Exploiting additional observables in the development of an advanced categorization scheme for detecting autoconversion from ground based observations

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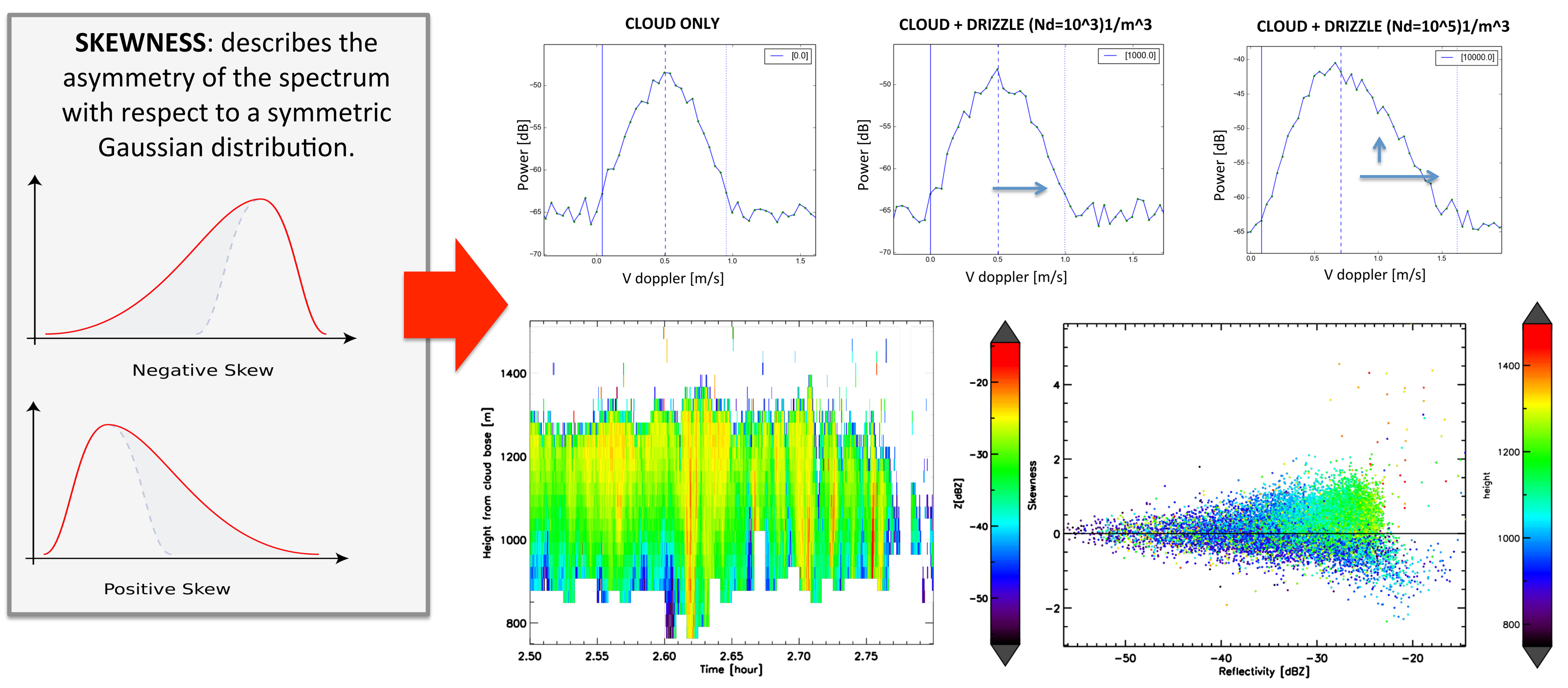
1. Motivation

- Autoconversion describes the mass transfer rate from cloud droplets to embryonic drizzle particles. It plays a key role in the atmospheric water cycle and for the short and long wave cloud radiative forcing in our climate system.
- Several parameterizations for autoconversion have been proposed for numerical models of varying scales. However, verification of the proposed schemes and their details (e.g., what is the typical size range of the embryo drizzle particles) remains not well understood, due to the lack of any direct observations.
- New variables formally called higher Doppler spectra moments (and among them, the skewness) from cloud radar showed potential in the early detection of drizzle in clouds[(2)], which remains challenging for commonly used target classification schemes (e.g, Cloudnet[(1)]).

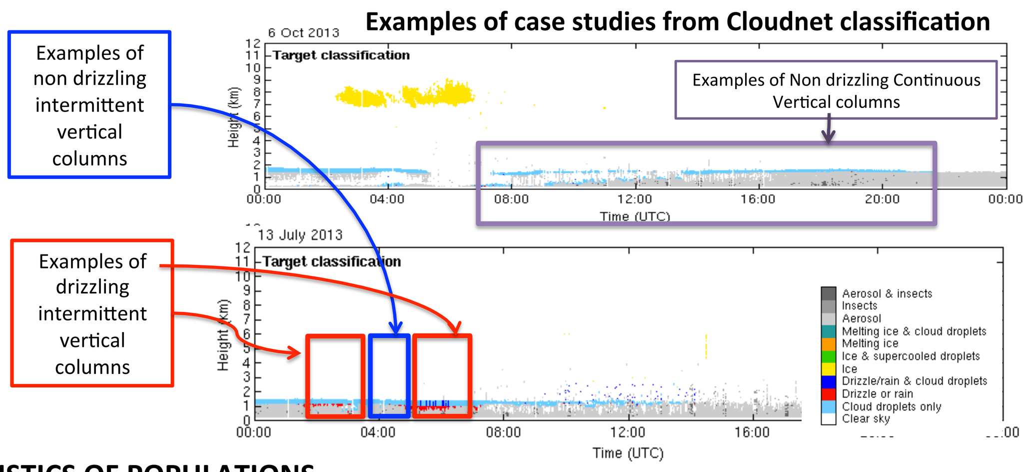
2. Skewness for drizzle onset detection



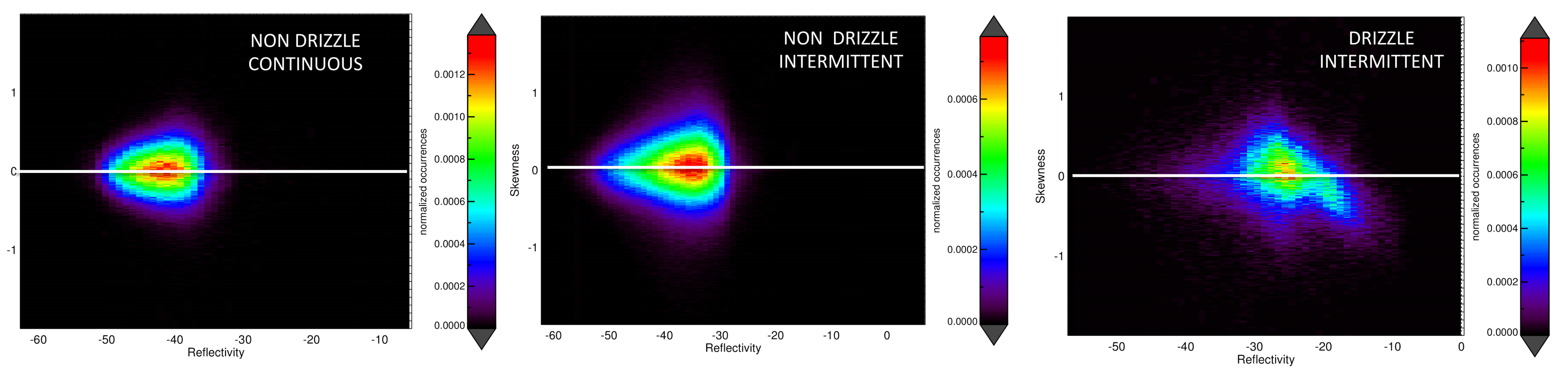
3. Current criteria and skewness exploitment

To evaluate Cloudnet's ability in detecting drizzle onset into clouds, we defined:

- An ensemble of non drizzling continuous in time vertical columns: these are taken in case studies in which Cloudnet only shows non drizzle columns made of "only cloud droplets" radar bins.
- An ensemble of non drizzling intermittent and drizzling intermittent in time vertical columns: these are taken from case studies in which Cloudnet identifies at some point during the day the presence of drizzle columns among the non drizzle ones.



STATISTICS OF POPULATIONS



1. Cloudnet is discriminating populations mainly on the basis of reflectivity thresholds. No specific features appear in terms of skewness for drizzling population.
2. In the purely non drizzling case, when the skewness of the spectrum is supposed to be zero, skewness values are distributed in the range +/- 0.5. This can be considered as skewness noise.

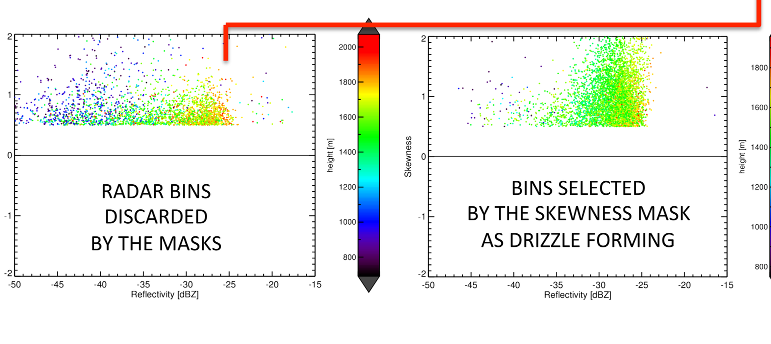
WHAT IF WE LOOK FOR POSITIVE SKEWNESS VALUES TO IDENTIFY DRIZZLING AREAS?

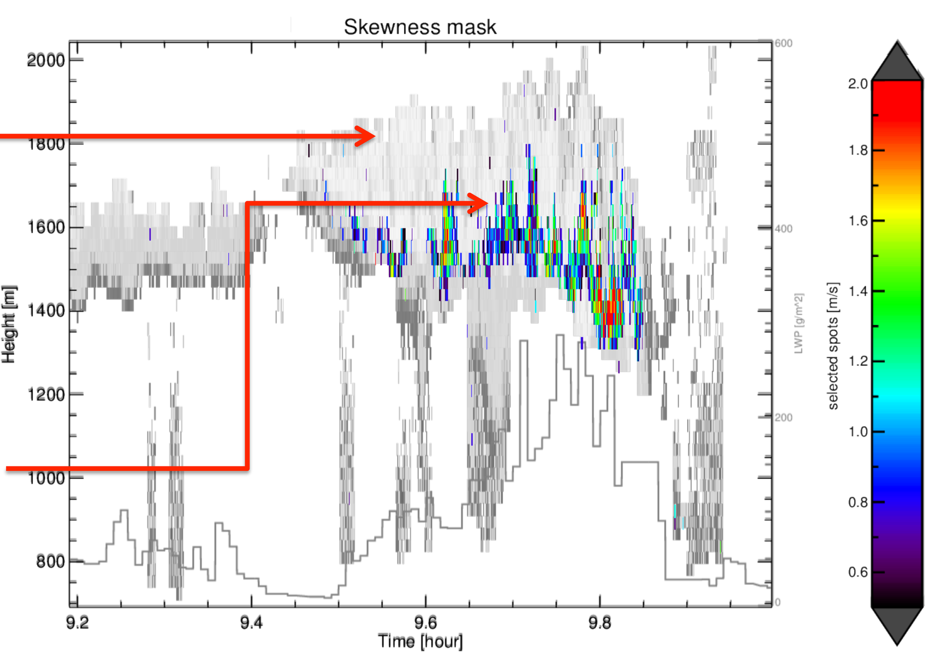
SKEWNESS MASK

Selection of all radar bins in time height within the cloud having:

- **Skewness value > 0.5**
- **At least two adiacent radar bins also having skewness > 0.5**

0.1	0.002	-0.32	0.124	0.424
0.56	-0.12	0.89	0.78	1.43
0.2	0.34	1.23	-0.1	0.34
-0.34	0.22	0.67	0.23	0.001
-0.78	0.15	-0.2	0.98	-0.21





- Bins selected by the mask show reflectivities between -30 dbZ and -25 dbZ.
- Radar bins discarded by the mask are distributed like noise over the whole range of reflectivities.
- Skewness shows potential in the identification of drizzling areas within the cloud.
- The skewness is very noisy and the threshold used at 0.5 can be a limitation for the effectiveness of the criteria.

OPEN QUESTIONS:

1. How to reduce skewness noise and get better skewness observations?
2. Which are the typical features of radar bins where autoconversion is occurring?
3. Which is the role played by turbulence?
4. Which microphysics behind positive skewness?

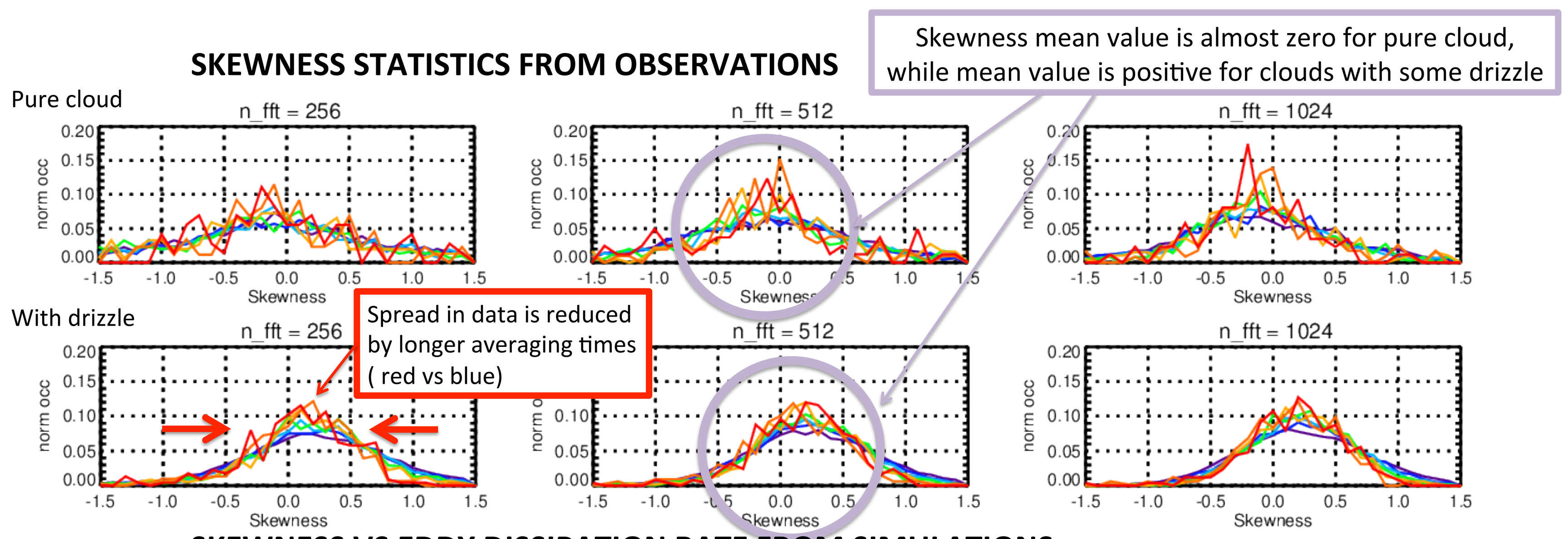
4. How to improve skewness measurements? IQ tests

Sensitivity studies on radar spectra: IQ experiment

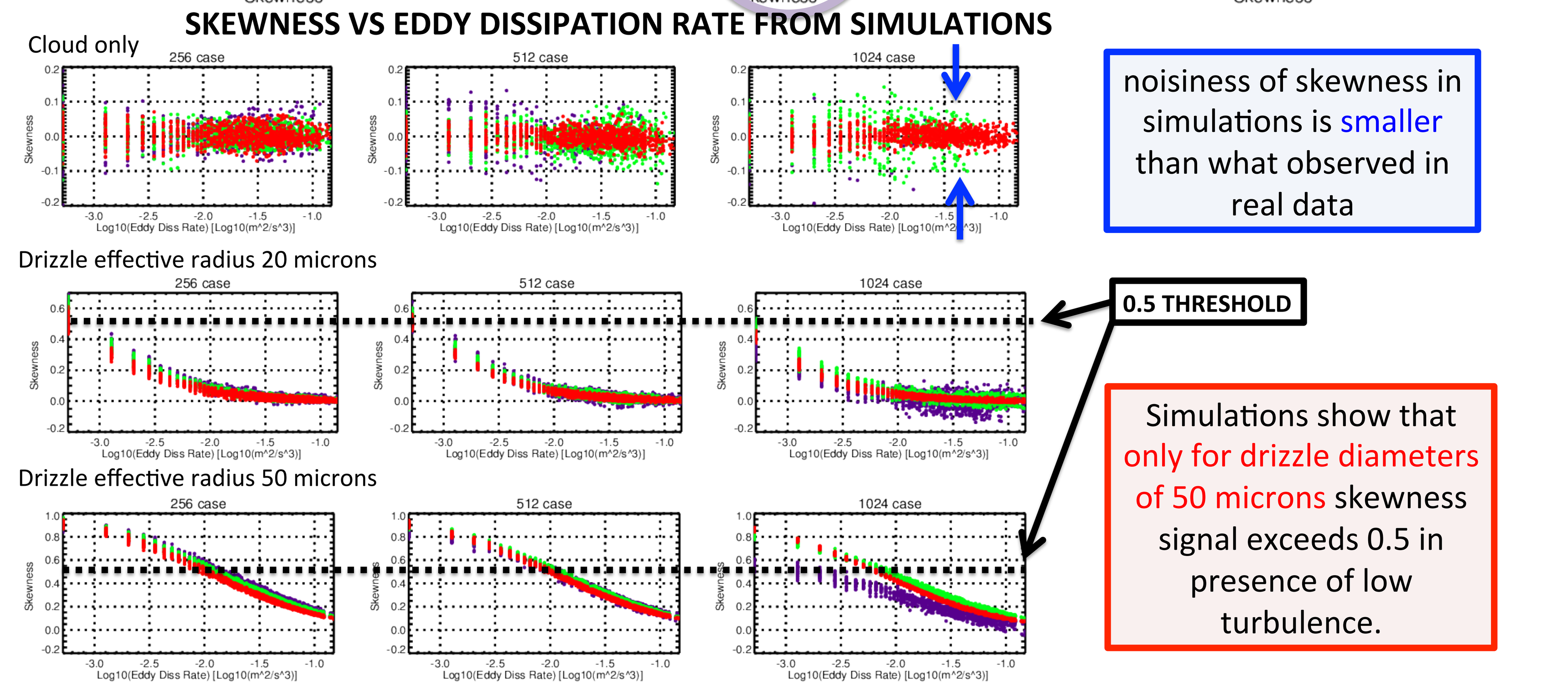
2 case studies (liquid cloud with and without drizzle):

- derivation of spectra and distributions of moments varying:
  - FFT length: 256, 512, 1024.
  - Averaging time: 0.2s(purple), 0.4s(blue), 0.8s(light blue), 2s(green), 4s(yellow), 8s(orange), 10s(red).
- Simulations of the IQ experiment providing lognormal distributions for cloud and drizzle

SKEWNESS STATISTICS FROM OBSERVATIONS



SKEWNESS VS EDDY DISSIPATION RATE FROM SIMULATIONS

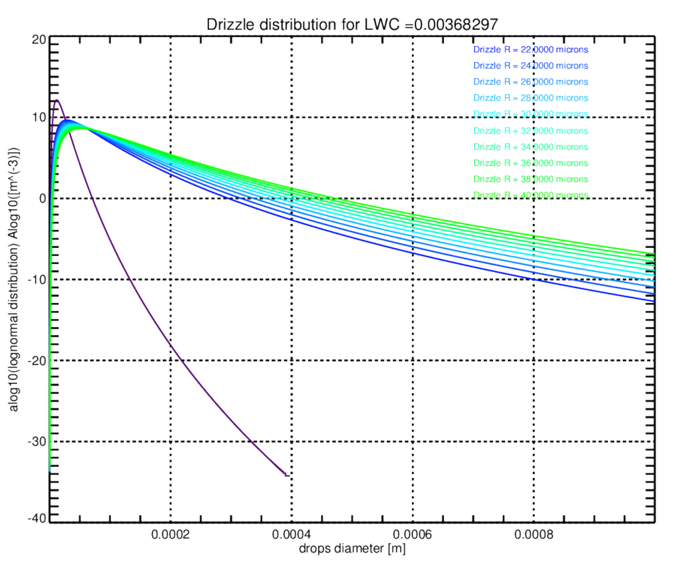


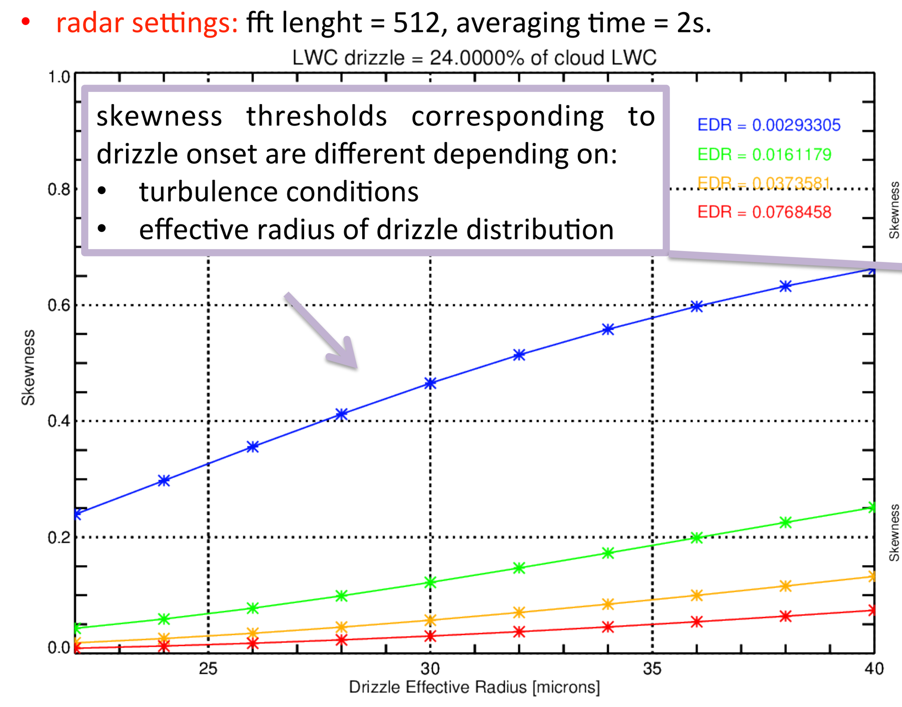
5. Simulating autoconversion: the role of turbulence

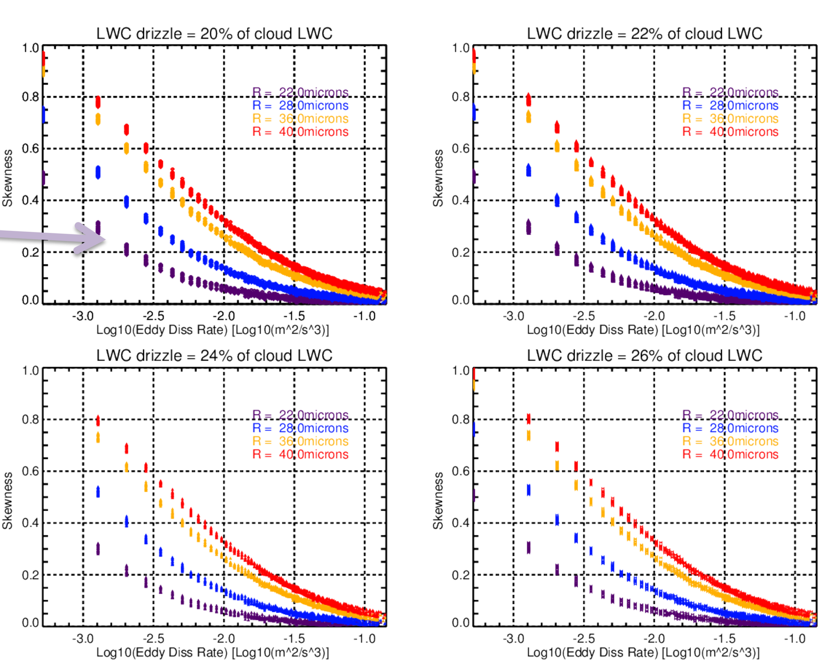
AIM: investigate Doppler moments variations in presence of autoconversion

SIMULATIONS SETUP:

- cloud drop size distribution: **lognormal (**Effective radius: 7.2*10^(-6) m, sigma=0.24, Ncloud=10^(7) [1/m^3]) (LWC cloud= 0.013 g/m^3)
- drizzle drop size distribution: **lognormal.** Different drizzle distributions are used to simulate autoconversion varying the effective radius and the number concentration in order to have the prescribed drizzle LWC between 20% and 30 % of cloud LWC:
  - LWC percentage = [0.2, 0.22, 0.24, 0.26, 0.28, 0.30]
  - Reff = [20, 22, 24, 26, 28, 30, 32, 34, 36, 38, 40] microns
  - sigma = 0.35
  - Ndrizzel (derived accordingly to LWC and Reff)
- 1000 runs: each of them having random eddy dissipation rate (EDR) and vertical velocity values taken from EDR and mean Doppler velocity distributions
- radar settings: fft lenght = 512, averaging time = 2s.







CONCLUSIONS AND FUTURE STEPS:

- The skewness mask shows potential in detecting drizzle onset: it identifies radar bins having a precise range of reflectivities between -30 dbZ and -25 dbZ, which is the same range indicated by cloudnet statistic of drizzling bins.
- Simulations show that in conditions of low turbulence only drizzle drop size distributions having effective radii of 50 microns are able to produce skewness signals above the 0.5 threshold.
- The IQ experiment and simulations suggest that a skewness noise threshold of 0.5 can possibly be reduced by using other radar settings: for liquid clouds, fft length of 512 and averaging time of 2seconds.
- Possibilities for improving the efficacy of the skewness mask come from simulations: adding additional information concerning turbulence is essential to properly identify drizzle formation.
- Simulations additionally help in characterizing the drizzling radar bins in terms of many other variables, like LWC, reflectivity, mean Doppler velocity, spectral width. Such information will be used to calculate a statistical probability of belonging to the non-drizzling, respectively the drizzling population for every bin selected by the skewness mask.

References:

(1) Cloudnet - continuous evaluation of cloud profiles in seven operational models using ground-based observations. Illingworth, A. J., R. J. Hogan, E. J. O'Connor, D. Bouniol, M. E. Brooks, J. Delanoe, D. P. Donovan, J. D. Eastment, N. Gaussiat, J. W. F. Goddard, M. Haeffelin, H. Klein Baltink, O. A. Krasnov, J. Pelon, J.-M. Piriou, A. Protat, H. W. J. Russchenberg, A. Seifert, A. M. Tompkins, G.-J. van Zadelhoff, F. Vinit, U. Willen, D. R. Wilson and C. L. Wrench, 2007. *Bull. Am. Meteorol. Soc.*, **88**, 883-898

(2) Separating cloud and drizzle radar moments during precipitation onset using doppler spectra. Edward P. Luke and Pavlos Kollias, 2013. *J. Atmos. Oceanic Technol.*, **30**, 1656–1671.

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