Unsupervised Classification of Vertical Profiles of Dual-Polarization Radar Variables

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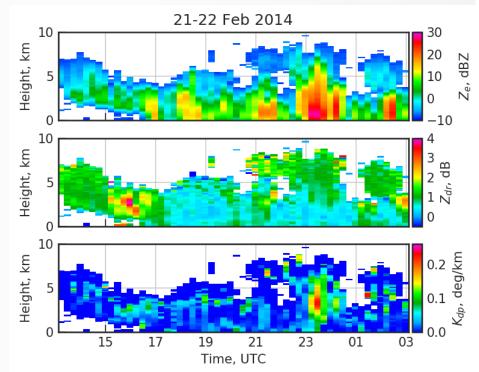


Niklas Sjöblom



Motivation

- Can we use vertical profiles of polarimetric radar variables as fingerprints of snow growth processes?
- Could this lead to:
 - Adaptive Z-S
 - Intelligent VPR correction

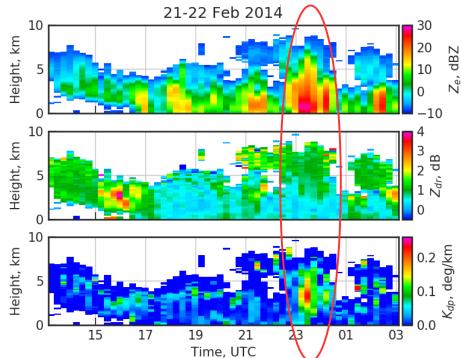




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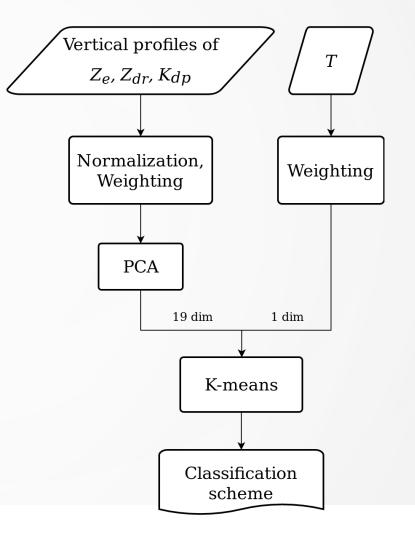
The first question to answer: can we classify vertical profiles to a finite number of classes and link them to the processes?





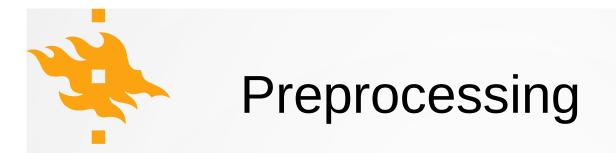
Classification method

- **1. Input:** Preprocessed polarimetric vertical profiles from RHI scans and ground temperature
- 2. Feature scaling and weighting of radar variables prior to Principal component analysis (PCA)
- **3. Dimension reduction** of vertical profiles using PCA
- K-means clustering of the combination of PCA-reduced profiles and weighted T
- 5. Output: Profile classes defined by Kmeans centroids

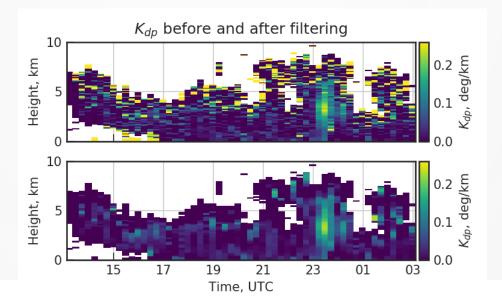


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- Vertical profiles extracted from RHI scans carried out every 15 minutes
- Z_{dr} and very noisy K_{dp} recovered using median filter
- A combination of median and threshold based filters for GC



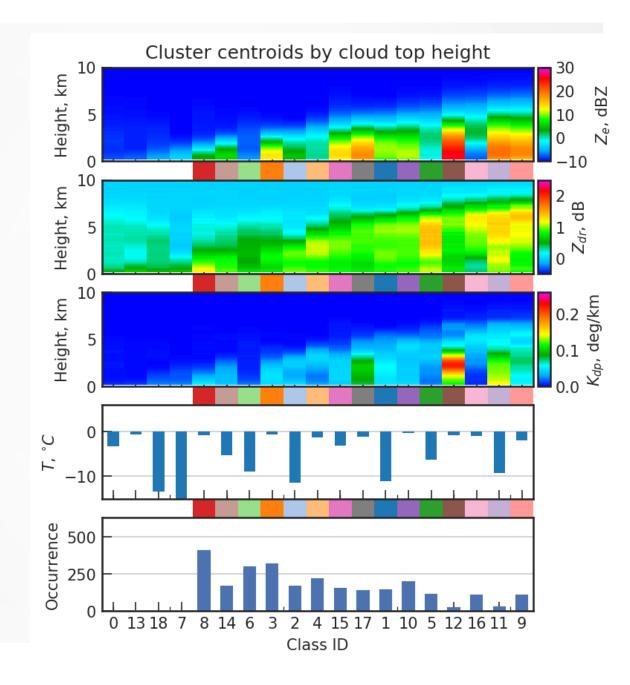


- 75 snow cases from 3 winters 2013/14, 14/15, 15/16
- Data collected over Hyytiälä, U. Helsinki measurement station in Finland
- RHI observations from the FMI Ikaalinen C-band radar, 64 km from the station
- Surface temperature is measured at the station



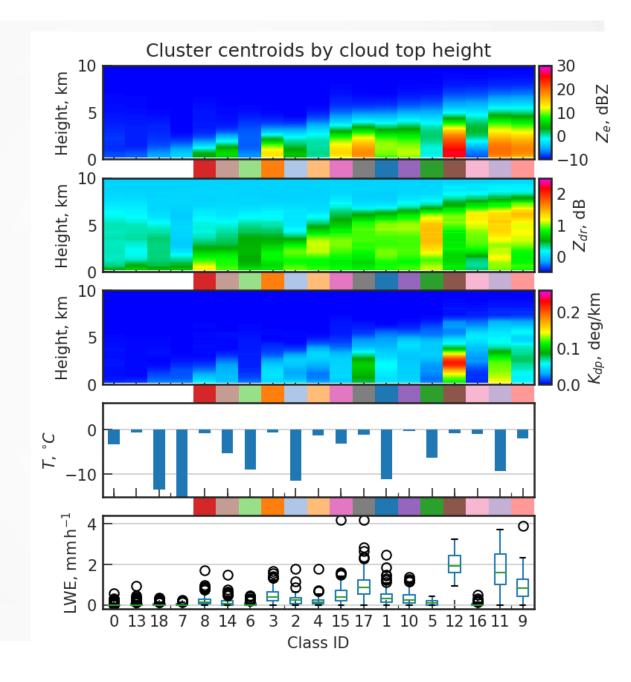


- Output of the classification: 19 profile classes (K-means centroids)
- They explain over 90% of the profile variance



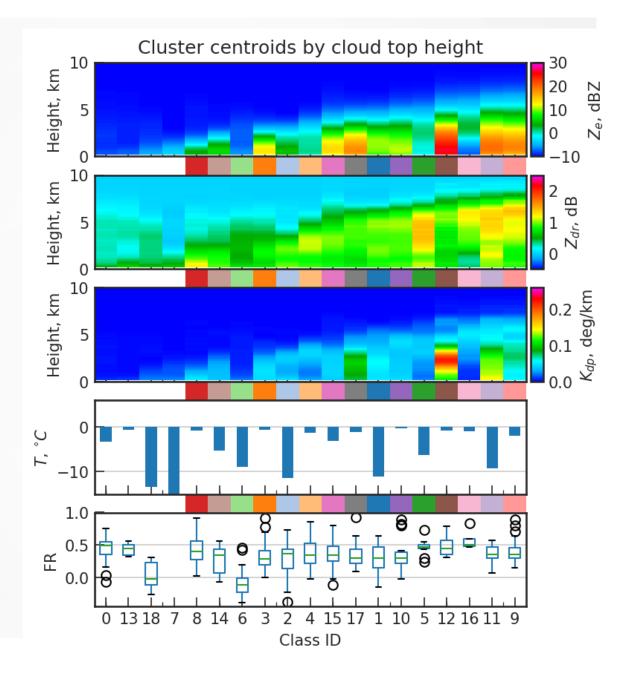


- Classification vs. mean LWE precipitation rate
- Sampled over next 15 minutes after each RHI





- Classification vs.
 Rime mass fraction
- Rime mass fraction is derived using Moisseev et al. (2017) method

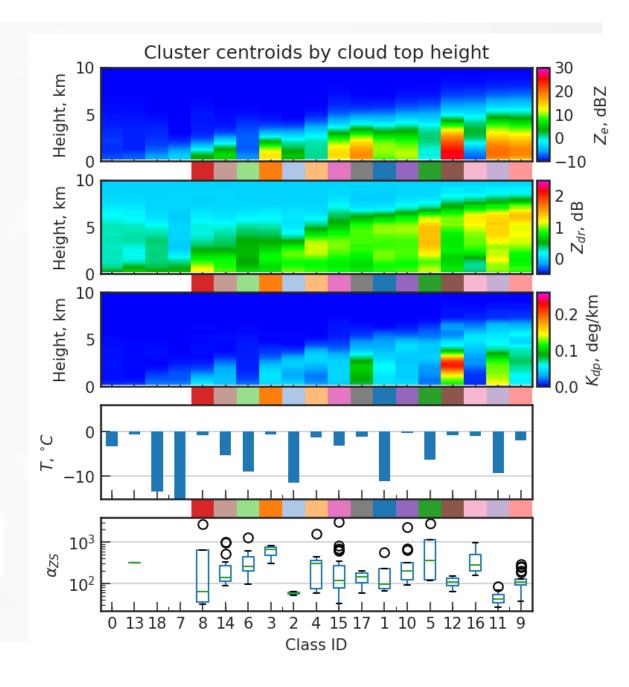


$$m = \frac{\alpha}{1 - FR} D^{\beta}$$



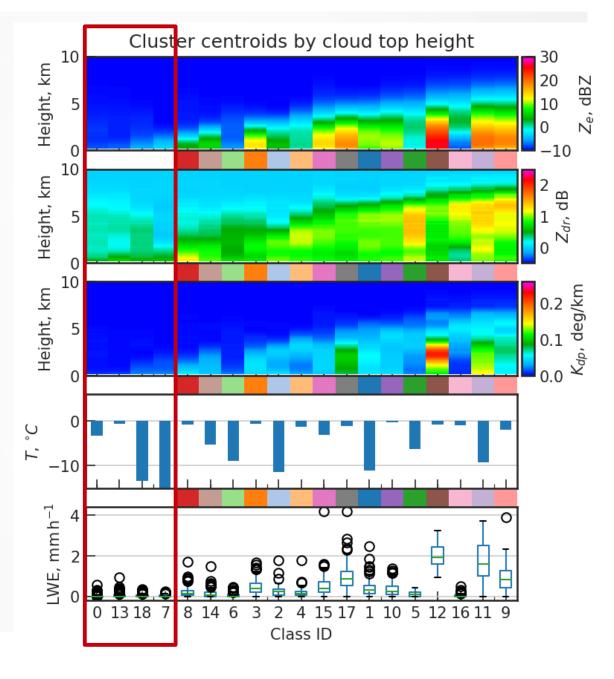
- Classification vs. prefactor of Z-S relation
- a_{zs} defined from 5 minute disdrometer observations assuming exponential PSD, using instantanious m(D) and v(D) relations (von Lerber et al. 2017)

$$Z_e = \alpha_{zs} S^{\beta_{zs}}$$





 Several classes may correspond to same growth processes

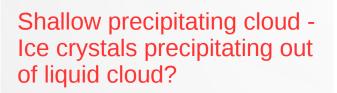


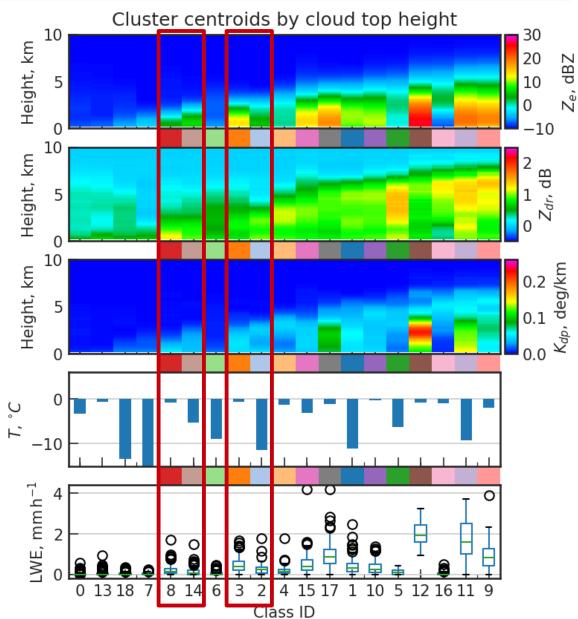
Non-precipitating classes

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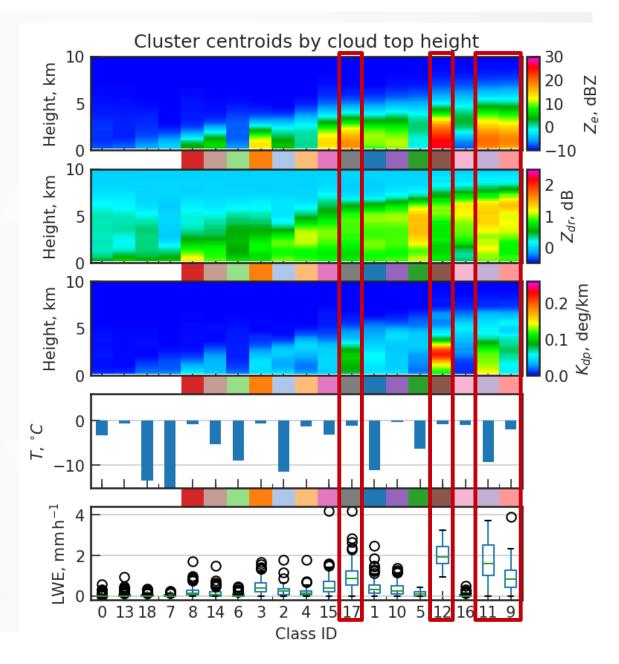




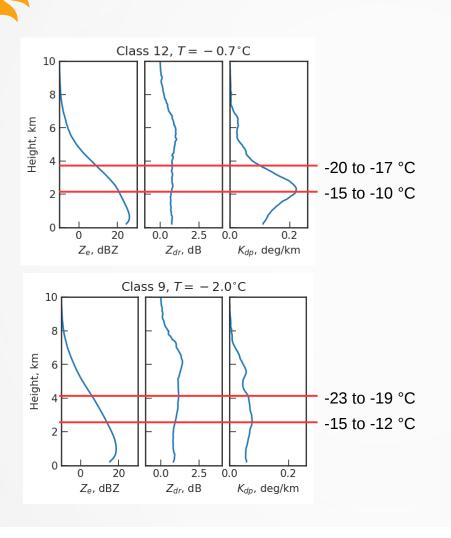


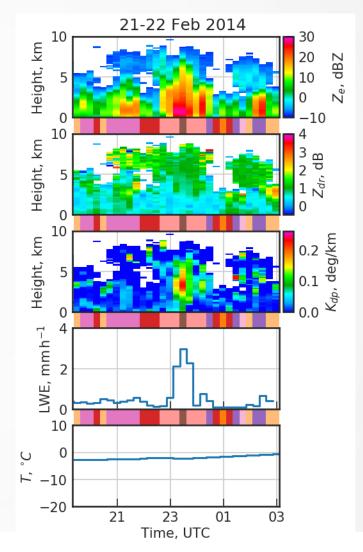
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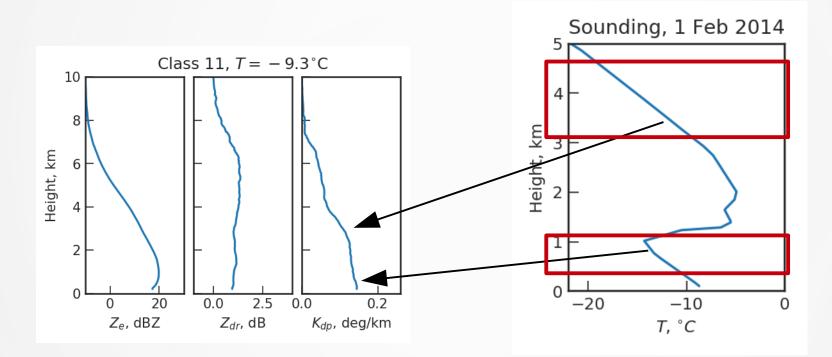
Dendritic growth: classes 12 & 9





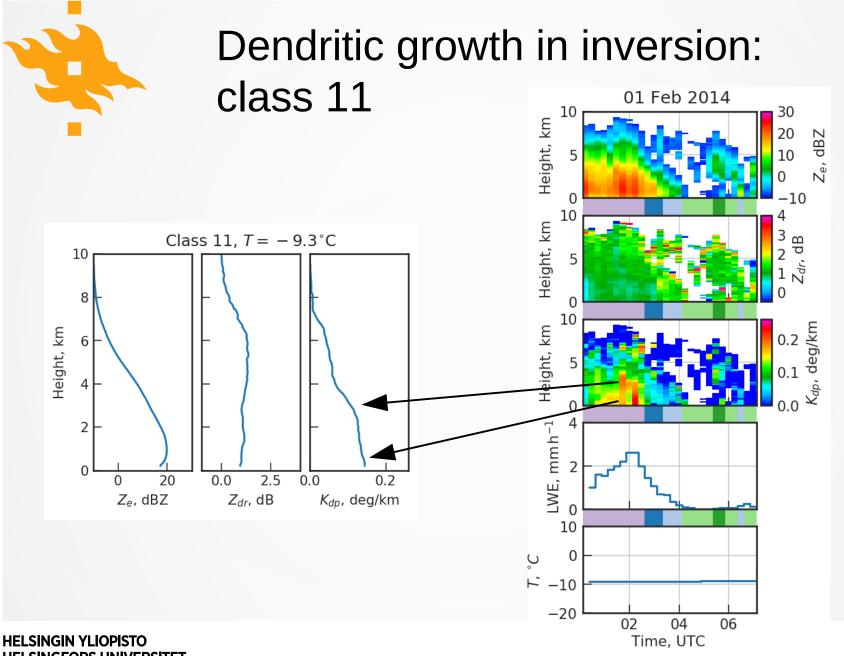


Dendritic growth in inversion: class 11



Blurred K_{dp} band caused by two growth layers

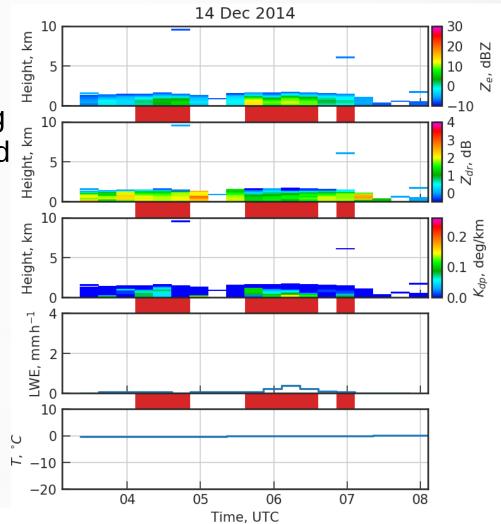
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Nimbostratus, class 8

- Ice crystals precipitating out of supercooled liquid cloud layer
- Shallow cloud, elevated Z_{dr} values
- Sounding shows saturation in respect to liquid





- The presented method that uses PCA and K-means produces profile classes with distinct, physically meaningful features
- Using the test data 19 classes were identified
- High K_{dp} classes are associated with increased snowfall rate
- Several classes could represent same growth processes and need to be combined
- Further study linking growth processes and profile classes is ongoing