P11.B11 REAL-TIME HYDROMETEOR CLASSIFICATION FOR THE OPERATIONAL FORECASTING ENVIRONMENT

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1. INTRODUCTION

Dual Polarization radar measurements of precipitation provide valuable information about the shape, size, orientation, phase state, and fall dynamics of hydrometeors. Characteristics of polarimetric signals from bulk hydrometeors and other scatterer types have been well documented within the research community. Utilizing this information for classification is a challenging mapping problem. Some of the classification techniques have often used a subset of polarimetric covariance matrix elements such as co-polar data measurements; some are specialized for hail identification. Initially, contours of Boolean logic equations were used to depict distinct populations of empirically identified hydrometeor classes in the parameter space. In the last decade, the fuzzy logic algorithms have proven successful, validated by in-situ observations (Liu and Chandrasekar 2000, Bringi and Chandrasekar 2001, Zrnić et al 2001, Lim et al. 2005, Baldini et al. 2005, Ryzhkov et al. 2005).

The fuzzy approach manages polarization diversity measurements that are available with varied levels of uncertainty. The procedure combines complementary knowledge from physical models, empirical information, and direct validation information – all which have value with acknowledged model uncertainties. The practical classification systems can be seen as a major outcome of the radar research community, and they have been applied to initial operational testing (Schuur et al 2003). Typically, these analyses have been constructed to consider data from full volume scans, which causes a delay of a volume scan time that is relevant in operational use.

In the fuzzy logic algorithms for radar echo classification, the input variables are first converted into membership functions (MBFs). MBFs quantify the degree of consistency between the polarimetric input variables. A low value (minimum 0) suggests the input variable has poor consistency with a class hypothesis, while a high value (maximum 1) indicates a good match. The membership sets are combined as expressions of rule strengths (RS). Each class is associated with a RS value that characterizes the overall consistency with inputs. The classification results are presented by labeling each bin with the hydrometeor class that is most compatible with the observations, i.e. by choosing the class of highest rule strength (defuzzification). Quality is controlled by imposing minimum thresholds for acceptable RS. The fuzzification into MBFs, the RS function inferences and defuzzification output formalize the meteorological interpretation encoded in the classification system. The algorithms are specified by the set of MBF and RS function parameters and thresholds, which can be customized for particular climates and application uses.

Polarimetric weather radars are becoming standard in operational nationwide networks, and commercial uses are emerging in the U.S television market. These call for general purpose hydrometeor classification techniques, which are robust, tunable, and output a compact set of hydrometeor classifications, promptly available in the rapidly developing environment. We chose to adapt the Lim et al. 2005 technique, hereafter known as the CSU classifier, which was configured to process co-polar variables available in the simultaneous transmission and reception mode of dual polarization. The method uses both additive and product rules in inference, which maximizes the degree of correct classifications and minimizes the degree of error.

Conceptually, the CSU classifier considers meteorological echoes in a smoothed, quality controlled data cube, while our implementation runs gate by gate on ray data. This motivates additional quality considerations. A fuzzy classification scheme for meteorological vs. non-meteorological targets evaluated in the Joint Polarization Experiment (JPOLE) (Schuur et al 2003) suited well as a quality enhancement tool, in combination with the quality control criteria of Doppler signal processing. In the preferred mode of operation the

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range gate data that are subject to signal processing thresholds are first passed to the JPOLE pre-classifier. Bins classified as precipitation are forwarded to the CSU classifier for consideration of the precipitation class. As net outcome, if Z_h has been thresholded by the signal processor at any given range bin the classification as precipitation is excluded. If Z_h is available but Z_{dr}, K_{dp}, and ρ_{hv} are all thresholded, classification is also excluded. In all other cases of input combinations, and outputs passing the RS thresholds, the result is a definite hydrometeor class. Figure 1 shows the processing steps of the overall implementation.

These classification techniques have been adapted to run within a signal processor using only one radial of input at any given moment. The classification can then be treated as a data type sent 'real-time' to a product generator along with the traditional polarimetric and Doppler moments. The radial approach implies that viable hydrometeor classifications could be available to a forecaster every 20 seconds (3 RPMs) compared to down-stream volume analysis which may have latencies from 5-15 minutes. The equivalent functionalities are implemented for processing archived radar data, which allows evaluation and optimization studies. We believe this is the first use of a hydrometeor classification algorithm within a signal processor.

2. THE PRE-CLASSIFIER

The first processing step in our adaptation is called the pre-classifier and is similar to that of Schuur et al (2003). Five radar variables are used to classify the data in the range bins as Ground Clutter / Anomalous Propagation, biological targets, or hydrometeor scatterers. The variables are horizontal reflectivity Z_h, differential reflectivity Z_{DR}, co-polar correlation coefficient ρ_{hv}, texture variables of the Z_h field $TX(Z_h)$, and of differential phase $TX(\Phi_{dp})$.

The textures are useful in separating meteorological echoes from other signals. These signatures are found to be general over various radar wavelengths. The other input variables characterize general features of precipitation, with reduced dependency on radar parameters. These aspects justify our convention to use the reference parameter settings for C-band, originally evaluated at S-band wavelength. For varied climatic regimes and applications, this approach is simple enough to allow adjustments, for example to improve sensitivity to weaker echoes.

3. THE HYDROMETEOR CLASSIFIER

The CSU classifier was developed using radar measurements from the CSU-CHILL radar which is an S-band, Doppler radar with full polarization agility and diversity at Colorado State University. The referenced classification system represents state-of-the-art knowledge and it has been verified by comparing the CSU-CHILL measurements with in-situ airborne observations made with instruments such as a 2-D cloud particle measurement probe, high volume particle sampler (HVPS) and hail spectrometer (Liu and Chandrasekar 2001 and Lim et al. 2005).

The reference CSU classifier characterized MBFs for eleven classes, while the results were interpreted in the scheme of nine final output classes. Reducing the number of classifications is useful when data is being used for operational forecasting purposes. The CSU classifier system was modified to have five output classifications namely: rain, wet snow, dry snow, graupel/small hail, and large hail. We believe these five classes will provide operational users with the needed hydrometeor types without causing information overload. A sixth category of 'rain and hail' is used internally to characterize mixture of these hydrometeors in a realistic fashion. However, as the design is intended for operational users, this 'rain and hail' class is merged into the final output classification of hail.

The existing CSU MBFs and rule strength coefficients were optimized for C-band weather radars operating in the simultaneous H/V transmit mode for these five output classes. Data samples of summer convection, winter storms, and stratiform frontal precipitation from the University of Helsinki research radar (Puhakka et al 2006) were used in the optimization. Data from other dual-polarized C-band weather radars were then processed for evaluation and the results are presented in section 4.

Depending on seasonal change it is appropriate to use different MBFs and rule strength to correctly identify the bulk hydrometeors. A set of 'warm season' MBFs and rule strength coefficients are used when the melting level (ML) has a positive value. During periods when the large scale melting layer may be absent, ML < 0, the MBF for height, rain, and wet snow change along with a different set of rule strength coefficients. However liquid forms of precipitation are not excluded during the 'cold season' (warm fronts, freezing rain) and significant convection may also occur in the 'cold season' producing heavy solid hydrometeors (hail). The ML height is taken from outside sources and fed to the signal processor.

This classification implementation has run smoothly in real-time with up to 2000 bins per radial while continuing to perform all of the other functions of the signal processor. The output delay of a radial while running this hydrometeor classification is in the order of 10's of microseconds. The primary product generator application may then apply a consensus smoothing algorithm or produce volumetric data products from the hydrometeor classification data type.

4. RESULTS

Hydrometeor classification data from the University of Helsinki research radar during a stratiform precipitation event with a ML height of 1600 m appear in figure 2. Rain precipitation types appear at the lower altitudes near the radar. As the beam propagates into the melting layer the algorithm starts to classify hydrometeors as wet snow. Above the melting layer dry snow hydrometeor type becomes dominant. At the higher elevation angle the same effects are seen but now this transition happens closer to the radar as the beam gain altitude faster. These classifications seem to fit our current understanding of the general structure of hydrometeors in a vertical column.

The University of Helsinki research radar was used for testing the pre-classifier's ability to distinguish between meteorological and other targets at the C-band wavelength. Data was acquired during a convective event without using spectral clutter filters and minimal thresholding. These scan parameters allowed for a large amount of non-meteorological targets, such as ground and sea clutter, radio frequency interference, birds, and ships within the data set. The polarimetric variables of this scan can be seen in figure 3. A large majority of the non-meteorological data has been identified and is labeled as 'non-met' in figure 4. The convective storms over Estonia are correctly identified as meteorological targets. Areas of anomalous propagation from the coastline of Estonia is mistakenly identified as meteorological. It is expected the use of spectral clutter filters would have reduced the number of these bins missed identified by the pre-classifier.

The hydrometeor classification algorithm was tested with data sets from different radars and climatology's from that of the University of Helsinki research radar. This testing attempts to quantify if the optimization of C-band MBFs and rule strengths using data from specific radars can be applied to other sites. Note that the algorithm is not running within the signal processor during these events. We have used the raw radial data as input to the classification.

Radar observations from the University of Huntsville ARMOR radar (Petersen et al 2005) during the 21 February 2005 hailstorm event discussed in Baldini et al 2005 are also evaluated. Data was acquired without ground clutter filtering and minimal thresholding which allows us to test both the quality control measures of the pre-classifier and the hydrometeor identification system. Figure 5 shows Z_h, Z_{dr}, ρ_{hv}, and K_{dp} for this event. Ground clutter can be seen extending to a distance of ~25 km in all directions around the radar. Precipitating storms are also within this ground clutter coverage which is implied from the ρ_{hv} data. Figure 6 shows the results of the classifications. The identified non-meteorological range bins have been thresholded from the output. The precipitation within the ground clutter has been identified as 'rain'. Performing hydrometeor classification in real time does not prevent volumetric products from being produced later in the processing chain. Figure 7 is a cross section through the strongest convective storms 60 km east of the radar.

Initial ground verification has been conducted using public severe storm reports. Data acquired by the University of North Dakota's Polarimetric Doppler Weather Radar during the evening of 11 May 2004 was processed and compared to severe storm reports obtained from the Storm Prediction Center. This data appears in figure 8. Again clutter filtering and data thresholding within the signal processor were not in use during the event. The pre-classifier has been fairly successful in identifying and eliminating non-meteorological bins. Ground clutter is mostly removed while second trip echo 'meteorological' bins remain processed by the by the classifier. Hail reports within ±15 minutes of the scan are plotted. The hydrometeor classification successfully identifies areas of hail for all locations of severe hail reports. The hail shaft southeast of the 0045Z report moves across the location during the 0040Z scan (not shown). A few other areas of possible hail were also identified but not positively verified.

Figure 9 shows data collected at 0935Z and 1125Z by the University of Helsinki research radar on 15 May 2006. Hail and graupel are identified in the lowest elevation angle at only 13 km distance from the radar. It is assumed this radar sample volume would be representative of the hydrometeor particles at the surface. Two frozen precipitation events were reported at the location of the '+' by an amateur observer. These PPI's correspond to the reported times of frozen precipitation. The observer's photographs of the hydrometeor particles during this event are shown in figure 10.

5. Summary and CONCLUSIONS

We have successfully implemented a hydrometeor classification system using polarimetric variables in radial polar coordinates. This allows classification in real-time. The parameters were optimized at one C band radar facility and successfully operated at other radar sites. Removing the non-meteorological echoes is very useful and adds value to the products further down the processing chain. The algorithm has also proven to be robust as it has been in continuous use for more than a year at two different sites.

6. ACKNOWLEDGEMENTS

We would like to acknowledge Dr. Walt Peterson and the University of Alabama-Huntsville ARMOR radar and the University of Helsinki for providing data for algorithm development and radar resources for testing real-time operations. Thanks to the University of North Dakota for providing additional data for testing purposes. Finally, thanks to Dr. Richard Passarelli for providing the insight to apply this technique within the signal processor.

Real time imagery of this hydrometeor classification technique used within a signal processor may be viewed at the ARMOR website: http://www.nsstc.uah.edu/ARMOR/webimage/.

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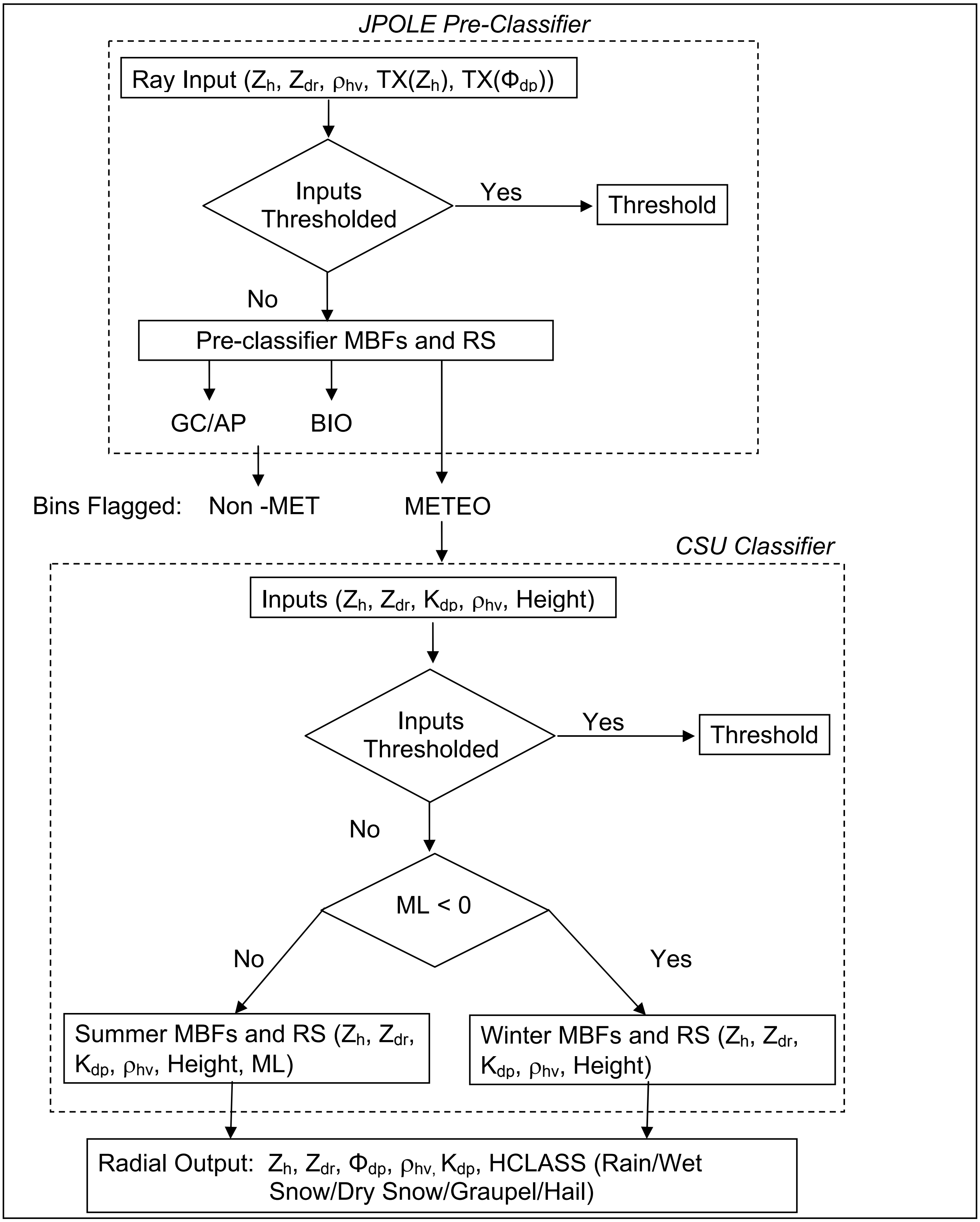
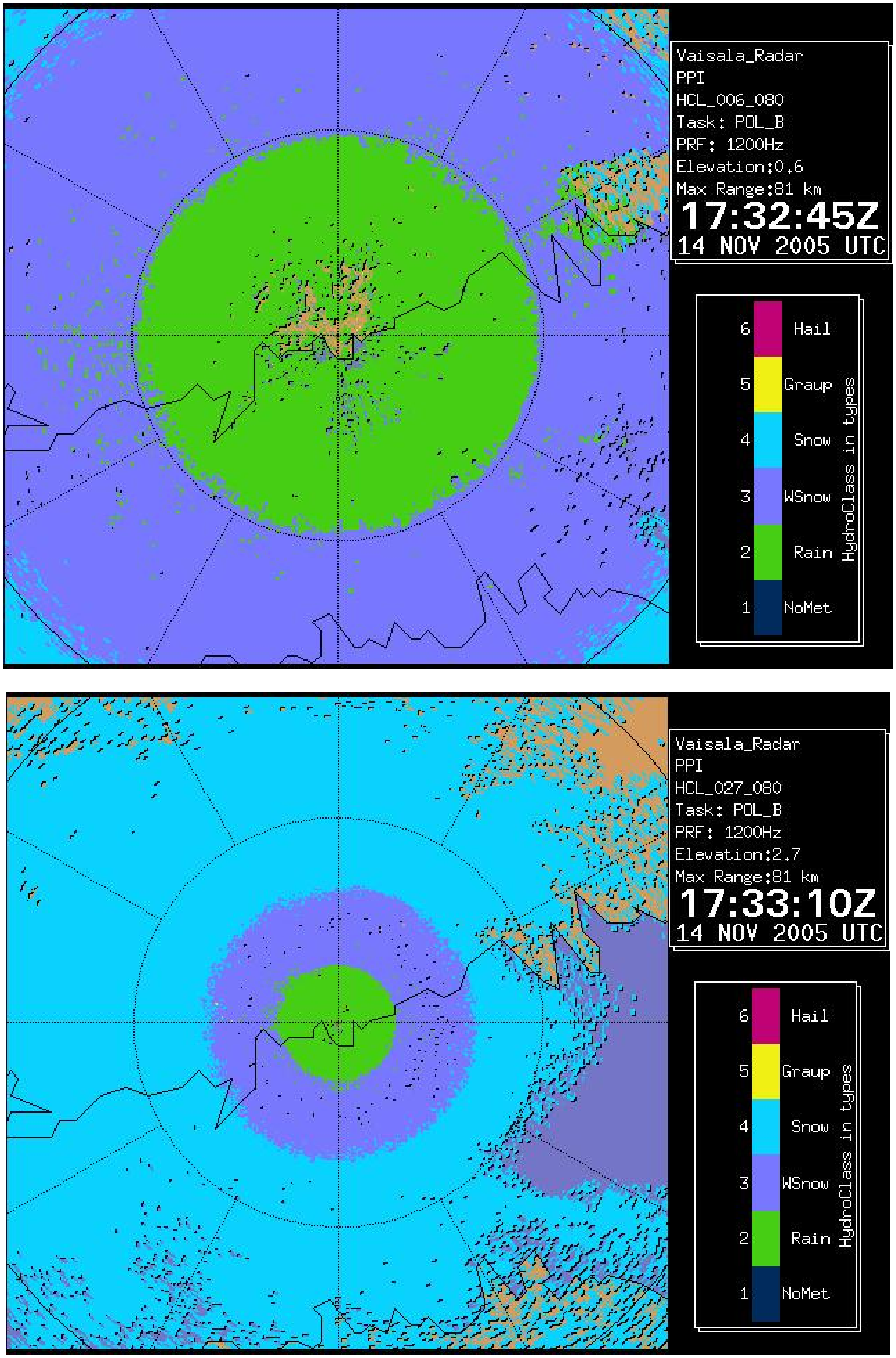


Figure 1. **Hydrometeor classification processing steps within the signal processor.**

(a)



(b)

Figure 2. Hydrometeor classification of 0.6 (a) and 2.7 (b) degree elevation PPI scans.

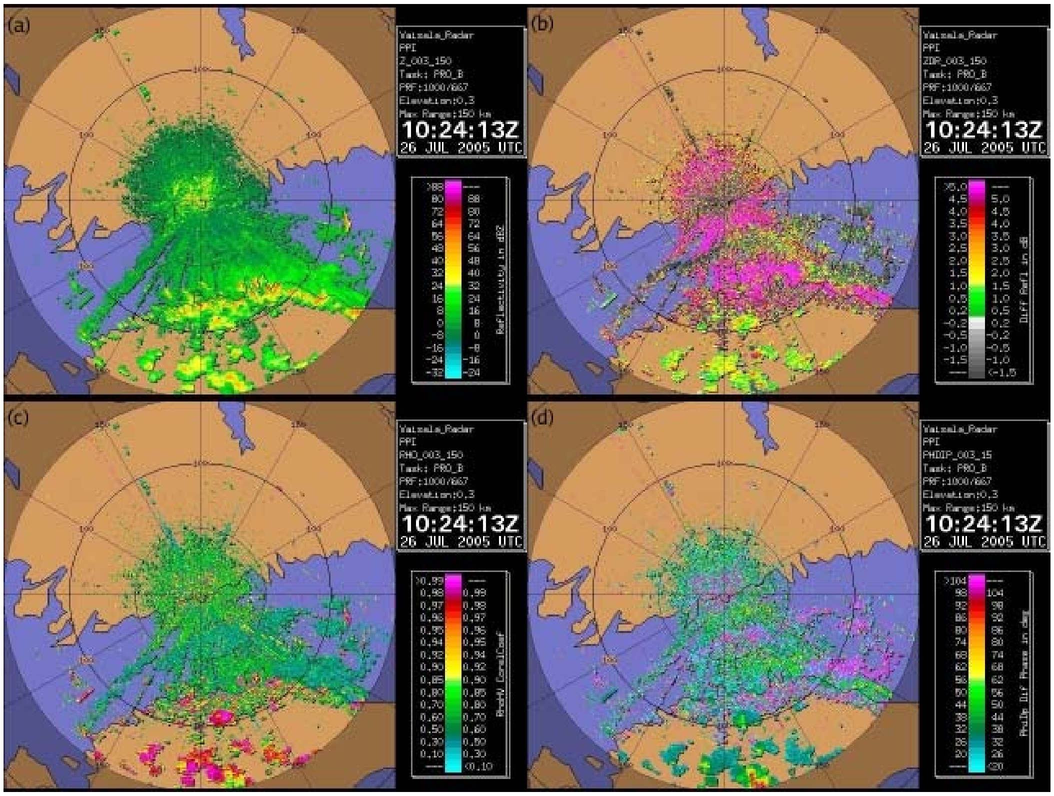


Figure 3. **0.3 degree elevation PPI scans of Z_h (a), Z_{dr} (b), ρ_{HV} (c), and Φ_{dp} (d) from University of Helsinki weather radar illustrating data artifacts.**

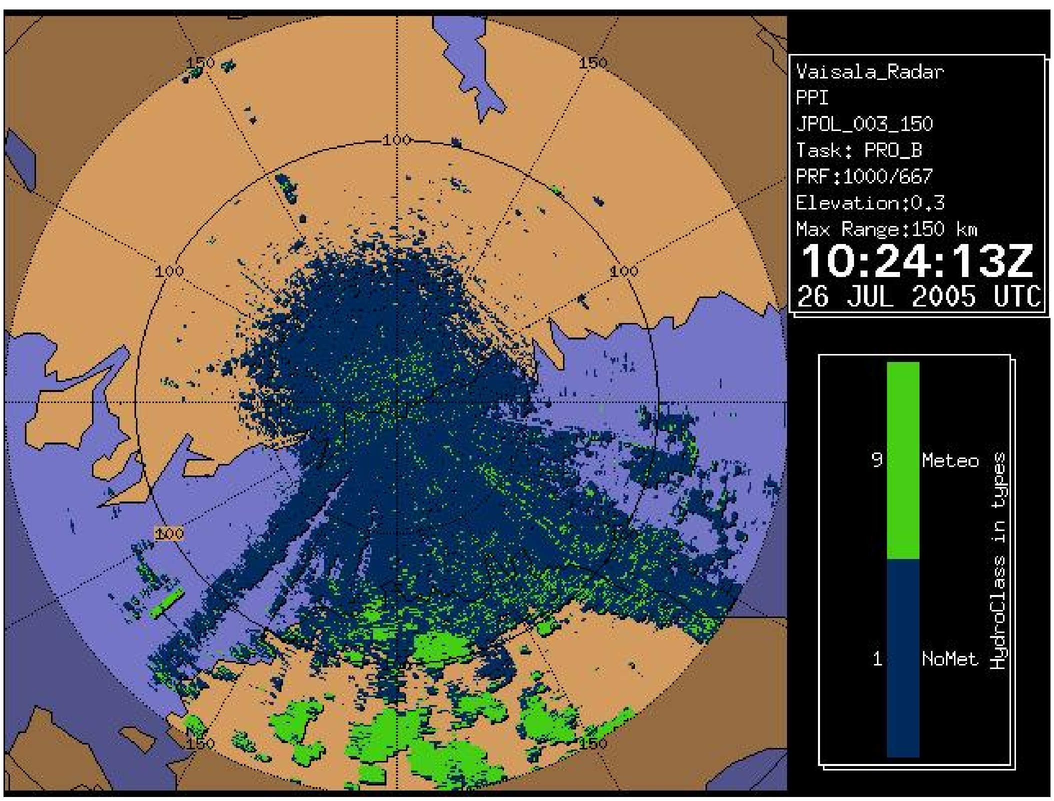


Figure 4. **0.3 degree elevation PPI scans showing results of JPLE pre-classifier using data from figure 3.**

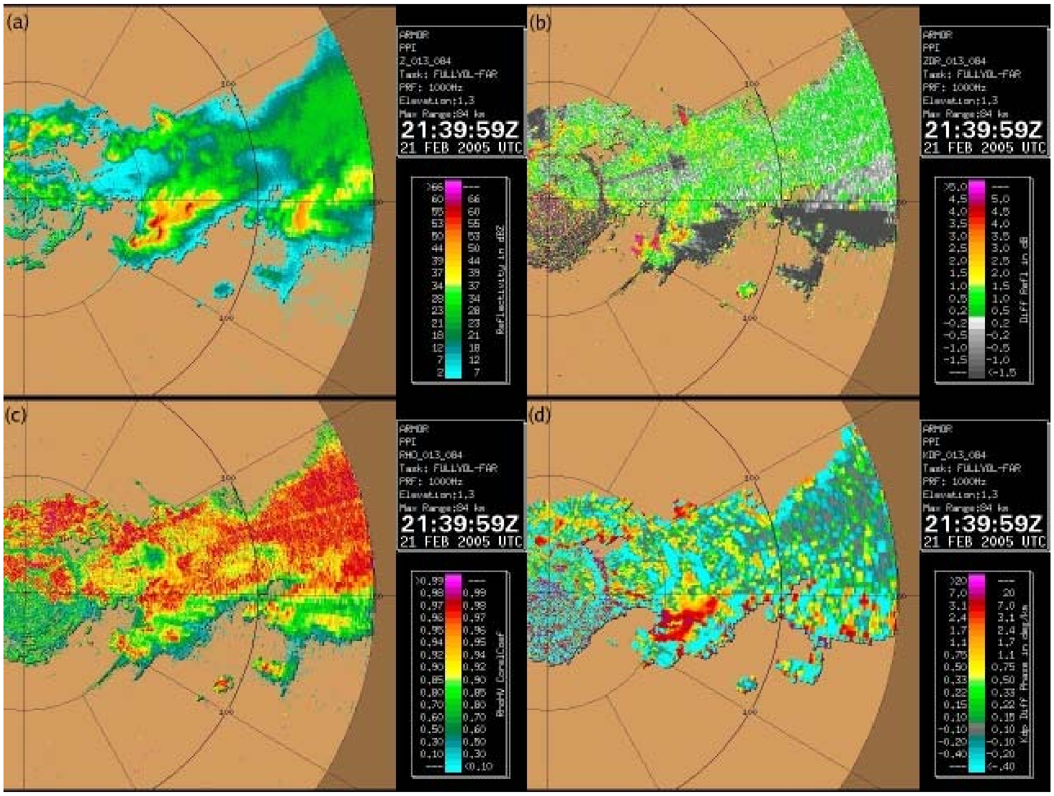


Figure 5. **1.3 degree elevation PPI scans of Z_h (a), Z_{dr} (b), ρ_{HV} (c), and K_{dp} (d) from ARMOR volume scan on 21 February 2005.**

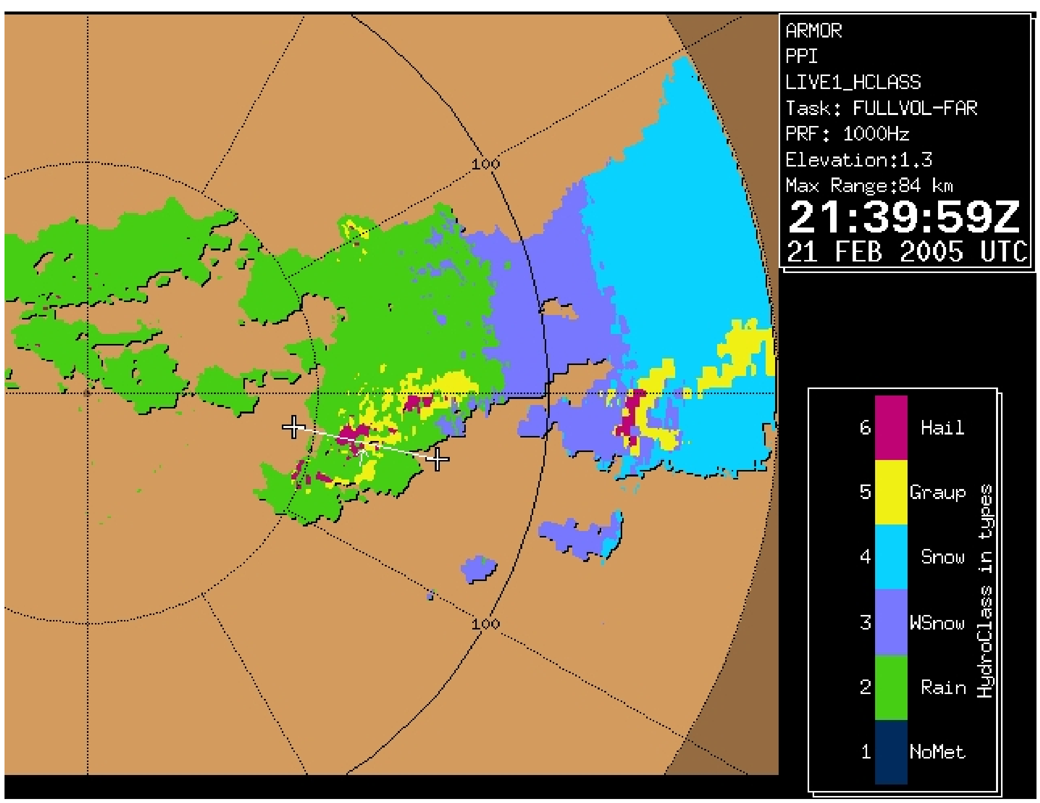


Figure 6. **1.3 degree elevation PPI scans of hydrometeor classification data from ARMOR volume scan on 21 February 2005. Location of cross-section in figure 7 shown.**

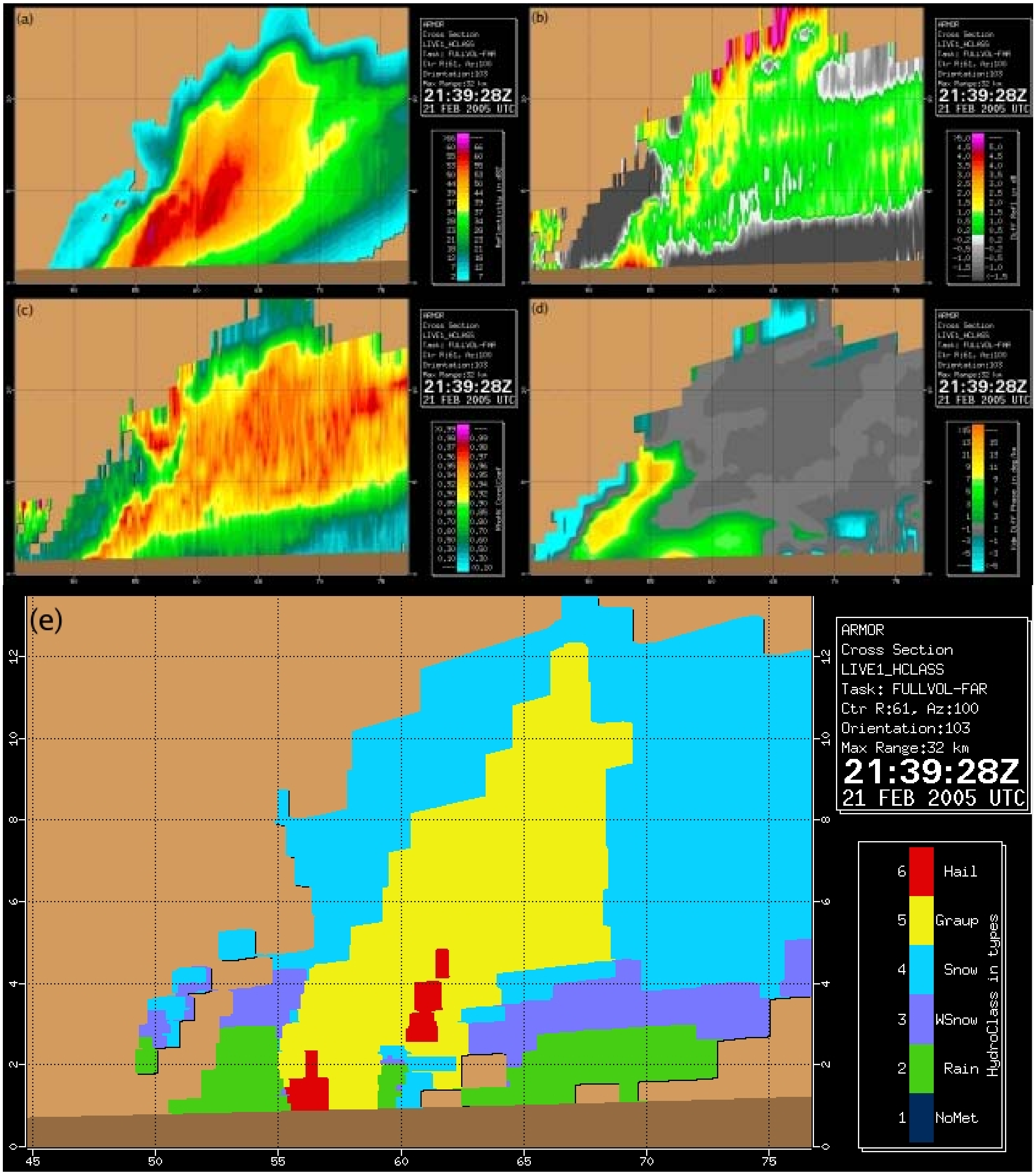
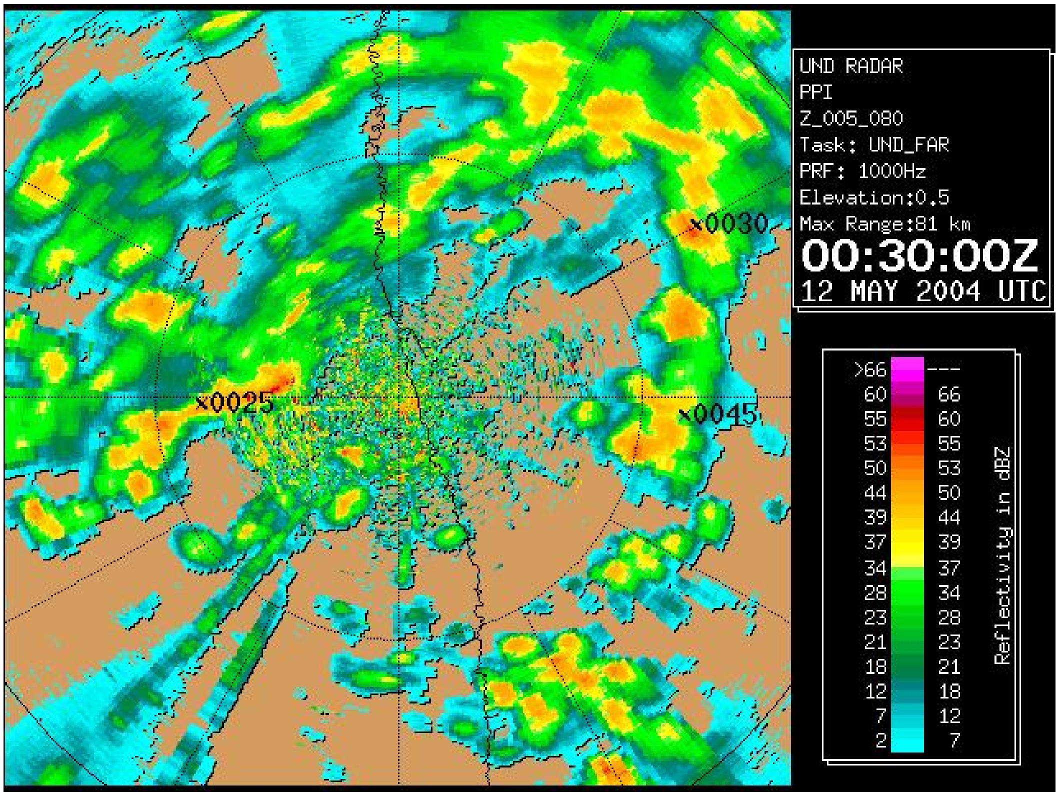


Figure 7. **Cross-section of Z_h (a), Z_{dr} (b), ρ_{HV} (c), K_{dp} (d), and hydrometeor classification (e) from ARMOR volume scan on 21 February 2005.**

(a)



(b)

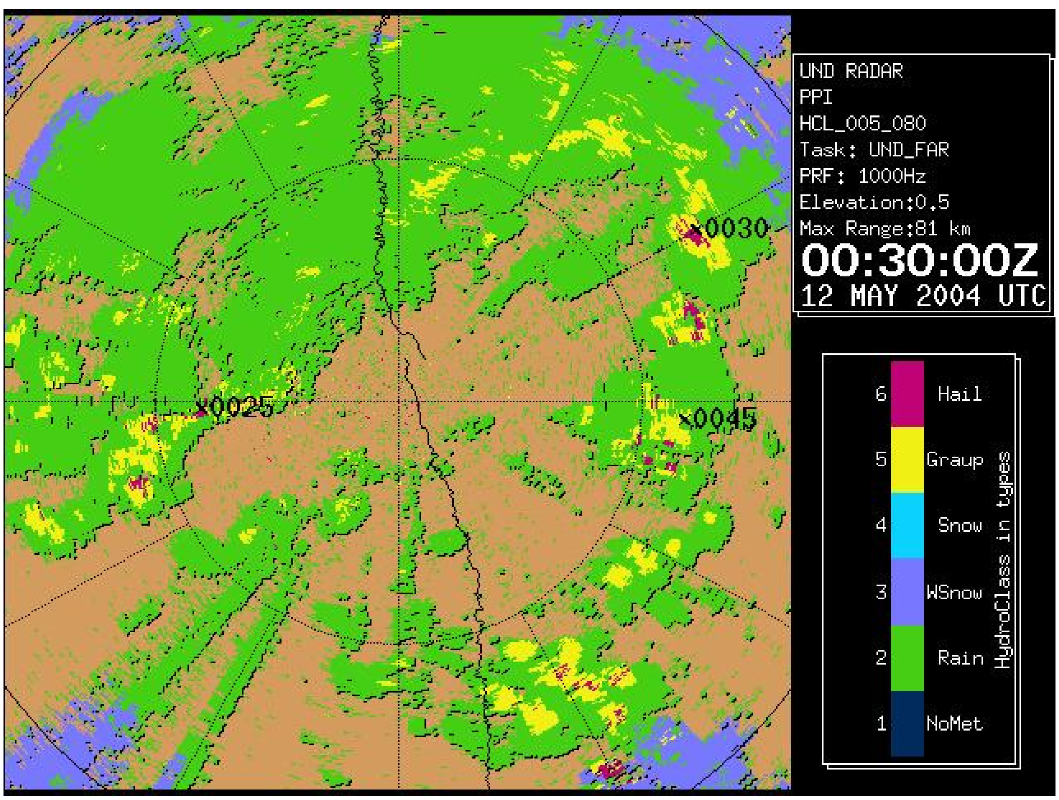


Figure 8. **Z_h (a) and hydrometeor classification (b) bin data from UND Radar at 0030Z 12 May 2004. Time and locations of severe hail reports within 15 minutes of volume time are plotted with the 'x' symbol. Hail locations taken from NCDC Storm archives.**

(a)

(b)

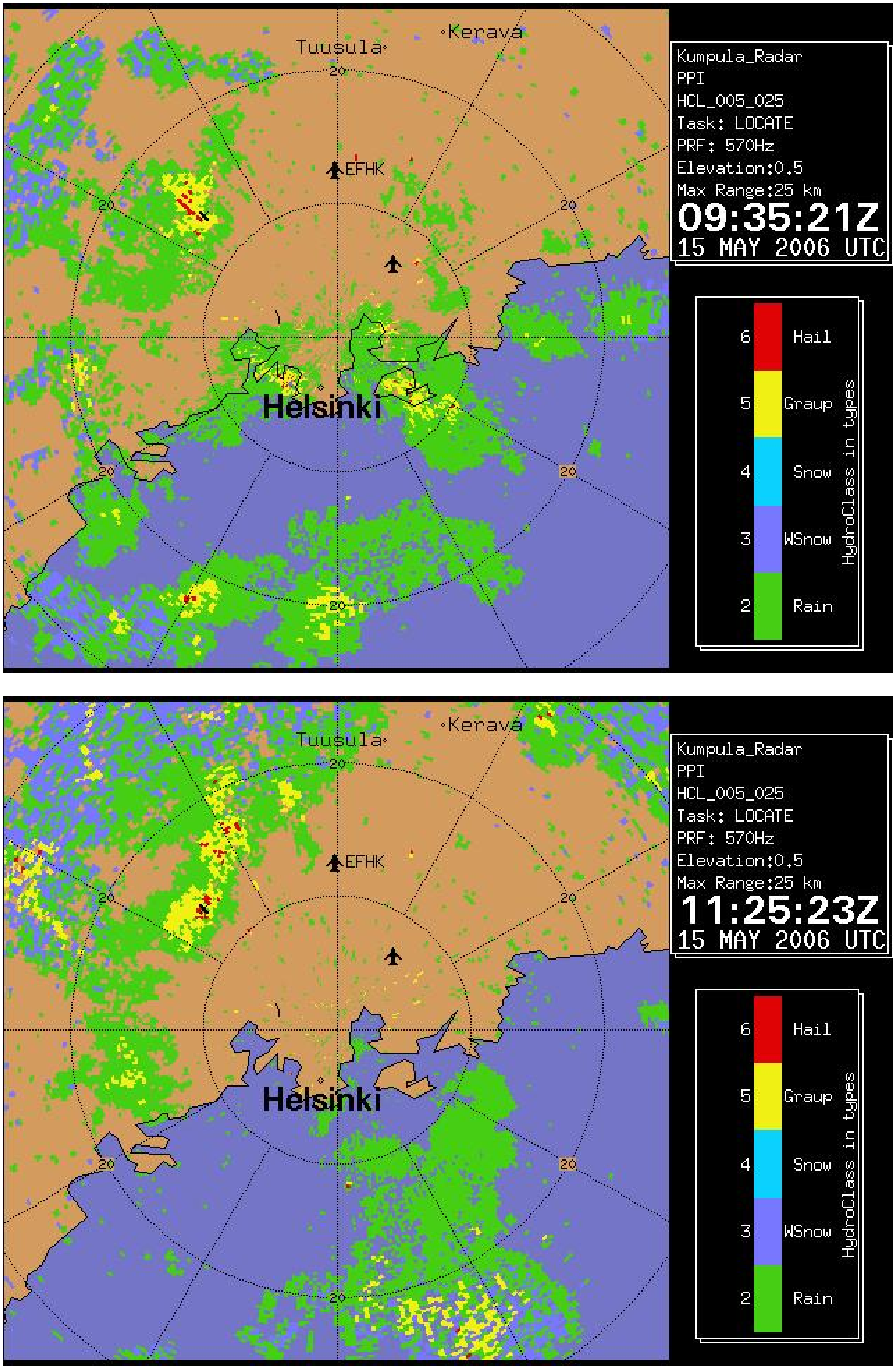


Figure 9. **Hydrometeor classification bin data from University of Helsinki research radar at 0935Z (a) and 1125Z (b) 15 May 2006. Location of '+' symbol 13 km northwest of radar site is location of photos in Figure 10.**

Figure 10. **Photos courtesy of Petri Nurkka-Tuorila**