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UNCERTAINTY ANALYSES OF THE OPERATIONAL WSR-88D HYDROMETEOR CLASSIFICATION PRODUCT

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1. INTRODUCTION

In the United States, the weather surveillance radar 1988 Doppler (WSR-88D, or "NEXRAD") network has finished upgrade with the dual polarization capability. The advantages of the new capability include improved hail detection for severe thunderstorm warning, improved rainfall estimation for flood and flash flood warning, rain/snow discrimination for winter weather warning and advisories, data retrieval from areas of partial beam blockage to improve services in mountainous terrain, and improved data quality for algorithms, numerical model input as well as for aviation weather needs (Smalley 2008). In the applications of dual polarization radars, the hydrometeor classification (HC) stands in a key position because the identification of hydrometeor properties such as phase state, shape, fall behavior is directly related and supportive to all the benefits brought with dual polarization capability.

As early as year 1993, the fuzzy logic method was introduced in the polarimetric classification algorithm (Straka and Zrnic 1993). During the past two decades, many weather radar scientists (Zrnic and Ryzhkov 1999; Liu and Chandrasekar 2000; Zrnic et al. 2001; Lim et al. 2005; Marzano et al. 2008; Park et al. 2009, and etc.) have been showing their interests in exploring the refinement of the classification routines to obtain a mature identification algorithm with robust performance. The hydrometeor classification algorithm (HCA) (Park et al. 2009) currently implemented in WSR-88Ds is developed by National Severe Storms Laboratory (NSSL) (Porter et al 2011). This HCA utilizes six polarimetric variables and it is able to discriminate between 10 different classes including light/moderate rain (RA), heavy rain (HR), hail possibly mixed with rain (RH), big drop (BD), wet snow (WS), dry snow (DS), graupel (GR), ice crystals (IC), biological scatterers (BI), and ground clutter/anomalous propagation (GC/AP). Some of these classes have similar polarimetric characteristics, which lead to uncertainty in the class assignment. This study is to analyze uncertainties associated with various hydrometeor categories in the HCA. A confidence index was developed for each HC decision through statistical analyses.

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2. UNCERTAINTY OF THE HCA DECISION

The fuzzy logic method is used as the base in the operational HCA, where the fuzzy logic membership function and weights are subjective and/or empirical based on case studies and researches.

In Park et al. (2009)'s algorithm, the classification scheme defines a quantified membership function for each polarimetric variable and a given hydrometeor category based on the variable's characteristic associated with the hydrometeor, The membership functions for a particular hydrometeor class from all variables are then combined and the aggregated value characterizes the likelihood that this particular class. The class with the highest aggregation score (A1) is assigned as the final HC product for each radar data bin. Figure 1 shows an example of the HC outputs and their associated aggregation scores. It can be observed that the majority category of this precipitation event—RA has an overall high A1-score in the region close to radar KICT, and the score has a minor decrease in the north and south small area regions. The WS and GR in the west region obtain a lower A1-score than the RA; the locations that are classified as RH and BD are associated with a relative low A1-score. Does a higher A1-score always represent a better quality of the HC product? Not necessary. It is because we still have to consider another influence factor in the aggregation step: the score competing.

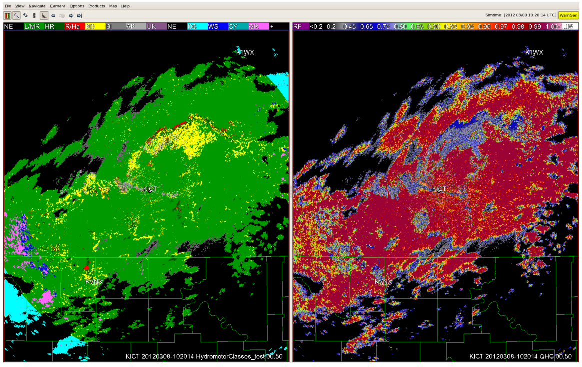
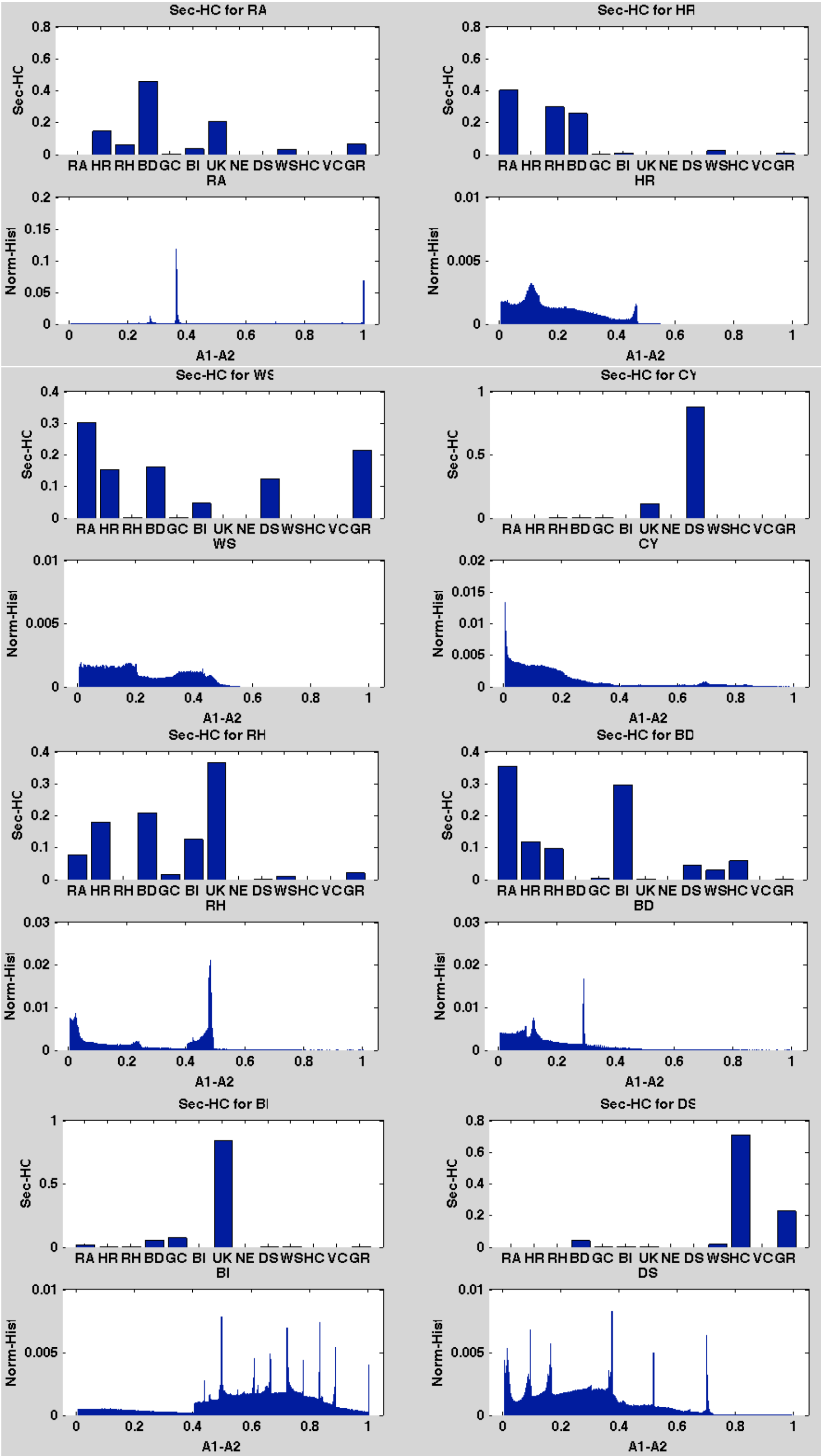


Figure 1. The field of the hydrometeor classification derived by radar KICT (left) and the associated map of aggregation factor (right). The data is valid for a scan at the elevation angle of 0.5 degrees at 10:20:14 UTC on 8 Mar. 2012.

The ten pre-defined hydrometeor or non-hydrometeor species are based on the previous theoretical and experimental understanding of dual-pol radar characteristics. Some of these classes have overlapping polarimetric characteristics, thus the aggregation scores of those classes could be close in certain aspects. The final HC product only takes the most likely category with the highest aggregation score, even though the top two (or more) most-likely classes could be very competitive and thus affects the confidence of the algorithm decision. Figure 2 shows statistic results of the competitive categories with two highest aggregation scores for each class during a precipitation event (at 06:00-06:59 UTC on 3 Mar. 2012) observed by KFFC, where volume scan pattern (VCP) 212 was applied. In every radar bin, the aggregation value of each of the hydrometeor specie is calculated, and then a class with the highest score is assigned. The HC decision that is associated with the highest A1 score and the 2^{nd} candidate HC type with the second highest (A2) scores in this process are recorded for each bin to enter the statistic database in every volume scan. Figure 2 includes the probability distributions of the 2^{nd} candidate HC type, as well as the relative frequencies of the difference between A1 and A2 in the class designation (A1-A2). The histograms are normalized with the total number of data integration as 1. For each HC type, the top panel shows the frequencies of the 2^{nd} candidate HC types; the bottom panel is the normalized histogram of the level of competition, difference between A1 and A2. For example, in the designation of class RA, the 2^{nd} candidate hydrometeor types could be HR, RH, BD, BI, UK, WS, and GR, among which the most competitive type is BD that takes approximate one half of all the RA cases. On the other hand, the lower panel shows that the level of competition is relatively low since the values of A1-A2 are generally high. When the histograms for the class of BI are observed closely, it is noticed that one special candidate class UK takes more than 80 percentages of the total cases. The UK candidate represents the situation that the aggregation scores (A-scores) for all the classes are zero except the designated class (i.e. BI for this case), and no competition in the class designation. During the calculation of the A-scores and class designation in the HCA algorithm (Park et al., 2009), the A-scores of some classification are zeros when the dual-pol variables fall out of the possible range of this hydrometeor types. At the same time, zero A-scores also happen when the empirical hard thresholds are used to suppress apparently wrong designations. For example, the class of BI is suppressed when RhoHV is larger than 0.97, it is impossible for the class of DS if Zdr is larger than 2dB, and etc. Therefore, the UK candidate class represents there is no competition in the class decision.

The histogram plots of A1-A2 show that some species are identified with more confidence than others from the statistical aspect, because their A1-scores are significantly higher than the 2^{nd} candidates and the competition is low. For example, most of RA pixels have A1 scores close to 1, among more than $3.5\text{x}10^{6}$ samples. The large difference between A1 and A2 provides a relatively high confidence and certainty for the classification of RA. Similarly, the relative large values of A1-A2 prove high certainty in the class assignments of BI. Based on the information from Figure 2, Figure 3 is provided to clearly show the relations between the designated HC types and candidate classes. There are eleven circled classes including ten testing hydrometeor types and the UK class. Except for UK and GC, each of the classes sends out two single-ended arrows pointing to a couple of the most possible candidates. Because the majority (93%) of the 2^{nd} candidate class is BI in GC designation, only one single-ended arrow is started from the GC. In this figure, the red double-ended arrows are used to highlight the mutual relation when the two classes show up in each other's candidate list correspondingly.


Sec-HC for RA
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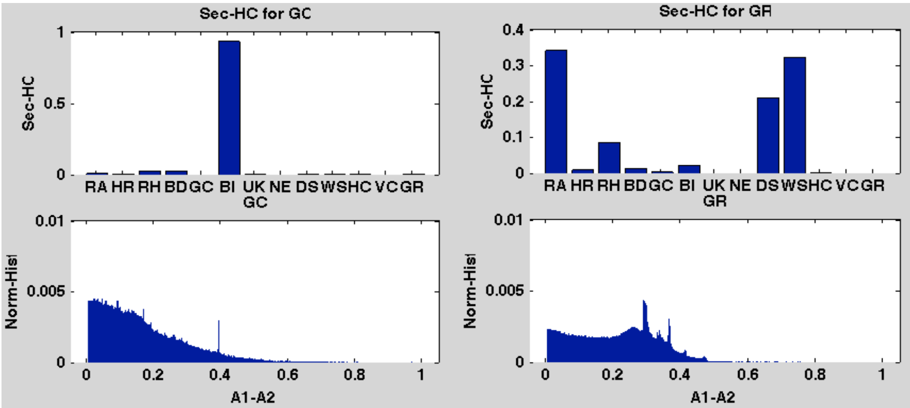

Figure 2: The statistical normalized histograms of the candidate HC classes that is associated with the second highest A-scores, and histogram of the difference between the highest (A1) and second highest (A2) A-scores. The data is selected using the precipitation event at 06:00-06:59 UTC on 3 Mar. 2012 observed from radar KFFC.

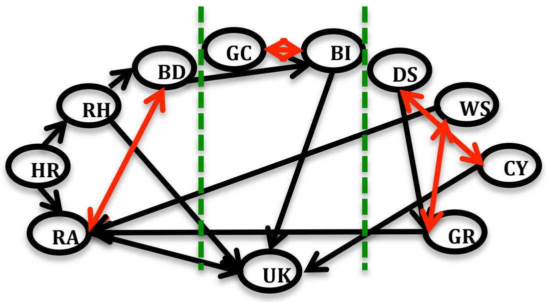

Figure 3: The relations between the designated HC types and the 2nd candidate classes.

Based on the confidence level in their class designation, we statistically divide ten classifications into three groups: convinced, moderate and diffident. Reading Figures 2 and 3, four classes RA, RH, BI and CY have some portion of cases with the class UK as the candidate choice, i.e. for these cases, the class designation is really confident. Among these four classes, BI designation is the most assertive since the UK candidate is in about 84% of the cases; UK class takes 37% of the cases in RH designation; RA has 20% of the cases and CY has 12%. Therefore, the classes BI and RH are considered as convinced. The RA designation is also counted as convinced because the competitive level is low according to the normalized histogram of A1-A2 shown in Figure 2. The GC designation does not have UK candidate class but it shows a consistent candidate of BI (93%). Both of GC and BI are deemed as contaminations by weather radar users if the research of bird migration is out of the discussion. The class of GC and BI are combined into new classification of clutter, and its designation is confident. The convinced group includes RA, RH and (GC/BI). On the other hand, highly competitive A1 and A2 scores and multiple species in the candidate classes are observed in the classes of WS, BD and GR, since their normalized histograms are widely spread at low values of A1-A2 (Figure 2). Classes WS, BD and GR are considered as the group of diffident in class designation. All these three types of hydrometeor could appear below or among the melting layers, and they are often mixed among the large area of liquid and frozen precipitation echoes, where the BD category has the most scattering distribution. When the size of the BD exceeds the length of Rayleigh scattering (~1/15 of wavelength) and falls in Mie scattering, the quality of this classification becomes questionable. Classes HR, CY and DS are moderate in class designation.

3. QUANTITIATIVE MEASUREMENT OF HC QUALITY

After the qualitative analyses of the HCA classes, a quantitative measurement is proposed to scale the HCA reliability. In addition to the aggregation score and uncertainty of the HCA decision, there is another factor may cause the fluctuation of the HC decision: quality of the input dual polarization variables.

The assuredness and accuracy of the classification assignment directly depends on the quality of the polarimetric radar measurement (Q). According to Park et al. (2009), the factors that affect the data quality include radar mis-calibration (Giangrande and Ryzhkov 2005), attenuation, non-uniform beam filling (Ryzhkov 2007), partial beam blockage, the magnitude of RhoHV, and receiver noise. If the quality of a certain radar variable is compromised in a particular area of the radar echo, it was given a lower weight in the classifier. Beside the confidence consideration interior the classification algorithm, the qualities of the dual polarization variables need to be a part of the quality of HC products in the HC mosaicking research. The classification assignment in a radar data bin is questionable if the input data of this radar is overall biased and noisy. As shown in Figure 4, the class assignment inside the regions of rectangular contains higher quality and confidence than the ones inside the ellipse shape because the dual polarization variables Zdr, RhoHV and KDP have better qualities in the rectangular area. Please refer Park et al. (2009)'s work for detailed computation of the quality factors. A confidence factor (CF) is defined as a measurement of the HC quality at each of the radar data bins with three parameters of Q, A1, and A2, as represented in the Equation (1), where the q1-q6 represent the quality factors of the six dual-pol variables (Z, Zdr, RhoHV, KDP, SDZ, and SDPhiDP); σ (x) is defined as the spread range of variable x, therefore the values for each term inside the square brackets in Equation (1) are 6, 1, 1, respectively. The CF's calculation is associated with the HC derivation for every bin of the radar data. The HC assignment is more reliable with higher confidence factor.

4. APPLICATION OF THE CONFIDENCE FACTOR

Through case studies about the hydrometeor fields in the overlapping region, mismatched HC assignments from different radars confront in some of radar bins. The quality factor can be applied in mosaicking of the HC fields from multiple radars, since it is defined as a confidence measurement of the assignment of the hydrometeor classification by the operational HC algorithm (Park et al. 2009).

In Figure 5, subfigures (a, b) and (e, f) are the HC products derived from KTWX and KEAX, respectively. The vertical slices (a) and (e) are obtained starting from KTWX to KEAX, as shown the line in the plan position indicator of KTWX (b) and KEAX (f) at elevation angle of 0.5 degree. Comparing Figure 5(a) and (e), the two pairs of oval and rectangle regions show the incompatible outputs from the radars. In the selected white rectangle region at the height of 2-3 km, KTWX decides the RA while KEAX classifies them as the GR. Another severe inconsistence of the HC field is at the middle area between the radars at the height about 1 km, much more big drops are detected by KTWX than KEAX. Inconsistent HC assignments from adjacent radars are found at the same position, and then whose decision is more convincible? Figure 5 (c), (d), (g), and (h) are the corresponding fields of the confidence factor for the HC fields of (a), (b), (e) and (f). The CF fields provide one set of quantitative measurement of the qualities of the HC fields.

$$CF = \frac{1}{3} \times \left[\frac{\sum (q1+q2+q3+q4+q5+q6)}{\sigma\left(\sum (q1+q2+q3+q4+q5+q6)\right)} + \frac{A1}{\sigma(A1)} + \frac{A1-A2}{\sigma(A1-A2)} \right] \qquad (1)$$

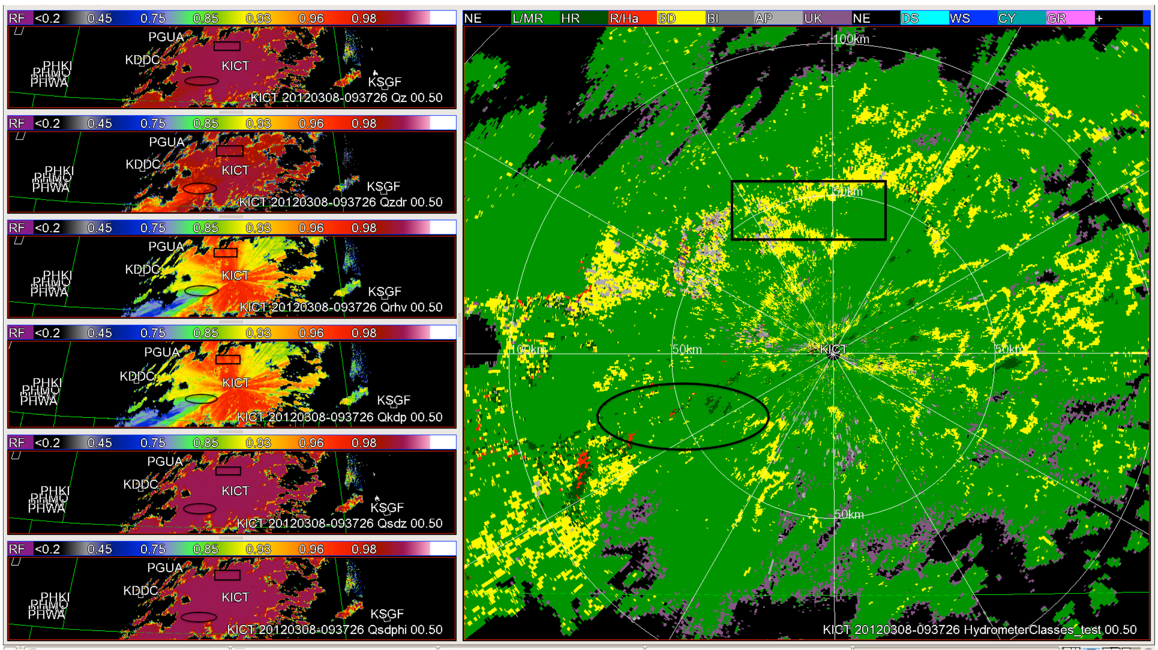

Figure 4: The quality factors of the dual polarimetric variables (left) and the derived HC products (right) of radar KICT at elevation angle of 0.5 degrees. The data is valid at 09:37:26 UTC on 08 Mar. 2012. The quality factors of variables are place in the order of Z, Zdr, RhoHV, KDP, SDZ and SDPhiDP from the top to bottom in the left column.

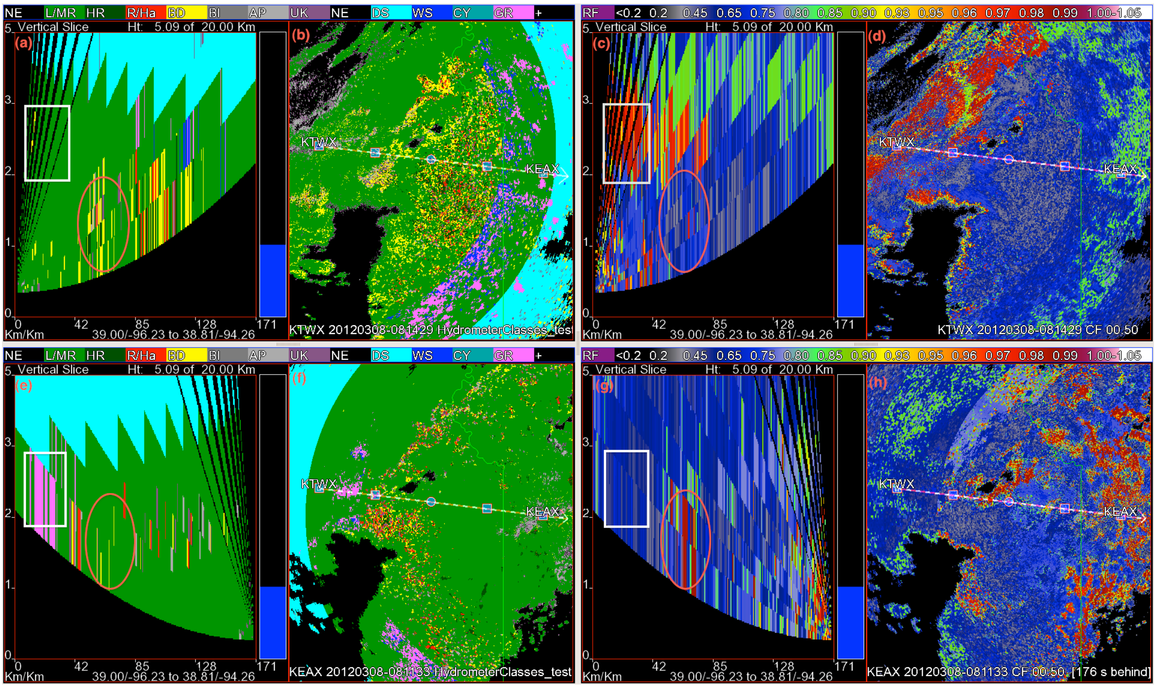

Figure 5: The fields of hydrometeor classification (a, b, e, f) and their associated maps of quality factor (CF) (c, d, g, h) derived from radar KTWX (a-d) and radar KEAX (e-h). The vertical slices (a, c, e, f) are created along the line connecting the radar KTWX and KEAX as shown in the plan position indicator at 0.5 degrees (b, d, f, h).

Comparing subfigures (c) and (g), the HC field derived from KTWX has lower-value of CF parameter in the red ellipse area but higher value in the white rectangular region, as a comparison to the HC field from KEAX. For each of the radar bins, the HC assignment with higher CF measurement is considered more reliable. Therefore, the conflicting HC decisions from adjacent radars would achieve consensus with assistance of associated confidence level at each radar bins.

5. CONCLUSIONS AND FUTURE WORK

Due to uncertainty of the HCA decision using fuzzy logic method, inconsistent HC products from different radars are observed at some overlapping region. To quantitatively evaluate the confidence of the HC assignment from various radars, the HC quality factor is introduced as a new characteristic of the classification species in every of the radar bins for each radars. The next step is to validate the accuracy of CF measurement, and this distinctive feature can be applied to create a nation wise 3D field of hydrometeor classification.

6. ACKNOWLEDGEMENT

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