**P3.30**

# A SNOWFALL RATE ESTIMATE BASED ON THE SNOW TYPES

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## 1. INTRODUCTION

Weather radar observations of snow depend on size, shape, orientation and density of the snow particles. Variability in these physical properties is one of the major uncertainty sources in quantitative snowfall estimation with radar (Mitchell et al. 1990). The conventional radar based snowfall estimation methods have used power-law relations between the equivalent radar reflectivity (Z) and the liquid equivalent precipitation rate (S). These methods generally show wide variability owing to physical properties and behavior of snow. The variability of parameters in the *Z-S* relations can provide more than a factor of two difference in snowfall estimation (Sergey et al. 2009). The classification of winter precipitation according to hydrometeor classes such as aggregates, graupel and rimed particles can give guidance for refinement of snowfall estimate techniques.

A snowfall estimation based on the snow types (SEST) has been developed, which is using snow type identification to guide the choice of the particular parameters of power law relations of equivalent radar reflectivity factor–liquid equivalent snow rate. In this method, snow types are categorized as snow, aggregate, rimed snow and high density ice (graupel). Data collected from the C-band operational Helsinki Vantaa radar (VAN) and ground instruments (Vaisala PWD-11, Pluvio and WTX) are used to evaluate the performance of the proposed algorithm.

## 2. SNOW TYPE IDENTIFICATION

Snow types can be inferred from different spatial variability. Even though aggregates and rimed snow case have similar reflectivity values, spatial structures of the reflectivity fields are different. The reflectivity field observed during the riming case exhibits more spatial variability than aggregates case (Chandrasekar et al., 2011). In addition, graupel can be discriminated with higher reflectivity and spatial variability than other snow types. Using combination of spatial variability and reflectivity value, a snow type classification is established. Figure 1 demonstrates decision boundary for identification between various snow types. The dot's and asterisk's are data collected by the Helsinki Vantaa radar on 20100104 and 20100107, respectively. Note that the decision boundary of snow type can depend on characteristics of radar system such as sensitivity, beamwidth and sidelobe. Therefore the boundary may need adjustment for different radar system. Boundary in figure 1 is adjusted with comparing Helsinki Vantaa radar and ground instrument such as WTX.

The normalized standard deviation of Z (NSTD) is expressed as

$$NSTD(Z_k) = \frac{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(Z_{i,j} - Mean(\{Z\}_k))^2}}{Mean(\{Z\}_k)}; \qquad \{Z\}_k = \sum_{i=1}^{M}\sum_{j=1}^{N} Z_{i,j}$$

where a and b indicate the azimuth and range of the gate and M and N represent number of gates at azimuth and range, respectively.

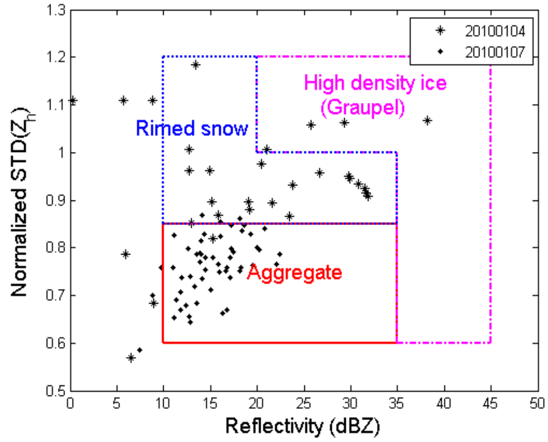


Figure 1. Snow type identification decision boundary in reflectivity versus normalized standard deviation of reflectivity. Asterisk's indicate data on 20100104 and dots on 20100107 from operational Helsinki Vantaa radar.

## 3. SNOWRATE ESTIMATE METHOD

Reflectivity and snowfall relations are expressed in terms of a power law:

$$Z_e = \alpha S^{\beta}$$

where $Z_e$ is the equivalent radar reflectivity factor in $mm^6m^{-3}$ and *S* is the snowfall rate (expressed as the liquid equivalent per unit volume) in $mmhr^{-1}$. The coefficients $\alpha$ and $\beta$ depend on environmental factors (temperature, humidity, wind speed) and microphysical properties (size, fall velocity, phase, and density).

The classification based radar snowfall estimation system is demonstrated in figure 2. First using the method described in section2, snow types are identified. Next select the parameters of Z-S relations according to classification results. Parameters of Z-S relations used here are shown in table 1. Note that these parameters adjusted for best agreement with ground instruments for these cases. Finally applying the selected parameters, snowfall rate is estimated.

Table 1. Parameters in Z - a$S^b$ relations

| Type | $Z_g = \alpha S^{\beta}$ | |
|---|---|---|
| | α | β |
| Snow | 170 | 1.5 |
| Aggregate | 78 | 1.2 |
| Rimed snow | 204 | 1.4 |
| High density snow (Graupel) | 12 | 3.8 |

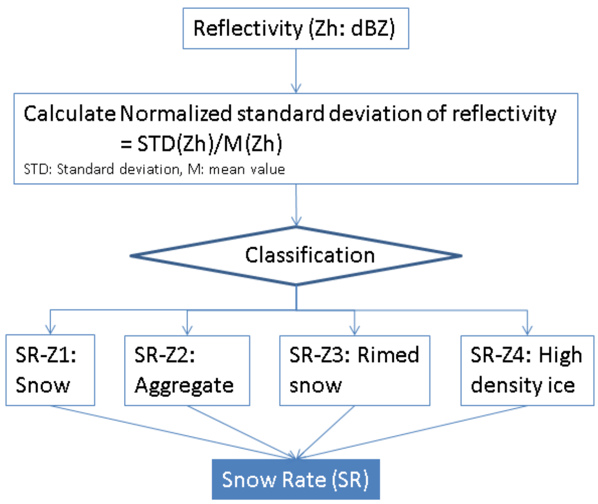


Figure 2. Block diagram of the classification based snowfall estimation system.

## 4. PRELIMINARY RESULTS

The proposed algorithm (SEST) has been tested by the operational C-band Helsinki Vantaa radar and ground instruments (Vaisala PWD-11 and Pluvio, which are located at the University of Helsinki Kumpula; WTX located at Hietaniemi cemetery). The WTX is capable of precipitation intensity measurements, as well as of identification between rain and hail. Two snow storm cases are studied. One is on 20100104 with graupel particles and the other is large scale snow storm from south-east in northerly surface winds on 20100107, respectively. Figure 3 shows the comparison between classification results by Vantaa radar observation and WTX on the 20100104 case. Figure 3(a) indicates Z and NSTD from Vantaa radar at the WTX site, whereas figure 3(b) is the classification result. Figure 3(c) and (d) are temperature and identification by WTX. From the comparison result of figure 3, we can see the classification results using spatial variability of radar reflectivity match well with classification from WTX, especially at high-density ice region. Rain from WTX can be more likely small high-density ice particles with low temperature corresponding to figure 3(c).

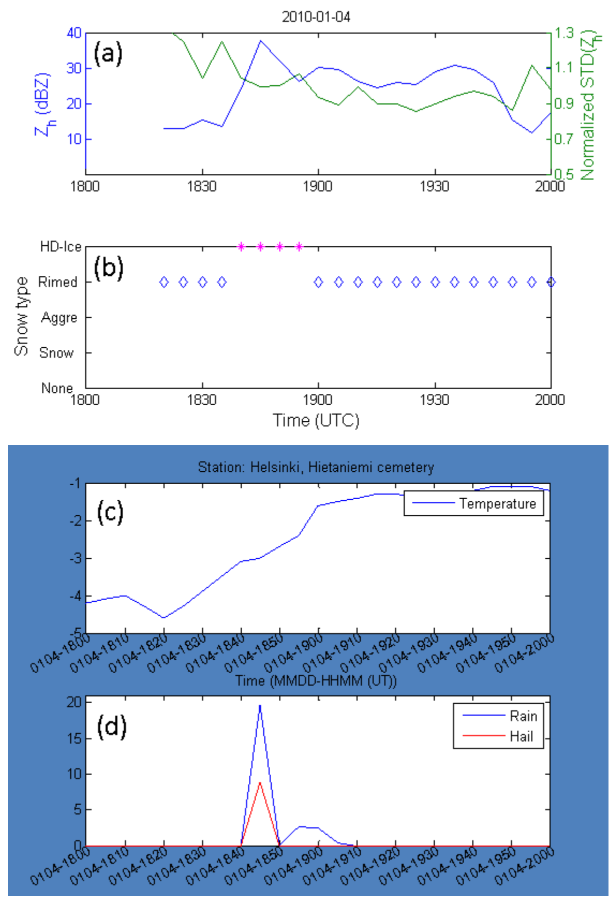


Figure 3. Comparison of classification from Helsinki Vantaa radar and WTX located on Hietaniemi cemetery, Helsinki. (a) Zh and normalized standard deviation of $Z_h$, (b) classification results by SEST from Vantaa radar, (c) temperature from WTX, (d) classification from WTX.

The results of snowfall rate estimation by the SEST have been compared with PWD-11 and Pluvio. For high-density ice case, Pluvio can give more accurate snowfall information than PWD-11 with a little delay time (say around 5 minute here). Figure 4 shows radar observation and comparison results of classification. Figure 4(a) indicates Z and NSTD from Vantaa radar at University of Helsinki Kumpula, whereas figure 4(b) is the classification result. Figure 4(c) depicts the comparison of snowfall rate from SEST, PWD-11 and Pluvio, and figure 4(d) and (e) show radar reflectivity plots at 1900 1940 UT on 20100104, respectively. Red circles indicate the location of the University of Helsinki Kumpula.

Results of case study for 20100107 are shown in figure 5. Figure 5(a) indicates Z and NSTD from Vantaa radar at University of Helsinki Kumpula, whereas figure 5(b) is the classification result. Figure 5(c) depicts snowfall rate from PWD-11 and Pluvio, whereas figure 5(d) shows snowfall rate from SEST. Figure 5(e) and (f) show radar reflectivity plots at 0810 and 1030 UT on 20100107, respectively. Red asterisks indicate the location of the University of Helsinki Kumpula. From the results of figure (4) and (5), we can see that classification based radar snowfall estimation agree well with ground instruments such as PWD-11 and Pluvio.

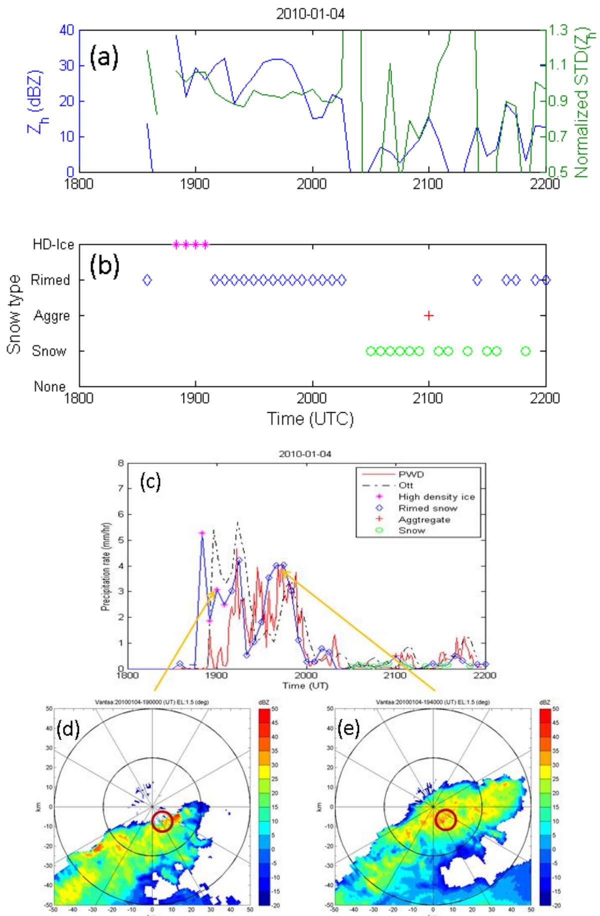


Figure 4. (a) Reflectivity and normalized standard deviation of reflectivity from Vantaa radar at University of Helsinki Kumpula, (b) classification result, (c) comparison of snowfall rate from SEST, PWD-11 and Pluvio, and radar reflectivity plots at (d) 1900 (e) 1940 UT on 20100104. Red circles indicate the location of the University of Helsinki Kumpula.

## 5. SUMMARY

A classification based snowfall algorithm has presented. The method uses snow type identification to guide the choice of the particular parameters of power law relations of equivalent radar reflectivity factor–liquid equivalent snow rate. This technique can reduce the errors in quantitative snowfall estimation due to various physical properties of snow. The proposed algorithm evaluated by using the C-band operational Helsinki Vantaa radar (VAN) and ground instruments (Vaisala PWD-11 and Pluvio). The preliminary results show that selective choice of power law parameters corresponding to snow types can provide more accurate snowfall estimation.

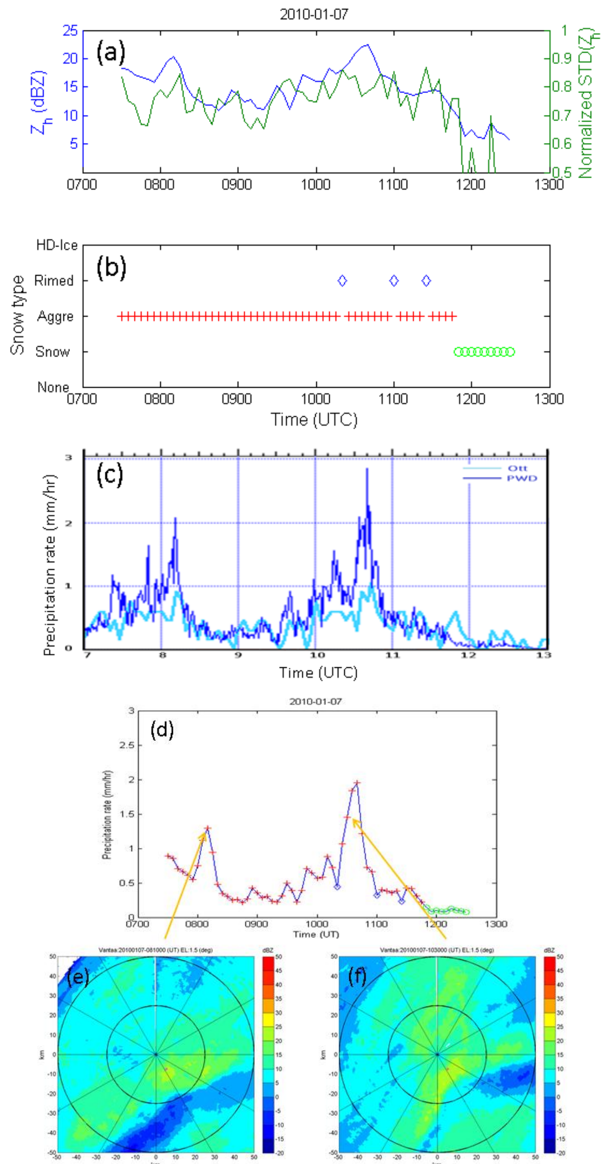


Figure 5. (a) Reflectivity and normalized standard deviation of reflectivity from Vantaa radar at University of Helsinki Kumpula, (b) classification result, snowfall rate from (c) PWD-11 and Pluvio, (d) from SEST and radar reflectivity plots at (d) 0810 (e) 1030 UT on 20100107. Red asterisks indicate location of University of Helsinki Kumpula.

## 6. ACKNOWLEDGEMENTS


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