Unsupervised Classification of Vertical Profiles of Dual-Polarization Radar Variables

Jussi Tiira and D. Moisseev
University of Helsinki, Finland

Photo
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

4. K-means **clustering** of the combination of PCA-reduced profiles and weighted $T$

5. **Output**: Profile classes defined by K-means centroids
Preprocessing

- 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
Data

- 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 instantaneous $m(D)$ 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
Several classes may correspond to same growth processes.

Shallow precipitating cloud - Ice crystals precipitating out of liquid cloud?
• Several classes may correspond to same growth processes

Classes with $K_{dp}$ bands – Dendritic growth zone?
Dendritic growth: classes 12 & 9

Class 12, $T = -0.7 \, ^\circ C$
-20 to -17 °C
-15 to -10 °C

Class 9, $T = -2.0 \, ^\circ C$
-23 to -19 °C
-15 to -12 °C
Dendritic growth in inversion: class 11

Blurred $K_{dp}$ band caused by two growth layers
Dendritic growth in inversion: class 11

Class 11, $T = -9.3^\circ C$

- $Z_e, \text{dBZ}$
- $Z_{dr}, \text{dB}$
- $K_{dp}, \text{deg/km}$

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- $Z_e, \text{dBZ}$
- $Z_{dr}, \text{dB}$
- $K_{dp}, \text{deg/km}$
- LWE, mm h$^{-1}$

$T, ^\circ C$

Time, UTC

02 04 06
Nimbostratus, class 8

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

- 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.