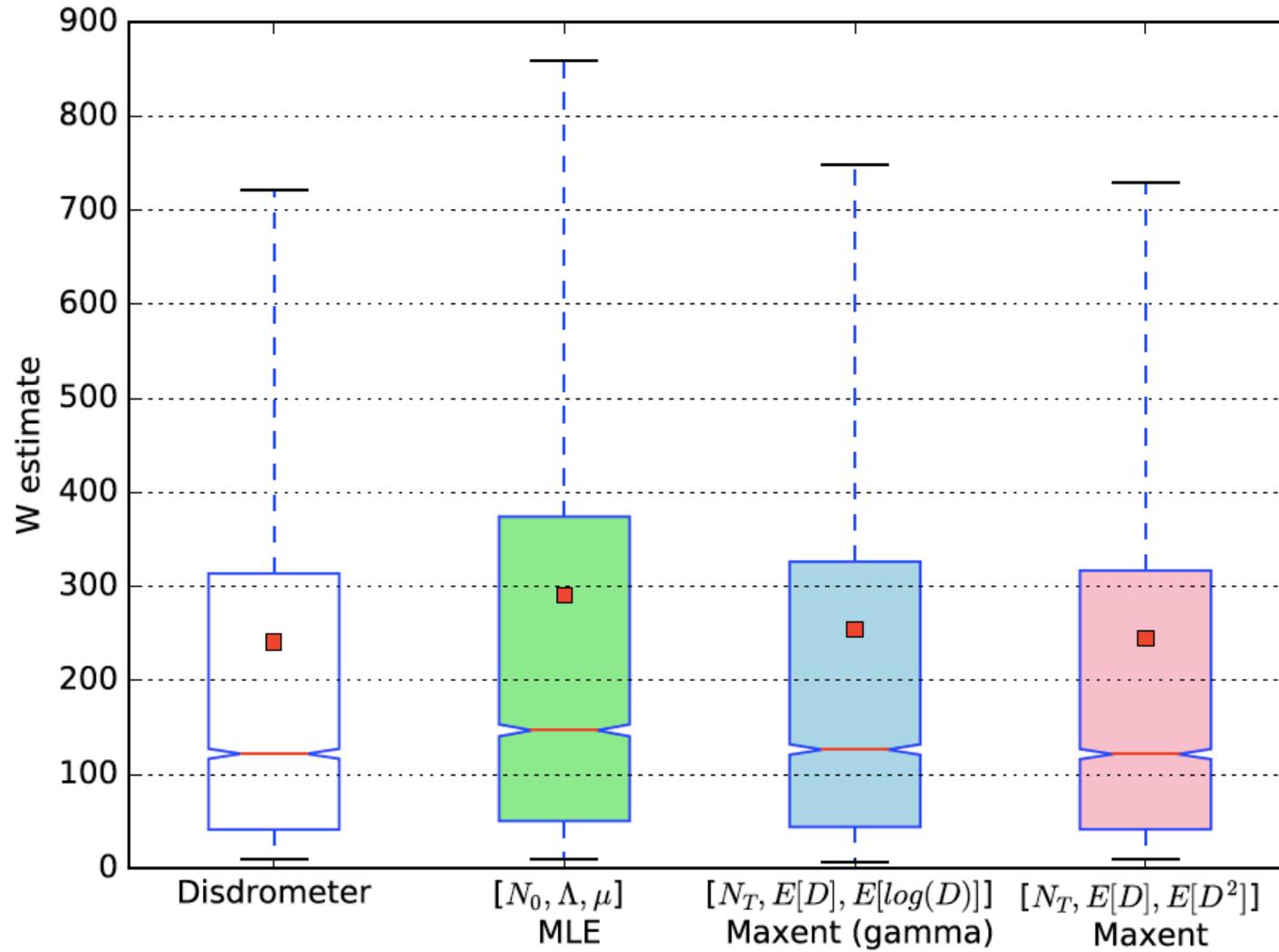


How good are the three models in estimating the actual shape?

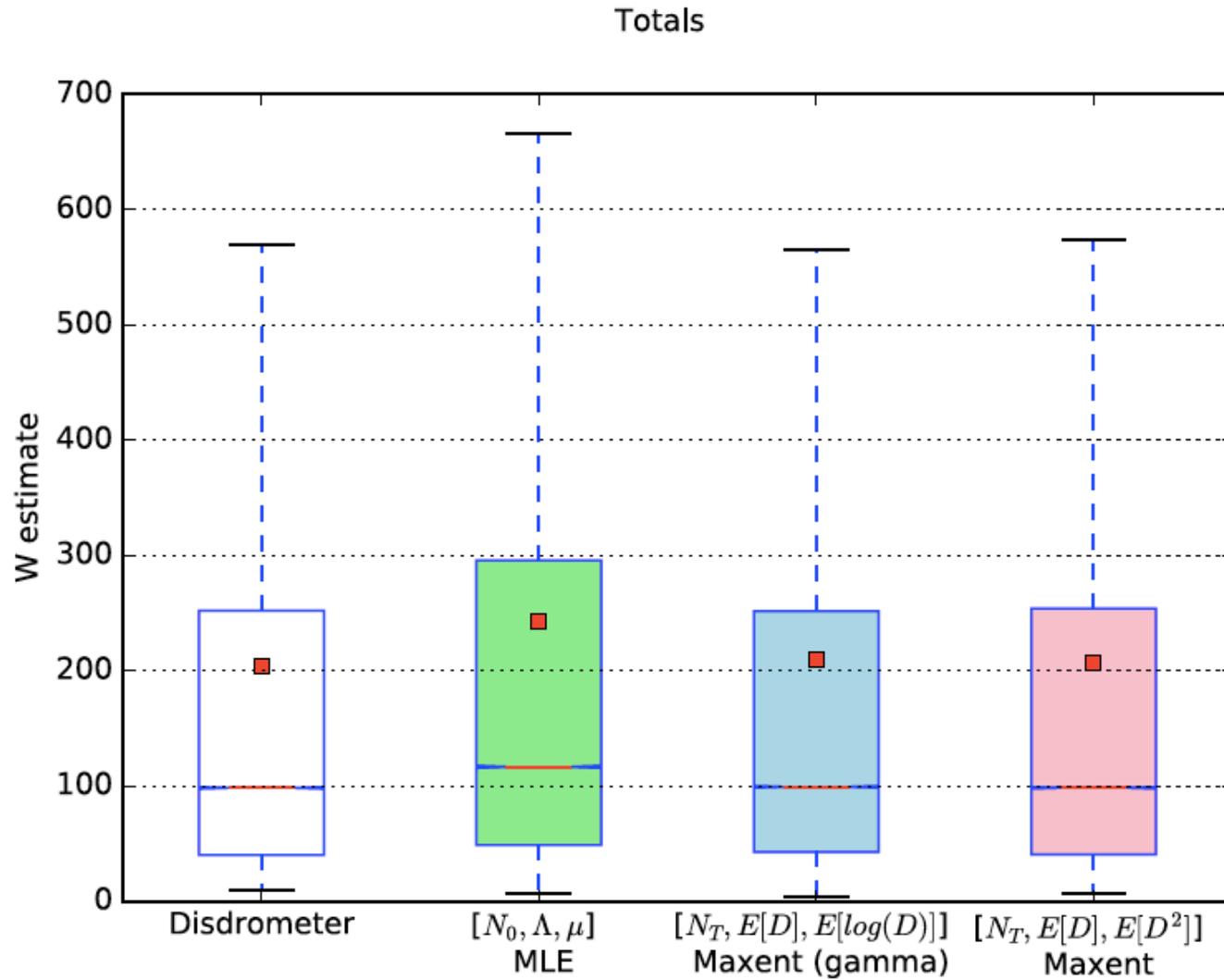




### Lavilledieu 30-11-2012 11-09-2012







Disdrometer measurements vs. Analytical estimates



# Objective mp characterization

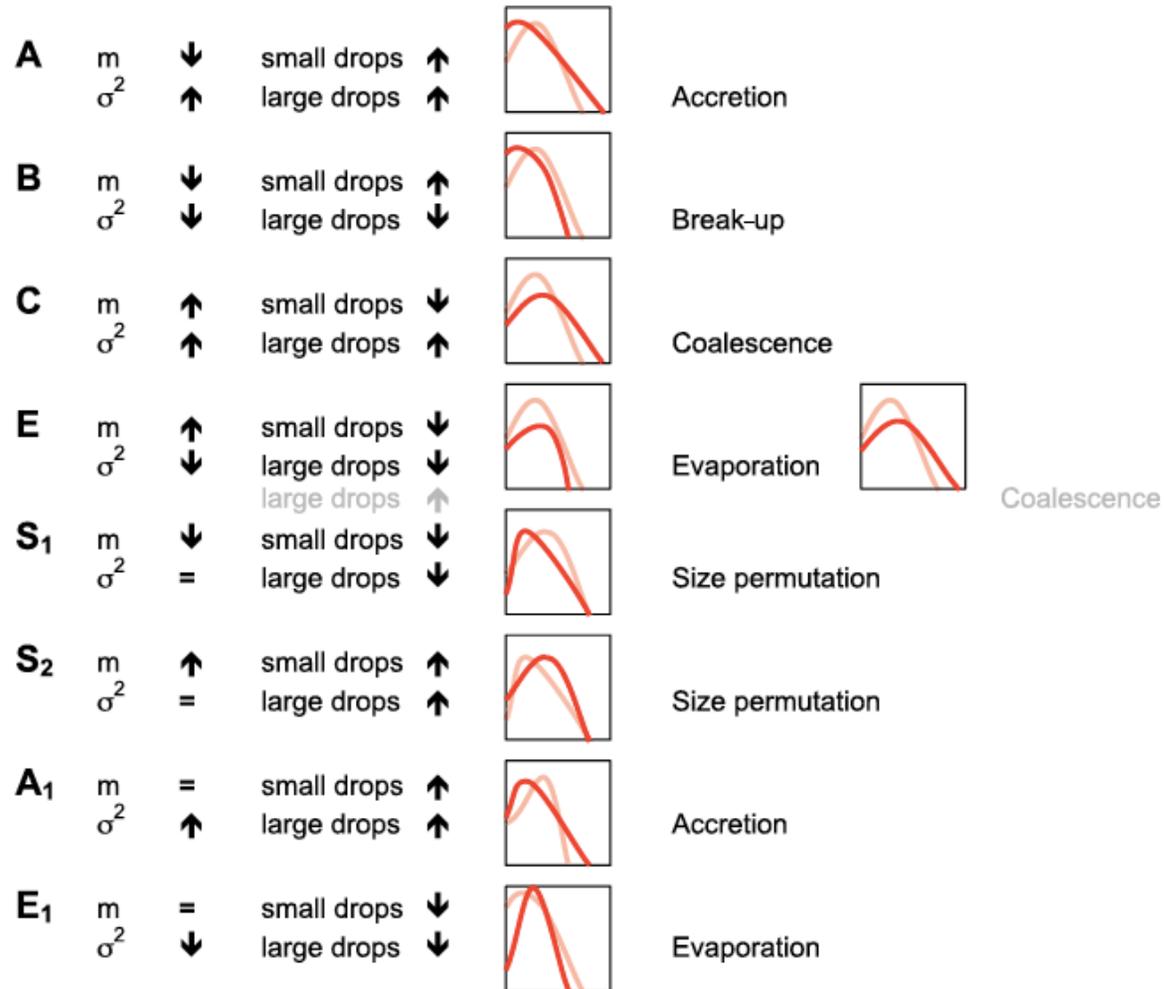


# mp processes

Code	Coding in Tapiador et al. 2014	Microphysics	Objective characterization of the microphysical process	Comments
1	A <sub>1</sub>	<b>Accretion</b>	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} > 0$	$\frac{\partial N_T}{\partial t} \sim 0, \frac{\partial E[D]}{\partial t} \sim 0$ , all drops increase in size
2	B	<b>Break-up</b>	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} < 0$	The main process creating new drops
3	S <sub>1</sub>	Size sorting 1	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} > 0$	$\frac{\partial N_T}{\partial t} \sim 0, \frac{\partial E[D^2]}{\partial t} \sim 0$
4	S <sub>2</sub>	Size sorting 2	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} < 0$	$\frac{\partial N_T}{\partial t} \sim 0, \frac{\partial E[D^2]}{\partial t} \sim 0$
5	E <sub>1</sub>	<b>Evaporation 1</b>	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} < 0$	Process destroying drops
6	C	<b>Coalescence</b>	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} > 0$	Major process destroying drops
7	E	Evaporation	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} < 0$	Process destroying (small) drops
8	A	Break-up+ Coalescence	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} > 0$	Large drops break; small drops coalesce



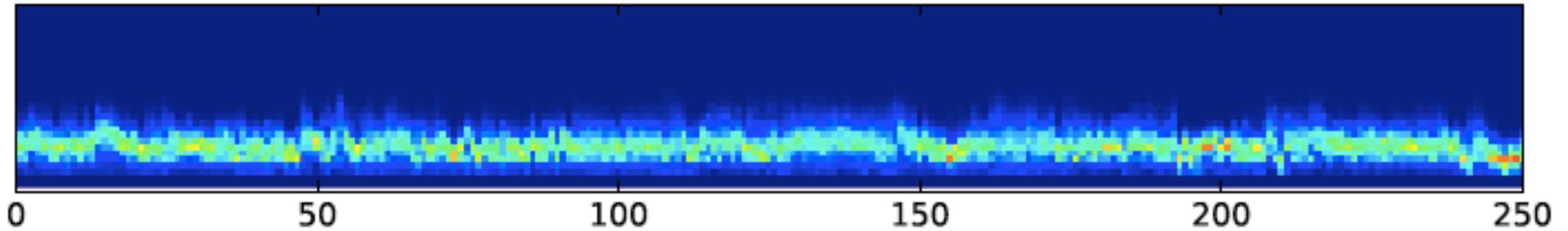
# mp characterization





# mp characterization

PSD spectrum (normalized)



Microphysics sequence



Code	<small>Collins et al. 2014</small>	Microphysics	Objective characterization of the microphysical process	Comments
1	A <sub>1</sub>	<b>Accretion</b>	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} > 0$	$\frac{\partial N_T}{\partial t} \sim 0, \frac{\partial E[D]}{\partial t} \sim 0$ , all drops increase in size
2	B	<b>Break-up</b>	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} < 0$	The main process creating new drops
3	S <sub>1</sub>	Size sorting 1	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} > 0$	$\frac{\partial N_T}{\partial t} \sim 0, \frac{\partial E[D^2]}{\partial t} \sim 0$
4	S <sub>2</sub>	Size sorting 2	$\frac{\partial N_T}{\partial t} > 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} < 0$	$\frac{\partial N_T}{\partial t} \sim 0, \frac{\partial E[D^2]}{\partial t} \sim 0$
5	E <sub>1</sub>	<b>Evaporation 1</b>	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} < 0$	Process destroying drops
6	C	<b>Coalescence</b>	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} > 0$	Major process destroying drops
7	E	Evaporation	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} > 0, \frac{\partial E[D^2]}{\partial t} < 0$	Process destroying (small) drops
8	A	<b>Break-up+ Coalescence</b>	$\frac{\partial N_T}{\partial t} < 0, \frac{\partial E[D]}{\partial t} < 0, \frac{\partial E[D^2]}{\partial t} > 0$	Large drops break; small drops coalesce



# Retrieval of DSD parameters from radar observables



# T-matrix calculations from disdrometer data

$$\vec{J} = \frac{1}{2} (\vec{x} - \vec{Z})^2$$

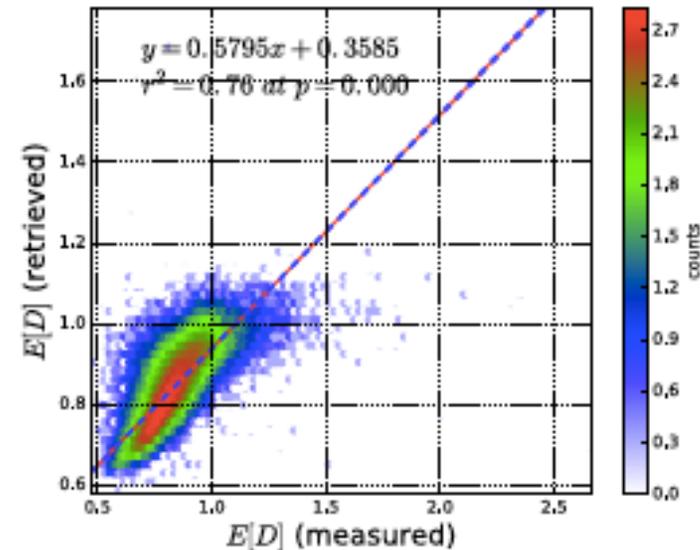
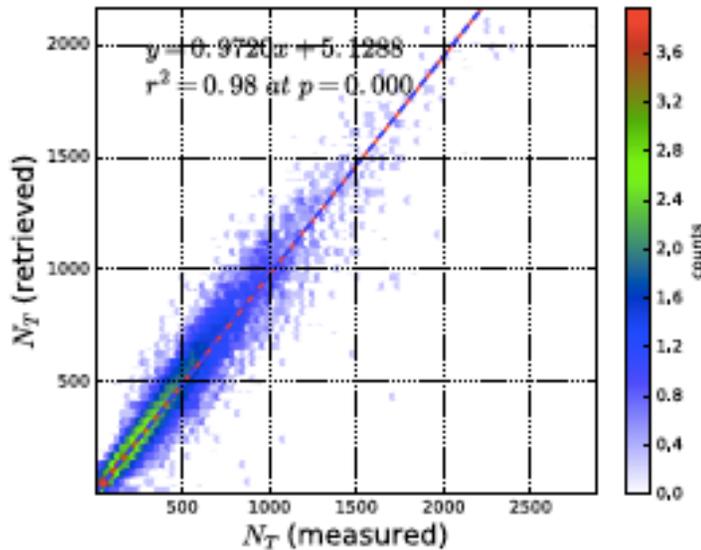
$$\vec{x} = g * \{A \cdot [g * (B \cdot \vec{Z})]\}$$

$$g(x) = 1 / (1 + e^{-x})$$



# Retrieval of RDSD params

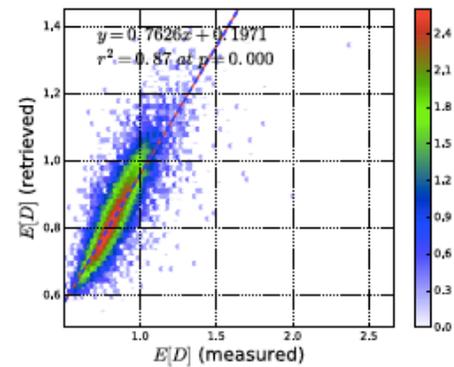
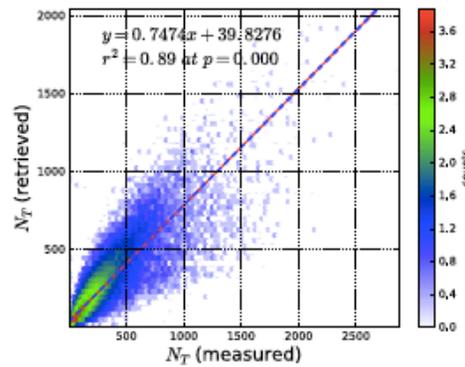
$$\vec{Z} = (Z_H(Ka), Z_V(Ka), Z_H(Ku), Z_V(Ku), Z_{DR}(Ku), Z_{DR}(Ka), K_{DP}(Ka), K_{DP}(Ku))$$



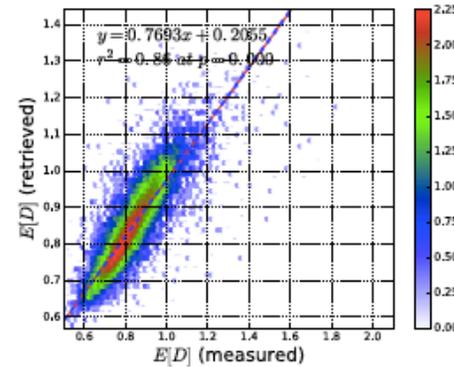
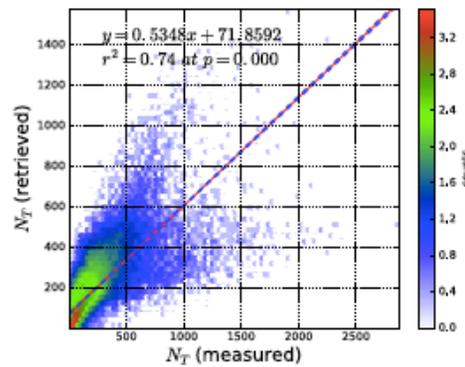


# Retrieval of RDSD params

$$\vec{Z} = (Z_V(Ka), Z_H(Ku), Z_{DR}(Ku), Z_{DR}(Ka))$$



$$\vec{Z} = (Z_H(Ka), Z_V(Ka), Z_H(Ku))$$





# Summary

1. mp modeling asks for decoupling

$N_T$  (number of drops) from the  
Shape (probability of given diameter)

2. Both  $N_0$  and  $N_W$  models present issues

3. Parameter independence is important in DSD modeling

4. The  $N_T$  model is conceptually stronger

5. The  $N_T$  model compares better with observations

6. The  $N_T$  model is better suited for remote retrieval (independence)