Reply to Referee

We appreciate the reviewer provided these important comments help us improving our manuscript. We'd like to address these comments as following.

First, language and text have to be improved. In this respect, I have noticed that several sentences do not appear sufficiently connected among them, with sentences and concepts that do not appear derived from the previous arguments. Moreover, several typos remain (for example lines 137, 146, 160).

Response: We appreciated the reviewer's comments. We double checked language and text parts in the manuscript. Got helps from writing center and professional writing software. Issues in grammar, sentence, and word should be corrected.

Second, I agree with the comment of Reviewer 1 on the quality of the datasets: only two meteorological events have been used for the training datasets, and the 17281 datasets are largely unbalanced towards stratiform data. I understand that this work deal of a prototype algorithm, and in this respect I could be acceptable so few events, anyway this limitation has to be clearly and extensively reported in the text (including §2.3.2, abstract and conclusions), and the indicated unbalance justified in some extent.

Response: Following the reviewer's comment, the limitations of the training data, including the total number and stratiform/convective ratio are clearly explained in abstract, section 2.3.2, and conclusions.
In abstract: The weight vector and bias in the support vector machine were optimized using well-classified data from two precipitation events.
In section 2.3.2: It should be noted that the size of training data is considered as small, and the data ratio of convective and stratiform is not well balanced. Much more data from various precipitation events should be included in the training process if the proposed algorithm is implemented in operation.
In section conclusion: Moreover, only very limited training data is used in the current work. Much more data from various precipitation events should be included in the training process if the proposed algorithm is implemented in operation.

Finally, I retain answers to Reviewers acceptable, but not fully addressed in the text. In other words, answers give a detailed justification to the points indicated by Reviews but the revised text in most cases addresses the point in a sentence not sufficiently complete. My general comment is to take answers to Reviewers and insert them in the text as much as possible "as is". In particular, I retain necessary the justifications for the following points:
1. The selection of the datasets, as previously indicated;

Response: Please refer to the response to the first comment.

Response: Following the reviewer's comment, the manuscript is modified as:

Convective type precipitation also produces a higher rainfall rate (R) than stratiform type (Anagnostou, 2004). Given the fact that the radar reflectivity (Z) from a stratiform precipitation generally is less than 40 dBZ (Steiner et al., 1995) (hereafter SHY95), the R estimated from stratiform precipitation is less than 11 mm hr^{-1} following the standard Marshall-Palmer relationship ($Z = 200R^{1.6}$). In order to obtain accurate rainfall estimation, different R(Z) relationships according to the precipitation types should be applied in the quantitative precipitation estimation (QPE) (Kirsch et al., 2019).

Response: Following the reviewer's comment, following discussions were added into the manuscript as:

It should be noted that the ρ_{HV} threshold of 0.9 is used in the training data selection for both convective and stratiform precipitations. As reported in Park et al. (2009), the liquid phase precipitations (e.g., light to heavy rain) are associated with relatively high ρ_{HV} (>0.92). Other types of precipitations, such as the mixture of rain and hail, wet snow, and crystals may produce low ρ_{HV} (<0.85). Since the i is derived based on the raindrop size distribution assumption, the proposed SVM approach is only valid for liquid phase precipitation classification. The classification of other types of precipitation is not in the scope of this work. Therefore, 0.9 is a reasonable ρ_{HV} threshold in the training data selection. The training data used in this work is from pure liquid precipitation events, and the average ρ_{HV} is above 0.98. Similar training results are expected if higher ρ_{HV} threshold is used in the training data selection.

Response: to address the reviewer's comment, we made the following modification in the revised manuscript.

1.) Move the description about the bright band into section 2.1.
2.) The sentences about bright band was modified as:
Second, a VPR correction is generally needed on the reflectivity field to reduce the measurement biases because of the melting layer (Zhang et al., 2011). The enhanced backscattering amplitudes of melting hydrometeors within the melting layer (bright band) significantly enhance radar reflectivity. The bright band feature is one of the obvious indicators of stratiform precipitation, and normally can be observed from relatively high EAs (such as above 9.9°). Given the fact that data from 1.4° elevation angle is used within the maximum range of 150 km, and the melting layer is usually around 5 km in Taiwan, the radar data used in this work is well below the melting layer. Therefore, no VPR corrections are applied on the fields of Z and Z_{DR}.
3.) The section in training data selection was modified as:
For example, training data from convective precipitation is generally associated with relatively large reflectivity and high vertically integrated liquid (VIL). On the other hand, stratiform precipitations are generally associated with a prominent bright band signature.

When presenting the two principal study cases, it is necessary explicitly declare that small circle areas will be used for further analysis, reporting the justification of the answer to the Reviewer;

Response: following illustration is added into the revised manuscript:

A circle is inserted in Figures 5 and 6 to emphasize a region where BAL and SVM show different performances. Within this circle, BAL^0 ($BAL^{-0.5}$) classifies the least (most) echoes as convective, and SVM shows the most similar results as MRMS. The averages of Z and Z_{DR} within this region both show relatively large values (Z > 36 dBZ and Z_{DR} > 0.75 dB) as shown in Figure 6. This is a clear indication of convective type precipitation. Both SVM and $BAL^{-0.5}$ classify most of the area within the red circle as convective, and this result is consistent with the MRMS result. Since the separation indexes within the black circle are below or slightly higher than 0, most of the area is classified as stratiform type by BAL^0. For this moment, threshold −0.5 shows better performance than 0. Similar reasons may be applied to other regions.

Even if obvious, the values of the statistical parameters of the pure stratiform case have to be reported for symmetry with the other two cases, as declared in the answer but not done;

Response: The following sentence was added in the revision:

These three approaches showed consistent classification results with the MRMS result during an 8-hour period evaluation. For all three approaches, the scores of POD, FAR, CSI, and R^{CS} are 1, 0, 1, and 0, respectively.

Finally, also the justification respect the Zdr calibration bias have to be included in the text.

Response: The following justification respect to ZDR calibration bias was added in the text.

First, since this radar is used for the real-time QPE purpose, the calibration biases of Z and Z_{DR} should be within 1 dB and 0.1 dB, respectively. The data quality of RCMK was examined through validating the QPE performance in different works (e.g., Wang et al., 2013, 2014). Therefore, the calibration biases (Z and Z_{DR}) of RCMK should be within reasonable ranges.

Separation of Convective and Stratiform Precipitation Using Polarimetric Radar Data with A Support Vector Machine Method

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Abstract. A precipitation separation approach using a support vector machine method was developed and tested on a C-band polarimetric weather radar located in Taiwan (RCMK). Different from ~~some existing~~ those methods requiring a whole volume scan data, the proposed approach utilizes polarimetric radar data from the lowest unblocked tilt to classify precipitation echoes into either stratiform or convective type. In this algorithm, inputs of radar reflectivity, differential reflectivity, and the separation index are integrated through a support vector machine. The weight vector and bias in the support vector machine were optimized using well-classified ~~training data~~ data from two precipitation events. The proposed approach was tested with three precipitation events, including a widespread mixed stratiform and convective event, a tropical typhoon precipitation event, and a stratiform precipitation event. Results from the Multi-Radar-Multi-Sensor (MRMS) precipitation classification algorithm were used as the ground truth in the performance evaluation. The performance of the proposed approach was also compared with the approach using the separation index only. It was found that the proposed method can accurately classify the convective and stratiform precipitations, and produce better results than the approach using the separation index only.

1 Introduction

Convective and stratiform precipitations exhibit a significant difference in precipitation growth mechanisms~~and thermodynamic structures~~, thermodynamic structures, and precipitation intensities (e.g., Houghton, 1968; Houze, 1993, 1997). ~~Generally, a~~ For example, convective precipitation is generally associated with strong but small areal vertical air motion ($> 5\,\mathrm{m\,s^{-1}}$)~~(Penide et al., 2013), and delivers a high rainfall rate (R) (Anagnostou, 2004). On the other hand, a~~, but stratiform precipitation is associated with weak updrafts/downdrafts ($< 3\,\mathrm{m\,s^{-1}}$) ~~and relatively low~~ (Penide et al., 2013). Convective precipitation also produces a higher rainfall rate (R~~)~~) than stratiform type (Anagnostou, 2004). Given the fact that the radar reflectivity (Z) from stratiform precipitation generally is less than 40 dBZ (Steiner et al., 1995) (hereafter SHY95), the R ~~<~~ estimated from stratiform precipitation is less than 11 mm hr^{-1} ~~). Classifying a precipitation~~ following the standard Marshall-Palmer relationship ($Z = 200R^{1.6}$). In order to obtain accurate rainfall estimation, different $R(Z)$ relationships according to the precipitation types should be applied in quantitative precipitation estimation (QPE) (Kirsch et al., 2019). Therefore, accurate classifying precipitation into either convective or stratiform type can promote our understandings ~~in~~ of cloud physics and thermodynamics. ~~Moreover, since different~~

radar reflectivity (Z) and ~~R relationships are used in the quantitative precipitation estimation (QPE), accurate classification results also can help selecting the optimal relationship and improving the QPE~~, and enhance QPE accuracy. For these purposes, numerous methods using ground in situ measurements or satellite observations were developed and applied during the past forty years (e.g., Leary and Jr., 1979; Adler and Negri, 1988; Tokay and Short, 1996; Hong et al., 1999).

Ground-based weather radars, such as Weather Surveillance Radar, 1988, Doppler (WSR-88D), are currently used in all aspects of weather diagnosis and analysis. Precipitation classification algorithms using single- or dual-polarization radars were developed during the past three decades. For a single-polarization radar, developed algorithms mainly rely on Z and its derived variables (e.g., Biggerstaff and Listemaa, 2000; Anagnostou, 2004; Yang et al., 2013; Powell et al., 2016). For example, ~~Steiner et al. (1995) (hereafter~~ SHY95 ~~)~~ proposed a separation approach that utilizes the texture features derived from the radar reflectivity field. In this approach, a grid point ~~in the Z field~~ is identified as the convective center if its Z value is larger than 40 dBZ, or exceeds the average intensity taken over the surrounding background~~by specified thresholds~~. Those grid points surrounding the convective centers are classified as convective area, and far regions are classified as stratiform~~area~~. Penide et al. (2013) found that SHY95 may misclassify those isolated points embedded within stratiform precipitation or associated with low cloud-top height. Powell et al. (2016) modified ~~the~~ SHY95′s approach, and the new approach can identify shallow convection embedded within large stratiform regions. A neural network based convective-stratiform classification algorithm was developed by Anagnostou (2004). Six variables were used in this approach as inputs, including storm height, reflectivity at 2 km elevation, the vertical gradient of reflectivity, the difference in height, the standard deviation of reflectivity, and the product of reflectivity and height. Similar variables were also used in a fuzzy logic based classification approach proposed by Yang et al. (2013).

Motivations of developing a new classification algorithm are mainly from two aspects. First, according to the U.S. Radar Operations Center (ROC), the WSR-88D radars are currently operated without updating a complete volume during each volume scan, especially during precipitation events. New radar scanning schemes are designed to update data from low elevations ~~in~~ at a high frequency and data from high elevations ~~in~~ at a low frequency. Such an alternative scanning scheme enables the WSR-88D radars to promptly capture the storm development, ~~which can~~ and enhance the weather forecast capability~~and QPE accuracy~~. These new schemes include the automated volume scan evaluation and termination (AVSET), supplemental adaptive intra-volume low-level scan (SAILS), the multiple elevation scan option for SAILS, and the mid-volume rescan of low-level elevations (MRLE). With these new scanning schemes, the separation of stratiform/convective becomes a challenge for those algorithms requiring a full volume scan of data. Therefore, a separation algorithm using only low tilt radar data is desired. The second reason is to further explore the applications of the polarimetric variables. Polarimetric weather radars have been well applied in radar QPE, severe weather detection, hydrometeor classification, and cloud microphysics retrieval (Ryzhkov and Zrnic, 2019; Zhang, 2016). Extra information about hydrometeors' size, shape, and orientation could be obtained through transmitting and receiving electromagnetic waves along the horizontal and vertical directions. ~~Therefore, the polarimetric~~ Polarimetric measurements may reveal more precipitation ~~'s~~ microphysical and dynamic properties. Inspired by these features, a C-band polarimetric radar precipitation separation approach was developed by Bringi et al. (2009) (hereafter BAL), which classifies the precipitation into stratiform, convective, and transition regions based on retrieved drop size distribution (DSD)

characteristics. However, it was found that strong stratiform echoes might have similar DSDs to weak convective echoes and lead to wrong classification results (Powell et al., 2016).

In this work, a ~~novel precipitation separation algorithm using the separation index with other radar variables~~ support vector machine (SVM) based classification method was developed and ~~tested~~ test on a C-band polarimetric radar located in Taiwan. ~~This approach classifies precipitations into stratiform or convective type with a support vector machine (SVM) method.~~ ~~Different from~~ Unlike some existing classification techniques that require a whole volume scan of ~~radar~~ data, this new approach ~~uses~~ only requires the lowest unblocked tilt data in the separation. If the lowest tilt is partially or completely blocked, ~~then~~ the next adjacent unblocked tilt is used ~~instead. The major advantage of this method~~ in the classification instead. This method's major advantage is that it can provide classification results even when the radar is operated under AVSET, SAILS, and MRLE scanning schemes. ~~Under these schemes, a complete volume scan is not available.~~ This paper is organized as follows: Section 2 introduces the proposed method, including radar variables and data processing, the SVM method, and the training process. The performance evaluation is shown in Section 3, and the discussion and summary are given in Section 4.

2 Precipitation Separation With a Support Vector Machine Method

In the current work, the SVM precipitation separation approach was developed and validated on a C-band polarimetric radar (RCMK) located at Makung, Taiwan (Figure 1). The Weather Wing of the Chinese Air Force deployed this radar and made the data available to the Central Weather Bureau (CWB) of Taiwan since 2009. Together with three single-polarization S-band WSR-88D (RCCG, RCKT, and RCHL) and one dual-polarization S-band radar (RCWF), these five radars provide real-time products to CWB to support missions of flood monitoring and prediction, landslide forecasts, and water resource management. The wavelength of RCMK is 5.291 cm, and its range and angular resolutions are 500 m and $1°$, respectively. RCMK performs volume scans of 10 tilts ($0.5°$, $1.4°$, $2.4°$, $3.4°$, $4.3°$, $6.0°$, $9.9°$, $14.6°$, $19.5°$, and $25°$) ~~in~~ every 5 minutes.

The Central Mountain Range (CMR) of Taiwan is also shown in Figure1, which poses a major challenge ~~for radar based~~ to radar products. Radars located in complex terrain are prone to partial or total blockages, which cause data from the low elevation angles (EA) ~~to be~~ unavailable or problematic. Blockage maps of RCMK are illustrated in Figure 2. Since there are severe blockages at the $0.5°$ for RCMK, data from the $1.4°$ EA is used in the algorithm development.

2.1 Input polarimetric radar variables and preprocesses

Three measured or derived radar variables are proposed as inputs to the SVM approach: Z, differential reflectivity fields (Z_{DR}), and separation index (i). ~~In most of precipitation classification approaches~~ Because convective precipitation generally shows higher reflectivity values, Z is well used as one of the inputs ~~because reflectivity fields from convective precipitations generally show higher values than the fields from stratiform precipitations~~ in most of the precipitation classification approaches. For example, a radar echo, with the reflectivity of 40 dBZ and above, is automatically classified as convective type in the approach developed by SHY95.

Differential reflectivity, which is highly related to raindrop's mass weighted mean diameter (D_m), is another good indicator of precipitation type. It was found the values of D_m in stratiform and convective precipitation generally are within 1-1.9 mm and above 1.9 mm, respectively (Chang et al., 2009). Therefore, higher Z_{DR} values are expected from convective than from stratiform precipitations.

For short-wavelength radars such as C-band or X-band radars, the Z and Z_{DR} fields will be significantly attenuated when radar beam propagates through heavy precipitation regions. Both Z and Z_{DR} fields need to be corrected from attenuation before applied in the precipitation classification and QPE. Different attenuation correction methods were proposed using the differential phase (ϕ_{DP}) measurement such as the linear ϕ_{DP} approach, the standard ZPHI method, and the iterative ZPHI method (e.g., Jameson, 1992; Carey et al., 2000; Testud et al., 2000; Park et al., 2005). Because of its simplicity and easy implementation in a real-time system, the linear ϕ_{DP} method was applied in the current work.

$$Z(r) = Z'(r) + \alpha(\phi_{DP}(r) - \phi_{DP}(0)) \tag{1a}$$

$$Z_{DR}(r) = Z'_{DR}(r) + \beta(\phi_{DP}(r) - \phi_{DP}(0)) \tag{1b}$$

where $Z'(r)$ ($Z'_{DR}(r)$) is the observed reflectivity (differential reflectivity) at range r; $Z(r)$ ($Z_{DR}(r)$) is the corrected value; $\phi_{DP}(0)$ is the system value; $\phi_{DP}(r)$ is the smoothed (by FIR filter) differential phase at range r. The attenuation correction coefficients α and β depend on DSD, drop size shape relations (DSR), and temperature. The typical range of α (β) is found 0.06~0.15 (0.01~0.03) dB deg^{-1} for C-band radars (e.g., Carey et al., 2000; Vulpiani et al., 2012). Following the work from Wang et al. (2014), optimal coefficients α and β in Taiwan are 0.088 dB deg^{-1} and 0.02 dB deg^{-1}, respectively. The Z and Z_{DR} fields are further smoothed with a 3 (along azimuthal angle) by 3 (along range) moving window function after corrected from attenuation.

Other quality control issues on Z and Z_{DR} fields, including calibration, vertical profiles of reflectivity (VPR) correction, and ground clutter removal, were also considered in this work. First, since this radar is used for the real-time QPE purpose, the calibration biases of Z and Z_{DR} should be within 1 dB and 0.1 dB, respectively. The data quality of RCMK was examined through validating the QPE performance in different works (e.g., Wang et al., 2013, 2014). Therefore, the calibration biases (Z and Z_{DR}) of RCMK should be within reasonable ranges. Second, a VPR correction is generally needed on the reflectivity field to reduce the measurement biases because of the melting layer (Zhang et al., 2011). The enhanced backscattering amplitudes of melting hydrometeors within the melting layer (bright band) significantly enhance radar reflectivity. The bright band feature is one of the obvious indicators of stratiform precipitation, and normally can be observed from relatively high EAs (such as above 9.9°). Given the fact that data from 1.4° elevation angle is used within the maximum range of 150 km, and the melting layer is usually around 5 km in Taiwan, the radar data used in this work is well below the melting layer. Therefore, no VPR corrections are applied on the fields of Z and Z_{DR}. Third, since ground clutter is typically associated with a low correlation coefficient (ρ_{HV}), a ρ_{HV} threshold of 0.85 is used in the current work to remove radar echoes from ground clutter (Park et al., 2009).

~~Using~~ Another input variable is the separation index i ~~to identify convective from stratiform precipitation~~, which was initially proposed by BAL~~, where~~. The i was calculated under a normalized gamma DSD assumption:

$$i = log_{10}(N_W^{est}) - log_{10}(N_W^{sep}) \tag{2}$$

$$log_{10}(N_W^{sep}) = -1.6D_0 + 6.3 \tag{3}$$

where N_W^{est} is the estimated N_W (normalized number concentration) from observed Z and Z_{DR}, and is calculated as:

$$N_W^{est} = Z/0.056D_0^{7.319} \tag{4}$$

In Equation 4, D_0 is the median volume diameter and can be calculated as.

$$D_0 = 0.0203Z_{DR}^4 - 0.1488Z_{DR}^3 + 0.2209Z_{DR}^2 + 0.5571Z_{DR} + 0.801; \quad -0.5 \leq Z_{DR} < 1.25 \tag{5a}$$

$$= -0.0355Z_{DR}^3 - 0.3021Z_{DR}^2 + 1.0556Z_{DR} + 0.6844; \quad 1.25 \leq Z_{DR} < 5 \tag{5b}$$

The units of Z_{DR}, Z, N_w, and D_0 are dB, mm^6m^{-3}, $mm^{-1}m^{-3}$, and mm, respectively. The positive and negative values of index i indicate convective and stratiform rain, respectively, and $|i| < 0.1$ indicates transition regions (Penide et al., 2013). BAL pointed out that index i worked well in most of the cases in their study; however, incorrect classification results are likely obtained for low Z and high Z_{DR} cases in some convective precipitations.

2.2 Drop size distribution and drop shape relation

It should be noted that the relations between i, N_w, and D_0 were derived using the DSD data collected in Darwin, Australia. Coefficients in Equations 2~5 need to be adjusted according to the radar frequency or/and DSD and DSR features from the specific location (Thompson et al., 2015). In the current work, the separation index i is directly derived using Equations 2~5 without further adjustment. It was shown by Wang et al. (2013) that DSD and DSR features in Taiwan are very similar to those measured from Darwin, Australia. Similar $R(K_{DP})$ relationships were obtained using data collected from these two locations. Coefficients derived by BAL could be directly used in Taiwan without further modification. To verify this assumption, N_w and D_0 were calculated using DSD data collected from four impact-type Joss-Waldvogel disdrometers (JWD) located in Taiwan (Figure 1). The measurement range and temporal resolution of these JWDs are 0.359 mm $\sim$ 5.373 mm, and 1 minute, respectively. A total of 4306-minute data from 2011~2014 ~~are~~ is used in N_w and D_0 calculation following the approach described in Bringi et al. (2003). Similar to the work presented in BAL, the distribution of i along median volume diameter D_0 is shown in Figure ~~2, where~~ 3. Sample pairs ($log_{10}N_w$, D_0) ~~pairs~~ from stratiform and convective ~~types~~ are represented with gray circles and black stars, respectively. Although the relation described in Equation 3 can separate most stratiform from convective type, a large number of points are still classified incorrectly. Therefore, the single separation index is not sufficient in the precipitation separation, and other variables such as Z and Z_{DR} may be used as supplements.

2.3 Support vector machines (SVM) method

2.3.1 Introduction of SVM

155 ~~Machine learning~~ Artificial intelligence (AI) algorithms using meteorological radar data were well developed during the past two decades. With the assistance of AI, weather radar's capabilities in severe weather prediction, rainfall rate estimation, lightning detection were apparently improved (e.g., Capozzi et al., 2018; T. et al., 2019; Yen et al., 2019). ~~A support vector machine (SVM)~~ Inspired by these enhancements, a precipitation separation approach using a SVM was developed and tested in the current work. Generally, a SVM can be viewed as a kernel-based machine learning approach, which nonlinearly maps

160 the data from the low-dimension input space to a high-dimension feature space, and then linearly maps to a binary output space (Burges, 1998). Given a set of training samples, the SVM constructs an optimal hyperplane, which maximizes the margin of separation between positive and negative examples (Haykin, 2011). Specifically, given a set of training data $\{(X_i, y_i)\}_{i=1}^{N}$, the goal is to find the optimal weights vector W and a bias b such that

$$y_i(W^T X_i + b) \geq 1 \qquad i = 1, 2, ..., N \tag{6}$$

165 where $X_i \in \mathbb{R}^m$ is the input vector, m is the variable dimension ($m = 3$ in this work), N is the number of training samples, and y_i is the output with the value of $+1$ or -1 that represents convective or stratiform, respectively. The particular data points (X_i, y_i) are called support vector when Equation 6 is satisfied with the equality sign. The optimum weights vector W and bias b can be obtained through solving the Lagrangian function with the minimum cost function (Haykin, 2011).

Since the SVM can be viewed as a kernel machine, finding the optimal weight vector and bias in Equation 6 can be alterna-

170 tively solved through the recursive least square estimations of:

$$\sum_{i=1}^{N_s} \alpha_i y_i k(X, X_i) = 0 \tag{7}$$

where N_s is the number of support vectors, α_i is the Lagrange multipliers, and $k(X, X_i)$ is the Mercer kernel defined as:

$$k(X, X_i) = \Phi^T(X_i)\Phi(X) = exp\left(-\frac{1}{2\sigma^2}||X - X_i||^2\right) \tag{8}$$

With the solved $\{\alpha_i\}_{i=1}^{N}$, the SVM ~~calculate~~ calculates the classification results with new input data $Z \in \mathbb{R}^m$ as:

175 $$f(Z) = sign\left[\sum_{i=1}^{N_s} \alpha_i y_i \Phi^T(X_i)\Phi(Z)\right] \tag{9}$$

When $f(Z) = 1$, the output is classified as convective, otherwise ~~is classified~~ as stratiform.

2.3.2 Training of the SVM

In the SVM approach, the weight vector and bias in Equation 6 and the standard deviation vector in Equation 8 need to be optimized through a recursive least square estimation using training data. Since the training data ~~play~~ plays a critical role

180   in the SVM approach, Z, Z_{DR} and i from convective and stratiform precipitation events were carefully examined through three steps. Firstly, the training data was checked following general classification principles. For example, training data from convective precipitation is generally associated with relatively ~~strong~~ large reflectivity and high vertically integrated liquid (VIL). On the other hand, stratiform precipitations are generally associated with ~~a~~ prominent bright band ~~signature. The melting hydrometeors within the bright band increase backscatter during stratiform rainfall, which can significantly enhance radar~~

185 ~~reflectivity. The bright band feature is one of the obvious indicators of stratiform precipitation. Bright band signature normally can be observed from relatively high EAs (such as above 9.9°). In this work, the bright band feature from high elevation angles is only used in training data selection but not used as one of the inputs.~~ signatures. Secondly, the precipitation type is verified by ground observation, such as ground severe storm reports. Thirdly, the precipitation type is confirmed by the Multi-Radar-Multi-Sensor (MRMS) precipitation classification algorithm implemented in Taiwan (Zhang et al., 2011, 2016). In

190 this MRMS classification approach, a three-dimensional radar reflectivity field is mosaicked from 4 S-band single-polarization radars (Figure 1). The composite reflectivity (CREF) and other measurements, such as temperature and moisture fields, are then used in the surface precipitation classification (Zhang et al., 2016). The performance of MRMS has been thoroughly evaluated for years in QPE, flash flood monitoring, severe weather observation, and aviation weather surveillance (e.g., Gourley et al., 2016; Smith et al., 2016). It was found that MRMS system can provide robust and accurate products, and these products were

195 used as ~~the benchmark~~ benchmarks and/or ground ~~truth~~ truths in many studies (e.g., Grecu et al., 2016; Skofronick-Jackson and Coauthors, 2017). ~~At the current stage, the MRMS precipitation classification is considered as the appropriate benchmark in the training and validation of the proposed algorithm.~~ Moreover, since the MRMS classification is a mosaicked product derived from 4 S-band radars, it can be viewed as an independent reference. Therefore, the MRMS precipitation classification is considered as the appropriate reference in the training and validation.

200   Convective type training data is mainly from a ~~strong convective~~ precipitation event on 23 July 2014. ~~This thunderstorm, classified as convective precipitation by MRMS, was associated with strong updrafts/downdrafts and~~ Apparent squall line features could be identified from this thunderstorm, and MRMS classified this precipitation event as the convective type. Strong downdrafts triggered by this storm caused an aircraft crash on the airport of Makung at 1106 UTC. ~~The squall line features can be clearly identified from this storm.~~ Radar data collected from 1030 to 1130 UTC ~~were~~ was used as the convective type

205 ~~training data. The training~~ data, and data selection follows the criteria of $Z >$20 dBZ ~~, and $\rho_{HV} >$~~ and $\rho_{HV} >$0.9. Some ~~convective type radar data from the~~ samples from a mixed stratiform and convective precipitation event on 30 August 2011 are also ~~used as the convective training data. These convective radar data are identified by the MRMS results.~~ included as convective type data. The stratiform type data ~~are~~ is from the precipitation event on 30 August 2011, and only those data identified as a stratiform type by MRMS are used in training. It should be noted that the ρ_{HV} threshold of 0.9 is used in

210 the training data selection for both convective and stratiform precipitations. As reported in Park et al. (2009), the liquid phase precipitations (e.g., light to heavy rain) are associated with relatively high ρ_{HV} ($>$0.92). Other types of precipitations, such as the mixture of rain and hail, wet snow, and crystals may produce low ρ_{HV} ($<$0.85). Since the i is derived based on the raindrop size distribution assumption, the proposed SVM approach is only valid for liquid phase precipitation classification. The classification of other types of precipitation is not in the scope of this work. Therefore, 0.9 is a reasonable ρ_{HV} threshold

in the training data selection. The training data used in this work is from pure liquid precipitation events, and the average ρ_{HV} is above 0.98. Similar training results are expected if higher ρ_{HV} threshold is used in the training data selection.

A total of 17281 data sets (15144 sets of stratiform, and 2137 sets of convective) are used in the training process. ~~In this work, one~~ One data set is defined as the variables from a gate in terms of range and azimuthal angle. Be more specific, a set of training data means a vector of $[Z(a,r)\ Z_{DR}(a,r)\ i(a,r)\ d(a,r)]$, where a and r indicate azimuthal angle and range, respectively. The variable d is the ground truth (with 1~~and~~/-1 represents convective~~and~~/stratiform), ~~which is~~ and acts as the desired response in the training process. It should be noted that the size of training data is considered as small, and the data ratio between convective and stratiform is not well balanced. Much more data from various precipitation events should be included in the training process if the proposed algorithm is implemented in operation.

The number of support vectors is selected as 1000 in the current work, and the training process is considered as completed when the root-mean-square error reaches a stable value. In the SVM approach, the original three-dimension input space non-linearly maps to a 1000-dimension feature space, and then linearly maps to a binary output space (Burges, 1998). The higher dimension feature space (the number of support vector) potentially captures more input variables features with higher computation cost. Generally, after the number of support vector reaches some number, the enhancement ~~in the SVM 's performance~~ of SVM approach becomes slight. There is a balance between accuracy and computation cost. In the current work, the number of support vectors was tested with a value of 500, 750, 1000, 2000, and 5000. Since 1000 support vectors can produce less than 5% error with reasonable computation time, they are used in the current work.

3 Performance Evaluation

3.1 Description of the experiments

The performance of the proposed approach was validated with three precipitation events from 2009 to 2011, including one stratiform precipitation, one intense tropical precipitation, and one mixed convective and stratiform precipitation. In the validation, a ρ_{HV} threshold of 0.85 is first used to remove radar echoes not associated with liquid phase precipitation such as clutter and AP (Park et al., 2009). As discussed in section 2.3.2, some ice phased or mixed precipitation such as snow, the mixture of hail and rain, and crystals may be associated with low ρ_{HV} (<0.85). However, this work proposed an approach to classify liquid phase precipitation into either stratiform or convective types. Classification of other meteorological targets is not in the scope of this work. Two experiments based on the BAL approach with different thresholds (i.e., BAL^0 and $BAL^{-0.5}$) were also validated with the same events. In these two experiments, the separation index i from each radar gate was first calculated using Equations 2~5, and thresholds of $T_0 = 0$ and -0.5 were then used to separate convective type from stratiform type. A gate is classified as convective type if obtained i is larger than T_0, and as stratiform type otherwise. It was suggested that positive (negative) i is generally associated with convective (stratiform) precipitation (Bringi et al., 2009). Therefore, $T_0 = 0$ was selected as one of the thresholds. Another aggressive threshold of -0.5 was also tested in the current work, which will classify ~~much~~ many more pixels as convective. ~~This work aims to develop a complementary method using separation index i and other variables to separate convective from stratiform type. The proposed SVM and the BAL methods only use the lowest~~

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~~tilt unblocked radar data in the classification, which is suitable for fast scan and quick update purposes. Other classification approaches~~ Performances of those approaches requiring multiple elevation angles as introduced in ~~section~~ Section 1 ~~were not examined in the current work, because they require the data from multiple elevation angles. Therefore, their performance is not examined in~~ are not discussed in this work.

In the evaluation, three statistical scores of probability of detection (POD), false alarm rate (FAR), and critical success index (CSI) are used, and MRMS classification results are used as the "ground truth" in the calculation.

$$POD = \frac{hit}{hit + miss} \tag{10}$$

$$FAR = \frac{false}{hit + false} \tag{11}$$

$$CSI = \frac{hit}{hit + false + miss} \tag{12}$$

where "hit," "false," and "miss" are defined as a radar gate classified as convective type by MRMS and the evaluated approach simultaneously, by the evaluated approach only, and by MRMS only, respectively. Since these scores only partially capture the performance due to the time gap between MRMS and RCMK results (SVM and BAL), a new evaluation score R^{CS} (whole coverage convective ratio) is also used as a supplement:

$$R^{CS} = \frac{N^{con}}{N^{con} + N^{str}} \times 100\% \tag{13}$$

Where N^{con} and N^{str} are the total pixel numbers of convective and stratiform types within the coverage, respectively. The evaluation results are shown in the following sections.

3.2 Experiment results

3.2.1 Widespread mixed stratiform and convective precipitations

The performance of the proposed approach was first validated with one widespread stratiform and convective mixed precipitation event on 30 August 2011, and 24-hour data (0000 UTC∼2400 UTC) were used in the evaluation. Classification results from the proposed SVM were calculated with the trained weight vector and biases, and results from the BAL approach (BAL^0 and $BAL^{-0.5}$) were also calculated for the comparison purpose. It should be noted that the threshold of -0.5 is much lower than the value suggested by BAL, and $BAL^{-0.5}$ will classify more precipitations as convective type.

The time series of R^{CS} (A), CSI (B), FOD (C), and FAR (D) are calculated using Equations 10∼13 and shown in Figure 4, where results from MRMS, SVM, BAL^0, and $BAL^{-0.5}$ are presented by black, red, blue, and green lines, respectively. When the MRMS results are applied as the ground truth, BAL^0 obviously classifies more precipitation as stratiform type during this 24-hour period. The time series of R^{CS} from BAL^0 are much lower than the other three approaches. $BAL^{-0.5}$ classifies more

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pixels as convective than BAL^0 as expected, and the R^{CS} scores are much higher than BAL^0. The proposed SVM shows the most similar R^{CS} scores to MRMS comparing to BAL approaches. Since the $BAL^{-0.5}$ uses a very low threshold, it classifies more pixels as convective type, and the obtained R^{CS} scores are higher than MRMS. ~~In term of CSI, POD, and FAR,~~ SVM and $BAL^{-0.5}$ show similar results ~~,~~ in terms of CSI, POD, and FAR, but BAL^0 show apparently worse performance.

To better understand the performance of each approach, the classification results and radar variables (Z, Z_{DR}, and i) from two distinct moments are examined ~~and~~ as shown in Figures 5∼7. Figure 5 shows the classification results from 0303 UTC 30 August 2011, where BAL^0, $BAL^{-0.5}$, SVM and MRMS are shown in the panel 'A', 'B', 'C', and 'D', respectively. The ~~time stamp~~ timestamp for the MRMS result is 0300 UTC, and about 3 minutes earlier than the other three approaches. ~~These three~~ Three input variables of SVM at 0303 UTC are shown in Figure 6, where Z, Z_{DR}, and i are presented in panel 'A', 'B', and 'C'. ~~From Figures 4 and~~ A circle is inserted in Figures 5 ~~, it could be found that the R^{CS} from MRMS, SVM, and~~ and 6 to emphasize a region where BAL and SVM show different performances. Within this circle, $BAL^{-0.5}$ ~~show similar values, but R^{CS} from BAL^0 is distinctly low. Within the red circle of Figure 6, the~~ ($BAL^{-0.5}$) classifies the least (most) echoes as convective, and SVM shows the most similar results as MRMS. The averages of Z and Z_{DR} within this region both show relatively large values ($Z > 36$ dBZ and $Z_{DR} > 0.75$ dB) ~~, this~~ as shown in Figure 6. This is a clear indication of convective type precipitation. Both SVM and $BAL^{-0.5}$ classify most of the area within the red circle as convective, and this result is consistent with the MRMS result. Since the separation indexes within the black circle are below or slightly higher than 0, most of the area is classified as stratiform type by BAL^0. For this moment, threshold -0.5 shows better performance than 0. Similar reasons may be applied to other regions.

Figure 7 shows another example of classification results from 0650 UTC. At this moment, although SVM and $BAL^{-0.5}$ produce similar CSI (0.30 v.s. 0.25) and POD (0.48 v.s. 0.52), the R^{CS} from $BAL^{-0.5}$ (32%) is much higher than R^{CS} from MRMS (17%) and SVM (13%). These scores could also be found in Figure 4. In Figure 7, It could be found ~~from~~ that the MRMS, SVM, and $BAL^{-0.5}$ show similar classification results between the azimuthal angle of $180°$ and $270°$. However, $BAL^{-0.5}$ misclassifies gates between $90°$ and $180°$ as convective type, which produces such high R^{CS}. On the other hand, MRMS and SVM show similar classification results in this region.

3.2.2 Tropical convective

Typhoon Morakot (6∼10 August 2009) brought significant rainfall to Taiwan. Over 700 people were reported dead in the storm, and the property loss was more than 3.3 billion USD. For most of the time during its landfall in Taiwan, the precipitation was classified as a mixture of tropical convective and tropical stratiform types. The performances of SVM, BAL^0, and $BAL^{-0.5}$ were validated using 96-hour data from 6 to 9 August 2009, where the results from 10 August 2009 were not included in the evaluation because no significant precipitation was observed from that day. The time series plots of R^{CS} (A), CSI (B), POD (C) and FAR (D) are shown in Figure 8. It could be found that scores of R^{CS}, CSI, and POD from the BAL based approaches is evidently lower than the results from SVM and MRMS, and the latter two show similar performance during these four days.

Classification results from BAL^0, $BAL^{-0.5}$, SVM (0402 UTC), and MRMS (0400 UTC) from 9 August 2009 are shown in Figure 9A, 9B, 9C, and 9D, respectively. The classification results within two regions, highlighted with two circles, are

convective (SVM and MRMS) and stratiform (BAL^0 and BAL$^{-0.5}$). Radar variables from 0402 UTC are shown in Figure 10 including the reflectivity (A), differential reflectivity (B), and separation index (C), respectively. Figure 10D is the zoom-in reflectivity field inside the red rectangular box (A) for more details. It was found that a heavy precipitation band is on the top of RCMK (Figure 10D), and this may cause significant attenuation on Z and Z_{DR} fields. Although both Z and Z_{DR} fields
315 were corrected using Equation 1, deficient or excessive compensations on Z and Z_{DR} fields lead to increased uncertainty on the separation index. It may be the primary reason causing the small values of the separation index. Other reasons such as wet radome may also contribute to the Z and Z_{DR} issues. In Figure 10C, the separation index i are equal or less than -0.5 in the circled areas, and the BAL based approaches classify these regions as stratiform. On the other hand, these regions clearly show the convective precipitation features in the fields of Z (10A) and Z_{DR} (10B).

320 ### 3.2.3   Stratiform precipitation event

The performances of BAL^0, BAL$^{-0.5}$, and SVM were also evaluated with a widespread stratiform precipitation event on 26 March 2011. This is a typical stratiform precipitation event, and there were no convective type pixels identified by MRMS. These three approaches showed consistent classification results with the MRMS result during an 8-hour period evaluation. ~~Since no convective type pixels were detected by these three approacheseither, evaluation scores were not calculated and~~
325 ~~presented~~For all three approaches, the scores of POD, FAR, CSI, and R^{CS} are 1, 0, 1, and 0, respectively.

4   Conclusions

A novel precipitation classification approach using a support vector machine approach was developed and tested on a C-band polarimetric radar located in Taiwan. Different from other classification algorithms that use a complete volume scan data, the proposed method only utilizes the data from the lowest unblocked tilt to separate precipitation into convective or stratiform
330 type. This feature makes this approach an optimal option in new scanning schemes such as AVSET, SAILS, MRLE, and etc. Three radar variables of reflectivity, differential reflectivity, and the separation index derived by Bringi et al. (2009) are utilized in the new proposed approach. Both reflectivity and differential reflectivity need be corrected from attenuation and differential attenuation before applied in this approach. Although the separation index alone can be used in the precipitation classification, there are two potential limitations: thresholds and biases on reflectivity and/or differential reflectivity. A threshold of "0" was
335 suggested in separating convective type from stratiform type~~, however,~~ However, it was found that a single threshold may not be sufficient for all cases. Other thresholds (such as "-0.5" used in the current work), sometimes can produce better results than "0". On the other hand, although both reflectivity and differential reflectivity should be corrected from attenuation before used in the separation index calculation, the correction biases on either filed may cause large uncertainty in the derived separation index and further lead to a wrong ~~classification~~decision.
340   This work attempts to propose a complementary method to enhance the performance of using the separation index~~only~~. The proposed approach integrates input variables with a support vector machine method. The ~~weights vector and bias~~ parameters used in the support vector machine were trained with typical stratiform and convective precipitation events. It should be noted

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that the proposed approach has a flexible framework, and some other variables can be easily included. With newly added variables, the weight vector and bias need to be retrained. In the current work, the proposed approach was tested with multiple

345 precipitation events. Its performance was found better than using then separation index only and similar to a well developed approach, MRMS, which utilizes multiple tilts radar data in the classification. It should be noted that although the proposed approach shows better scores (POD, FAR, CSI and R^{CS}), this evaluation should be treated as qualitative evaluation instead of statistical analysis. In order to obtained statistical evaluation results, more long-term precipitation events are needed.

There are some issues that need to be noticed before applying this approach for the operation purpose.

350 First, this approach is developed for the fast scan and fast update purpose, and data from the lowest unblocked tilt is used. If the radar is located in a complex orography area, radar beams could be partially or completely blocked in some regions. A possible solution for such a scenario is using data from different tilts to form a hybrid scan, and the hybrid scan is then used as the input. Given the fact that precipitation's microphysics (such as drop size distribution) from different altitudes may be significantly different, the performance of the proposed approach may be worse than expected. Second, the

355 performance of the proposed approach depends highly on the training data, which should be selected very carefully. In the current work, a threshold of $\rho_{HV} > 0.9$ is used in the data selection. Using a lower threshold may cause different performance, and more investigations on this issue are needed. Moreover, only very limited training data is used in the current work. Much more data from various precipitation events should be included in the training process if the proposed algorithm is implemented in operation. Third, coefficients in the separation index calculation depend on the local drop size distribution

360 and drop shape relation features. Therefore, new relations need to be derived for the optimal results. Moreover, the separation index only validates at liquid phase precipitation. For ice phase precipitation, such as mixed hail and rain, its performance is not well studied. Other hydrometeor classification schemes could be used for such a scenario. Fourth, the mis-calibration may significantly affect the performance of the proposed approach. The calibration biases for Z and Z_{DR} should be within 1 dBZ and 0.2 dB, respectively. Moreover, this work only presents a prototype algorithm. Given the flexible framework, other variables

365 (such as differential phase) could be easily integrated into this algorithm, and the performance could be further enhanced.

References

Adler, R. F. and Negri, A. J.: A satellite infrared technique to estimate tropical convective and stratiform rainfall, J. Appl. Meteor., 27, 30–51, 1988.

Anagnostou, E. N.: Doppler radar characteristics of precipitation at vertical incidence, Rev. Geophys. Space Phys., 11, 1–35, 2004.

Biggerstaff, M. I. and Listemaa, S. A.: An improved scheme for convective/stratiform echo classification using radar reflectivity, J. Appl. Meteor., 39, 2129–2150, 2000.

Bringi, V. N., Chandrasekar, V., Hubbert, J., Gorgucci, E., Randeu, W. L., and Schoenhuber, M.: Raindrop size distribution in different climatic regimes from disdrometer and dual-polarized radar analysis, J. Atmos. Sci., 60, 354–365–2122, 2003.

Bringi, V. N., Williams, C. R., Thurai, M., and May, P. T.: Using dual-polarized radar and dual-frequency profiler for DSD characterization: a case study from Darwin, Australial, J. Atmos. Oceanic Technol., 26, 2107–2122, 2009.

Burges, C. J. C.: A tutorial on support vector machines for pattern recognition, Data Min. Knowl. Discovery, 2, 955–974, 1998.

Capozzi, V., Montopoli, M., Mazzarella, V., Marra, A. C., Panegrossi, N. R. G., Dietrich, S., and Budillon, G.: Multi-variable classification approach for the detection of lightning activity using a low-cost and portable X band radar, Remote Sens., 10, 1797, 2018.

Carey, L. D., Rutledge, S. A., Ahijevych, D. A., and Keenan, T. D.: Correcting propagation effects in C-band polarimetric radar observations of tropical convection using differential propagation phase, J. Appl. Meteor., 39, 1405–1433, 2000.

Chang, W.-Y., Wang, T.-C. C., and Lin, P.-L.: Characteristics of the raindrop size distribution and drop shape relation in typhoon systems in the western Pacific from the 2D video disdrometer and NCU C-band polarimetric radar., J. Atmos. Oceanic Technol., 26, 1973–1993, 2009.

Gourley, J. J., Flaming, Z. L., Vergara, H., Kirstetter, P.-E., Clark, R. A., Argyle, E., Arthur, A., Martinaitis, S., Terti, G., Erlingis, J. M., Hong, Y., and Howard, K.: The FLASH project: improving the tools for flash flood monitoring and prediction across the United States, Bull. Amer. Meteor. Soc., 94, 799–805, 2016.

Grecu, M., Olson, W. S., Munchak, S. J., Ringerud, S., Liao, L., Haddad, Z. S., Kelley, B. L., and McLaughlin, S. F.: The GPM combined algorithm, J. Atmos. Oceanic Technol., 33, 2225–2245, 2016.

Haykin, S. O., ed.: Neural networks and learning machines, Pearson Higher Ed., PP 936, 2011.

Hong, Y., Kummerov, C. D., and Olson, W. S.: Separation of convective and stratiform precipitation using microwave brightness temperature, J. Appl. Meteor., 38, 1195–1213, 1999.

Houghton, H. G.: On precipitation mechanisms and their artificial modification, J. Appl. Meteor., 7, 851–859, 1968.

Houze, R. A. J., ed.: Cloud Dynamics, Academic Press, PP. 573, San Diego, 1993.

Houze, R. L.: Stratiform precipitation in regions of convection: A meteorological paradox?, Bull. Amer. Meteor. Soc., 78, 2179–2196, 1997.

Jameson, A. R.: The effect of temperature on attenuation correction schemes in rain using polarization propagation differential phase shift, J. Appl. Meteor., 31, 1106–1118, 1992.

Kirsch, B., Clemens, M., and Ament, F.: Stratiform and convective radar reflectivity-rain rate relationships and their potential to improve radar rainfall estimation, J. Appl. Meteor. Climatol., 58, 2259–2271, 2019.

Leary, C. A. and Jr., R. A. H.: Melting and evaporation of hydrometeors in precipitation from the anvil clouds of deep tropical convection, J. Atmos. Sci., 36, 669–679, 1979.

Park, H., Ryzhkov, A. V., Zrnić, D. S., and Kim, K.-E.: The hydrometeor classification algorithm for the polarimetric WSR-88D: Description and application to an MCS, Wea. Forecasting, 24, 730–748, 2009.

Park, S. G., Maki, M., Iwanami, K., Bringi, V. N., and Chandrasekar, V.: Correction of radar reflectivity and differential reflectivity for rain attenuation at X-band. part II: evaluation and application, J. Atmos. Oceanic Technol., 22, 1633–1655, 2005.

Penide, G., Protat, A., Kumar, V. V., and May, P. T.: Comparison of two convective/stratiform precipitation classification techniques: radar reflectivity texture versus drop size distribution-based approach, J. Atmos. Oceanic Technol., 30, 2788–2797, 2013.

Powell, S. W., Jr., R. A. H., and Brodzik, S. R.: Rainfall-type categorization of radar echoes using polar coordinate reflectivity data, J. Atmos. Oceanic Technol., 33, 523–538, 2016.

Ryzhkov, A. V. and Zrnic, D. S., eds.: Radar Polarimetry For Weather Observations, Springer Atmospheric Sciences, PP 477, 2019.

Skofronick-Jackson, G. and Coauthors: The global precipitation measurement GPM mission for science and society, Bull. Amer. Meteor. Soc., 98, 1679–1695, 2017.

Smith, T. M., Lakshmanan, V., Stumpf, G. J., Ortega, K. L., Hondl, K., Cooper, K., Calhoun, K. M., Kingfield, D. M., Manross, K. L., Toomey, R., and Brogden, J.: Multi-Radar Multi-Sensor (MRMS) severe weather and aviation products: Initial operating capabilities, Bull. Amer. Meteor. Soc., 97, 1617–1630, 2016.

Steiner, M., Jr., R. A. H., and Yuter, S. E.: Climatological characterization of three-dimensional storm structure from operational radar and rain gauge data, J. Appl. Meteor., 34, 1978–2007, 1995.

T., A., Somula, R., K., G., Saxena, A., and A., P.: Estimating rainfall using machine learning strategies based on weather radar data, Int J Commun Syst, p. e3999, https://doi.org/10.1002/dac.3999, 2019.

Testud, J., Bouar, E. L., Obligis, E., and Ali-Mehenni, M.: The rain profiling algorithm applied to polarimetric weather radar, J. Atmos. Oceanic Technol., 17, 332–356, 2000.

Thompson, E. J., Rutledge, S. A., Dolan, B., and Thursai, M.: Drop size distributions and radar observations of convective and stratiform over the equatorial Indian and West Pacific Oceans, J. Atmos. Sci., 72, 4091–4125, 2015.

Tokay, A. and Short, D. A.: Evidence from tropical raindrop spectra of the origin of rain from stratiform versus convective clouds, J. Appl. Meteor., 35, 355–371–4125, 1996.

Vulpiani, G., Montopoli, M., Passeri, L. D., Gioia, A. G., Giordano, P., and marzano, F. S.: On the use of dual-polarized C-band radar for operational rainfall retrieval in mountainous areas, J. Appl. Meteor. Climatol., 51, 405–425, 2012.

Wang, Y., Zhang, J., Ryzhkov, A. V., and Tang, L.: C-band polarimetric radar QPE based on specific differential propagation phase for extreme typhoon rainfall, J. Atmos. Oceanic Technol., 30, 1354–1370, 2013.

Wang, Y., Zhang, P., Ryzhkov, A. V., Zhang, J., and Chang, P.-L.: Utilization of specific attenuation for tropical rainfall estimation in complex terrain, J. of Hydrometeorology, 15, 2250–2266, 2014.

Yang, Y., Chen, X., and Qi, Y.: Classification of convective/stratiform echoes in radar reflectivity observations using a fuzzy logic algorithm, J. Geophys. Res. Atmos., 118, 1896–1905, 2013.

Yen, M., Liu, D., and Hsin, Y.: Application of the deep learning for the prediction of rainfall in Southern Taiwan, Sci. Rep., 9, 12 774, 2019.

Zhang, G., ed.: Weather Radar Polarimetry, CRC Press PP 304, 2016.

Zhang, J., Howard, K., Langston, C., Vasiloff, S., Kaney, B., Arthur, A., Cooten, S. V., Kitzmiller, K. K. D., Ding, F., Seo, D.-J., Wells, E., and Dempsey, C.: National mosaic and multi-sensor QPE (NMQ) system: Description, results, and future plans, Bull. Amer. Meteor. Soc., 92, 1321–1338, 2011.

Zhang, J., Howard, K., Langston, C., Kaney, B., Qi, Y., Tang, L., Grams, H., Wang, Y., Cocks, S., Martinaitis, S., Arthur, A., Cooper, K., Brogden, J., and Kitzmiller, D.: Multi-Radar Multi-Sensor (MRMS) quantitative precipitation estimation: initial operating capabilities, Bull. Amer. Meteor. Soc., 97, 621–638, 2016.
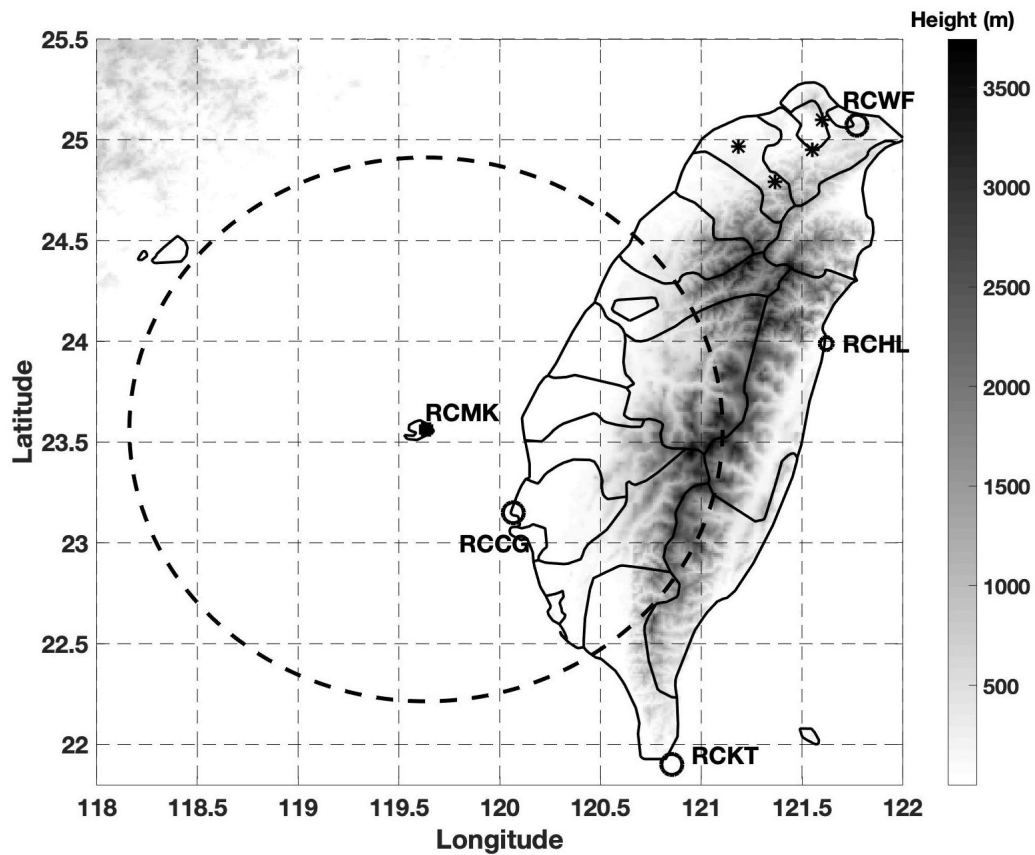
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Figure 1. The terrain of Taiwan, the location of a C-band polarimetric radar RCMK (marked with a black square), JWDs (marked with black stars), and four S-band single-polarization radar RCCG, RCKT, RCHL, and RCWF (marked with black circles). The continuous grey-scale terrain map shows the central mountain range of Taiwan.
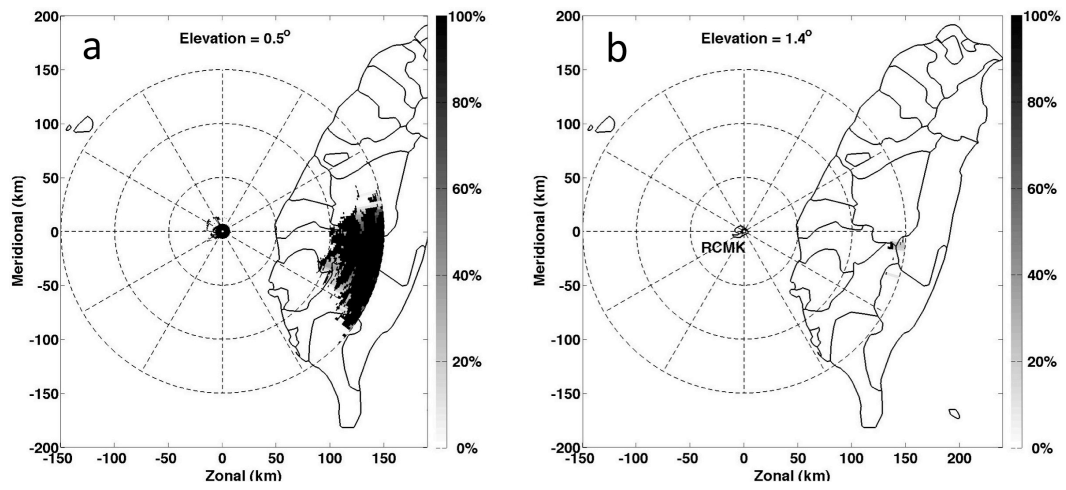
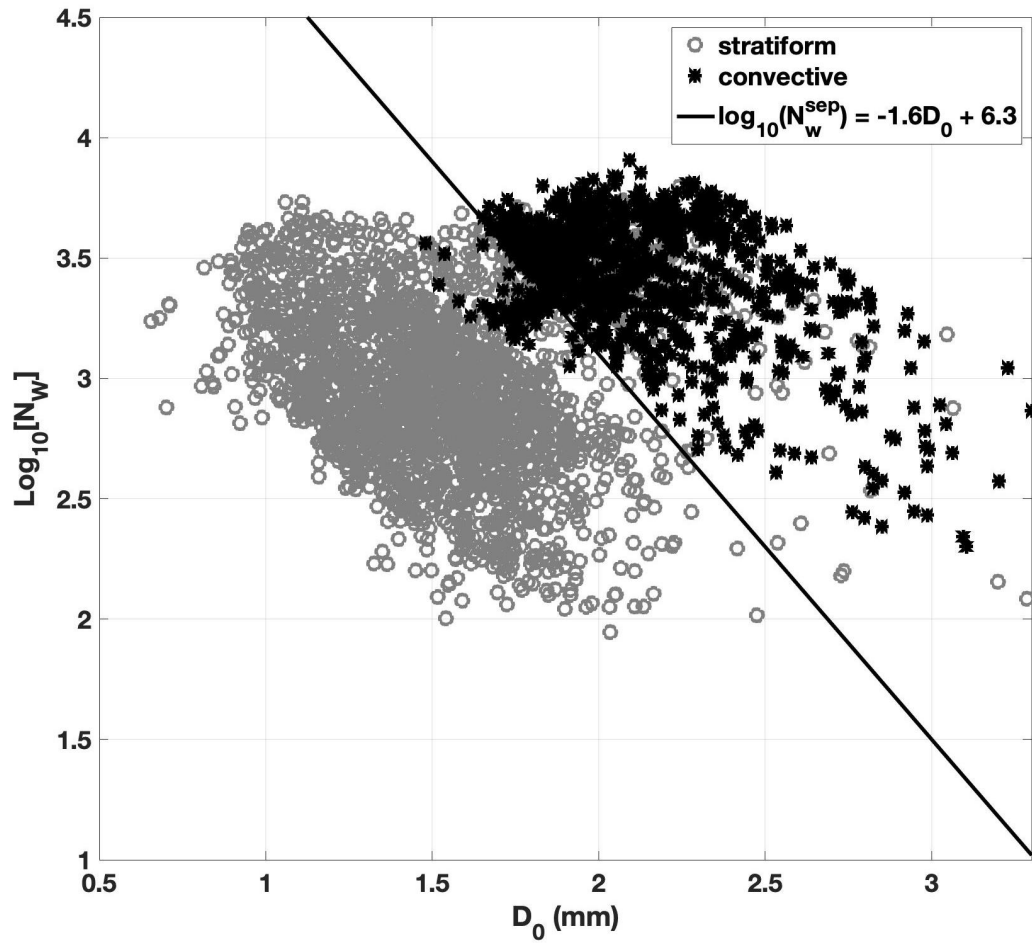**Figure 2.** Blockage maps of RCMK from the first 2 EAs (0.5° and 1.4°). The grey scale indicates the blockage percentages.

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Figure 3. The distribution of $log10(N_w)$ vs D_0. The DSD data from stratiform and convective precipitations are presented with gray circles and black stars, and the separator line is shown with a solid line.
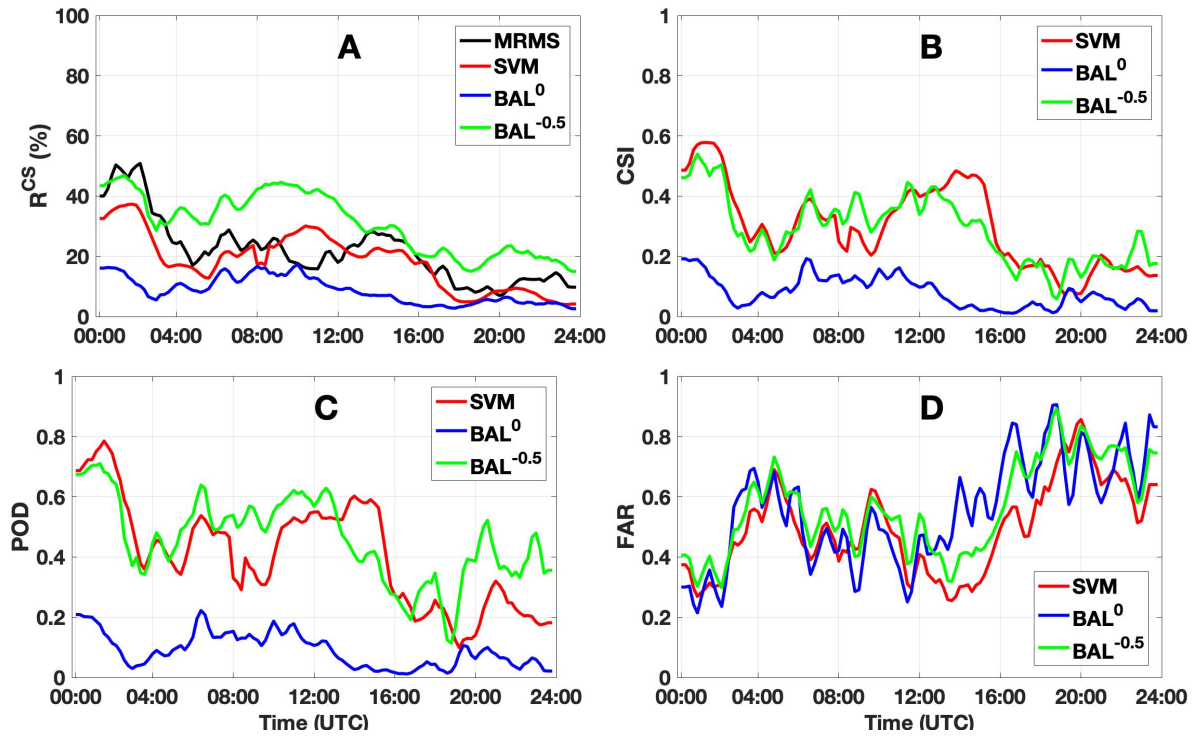
Figure 4. The time series plot of R^{CS}(A), CSI(B), POD(C), and FAR(D) from 30 August 2011. 24-hours data 0000 UTC 2400 UTC are used in each case. The results from BAL with threshold T_0 = -0.5, BAL with threshold T_0 = 0, SVM, MRMS, are presented by green, blue, red and black lines, respectively.
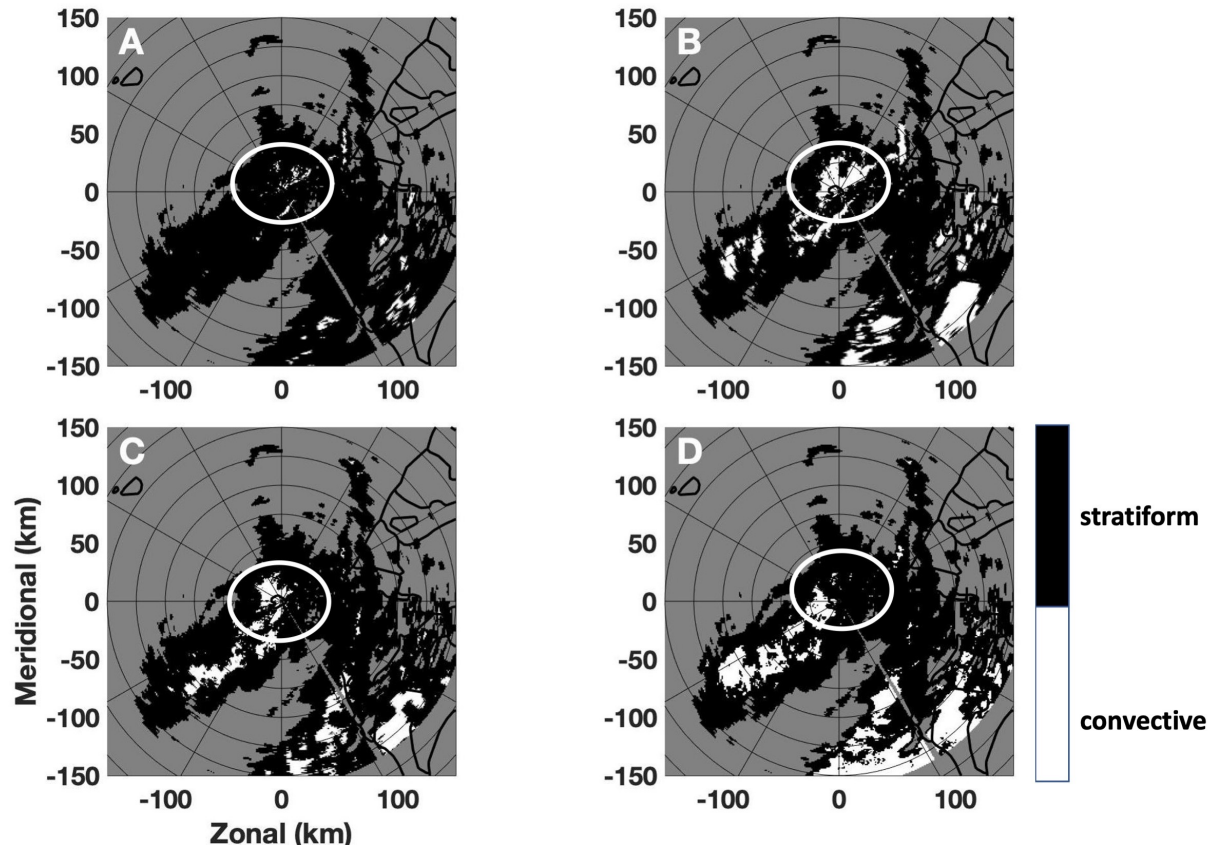
Figure 5. The classification results from BAL^0(A), $BAL^{-0.5}$(B), SVM(C) and MRMS(D). The time stamp for BAL^0, $BAL^{-0.5}$, and SVM is 0303 UTC 30 August 2011, and time stamp for MRMS is 0300 UTC 30 August 2011. The region inside the white circle is used in the analysis.

20
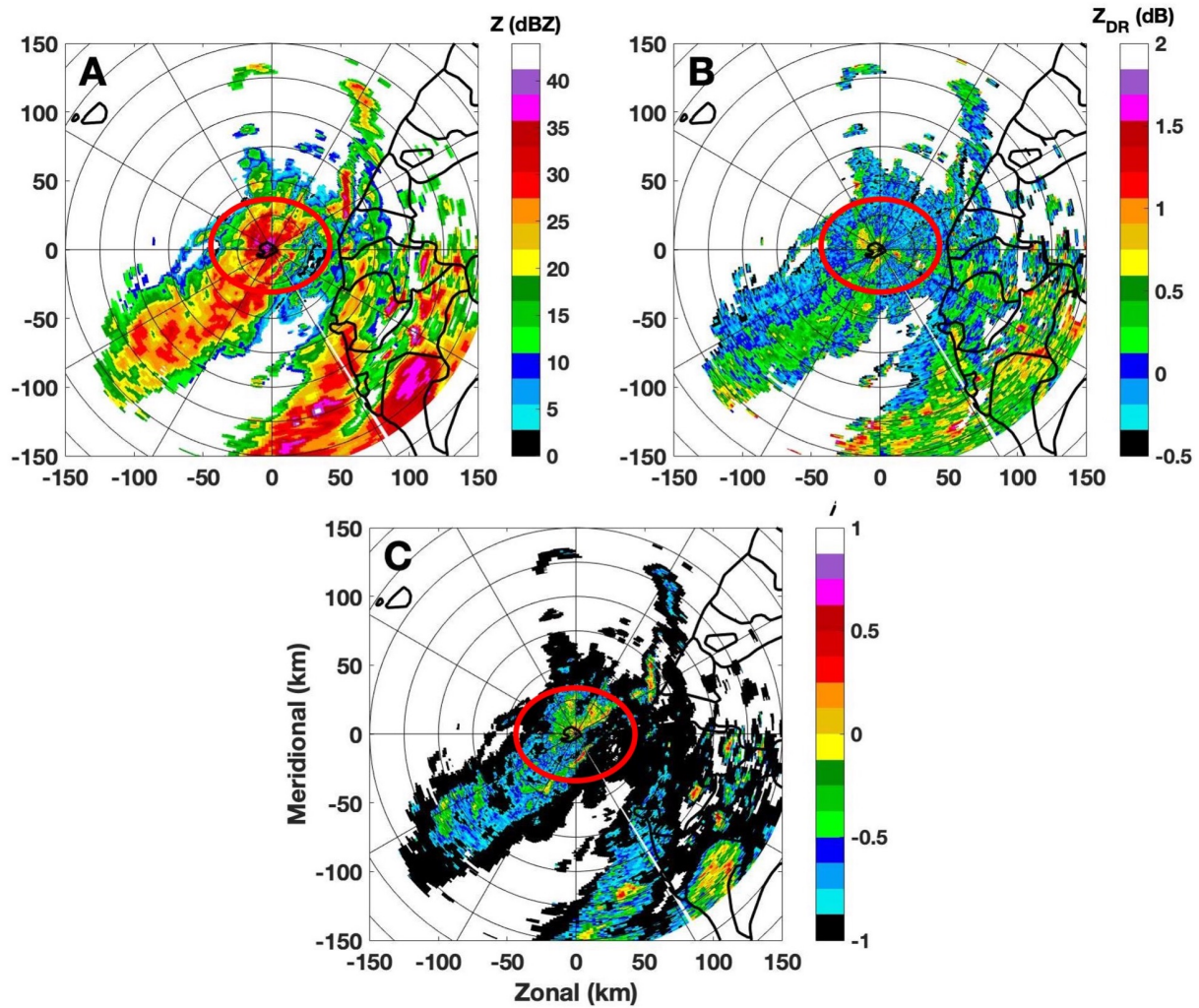
Figure 6. Radar variables of reflectivity (A), differential reflectivity(B), and separation index(C). The radar data was collected by RCMK at 0303 UTC 30 August 2011. The region inside the red circle is used in the analysis.
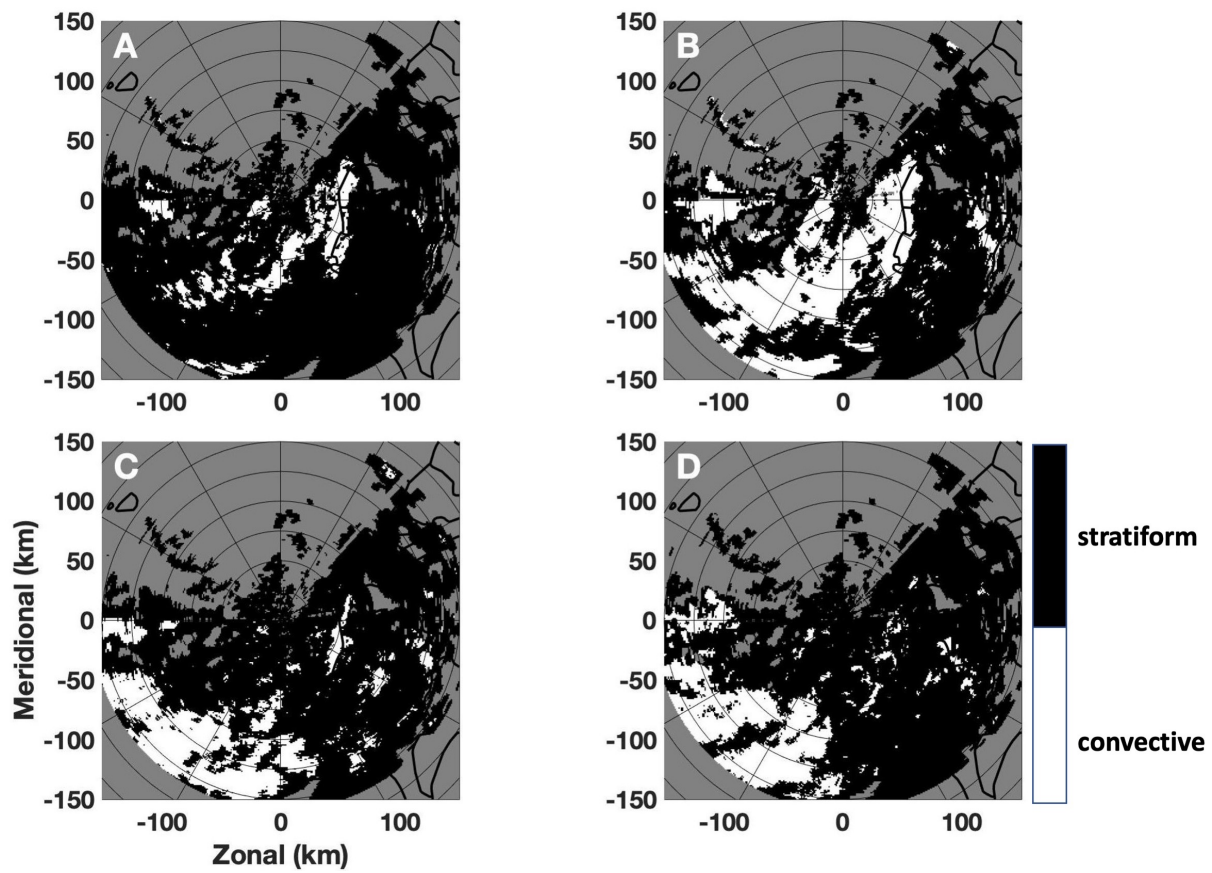
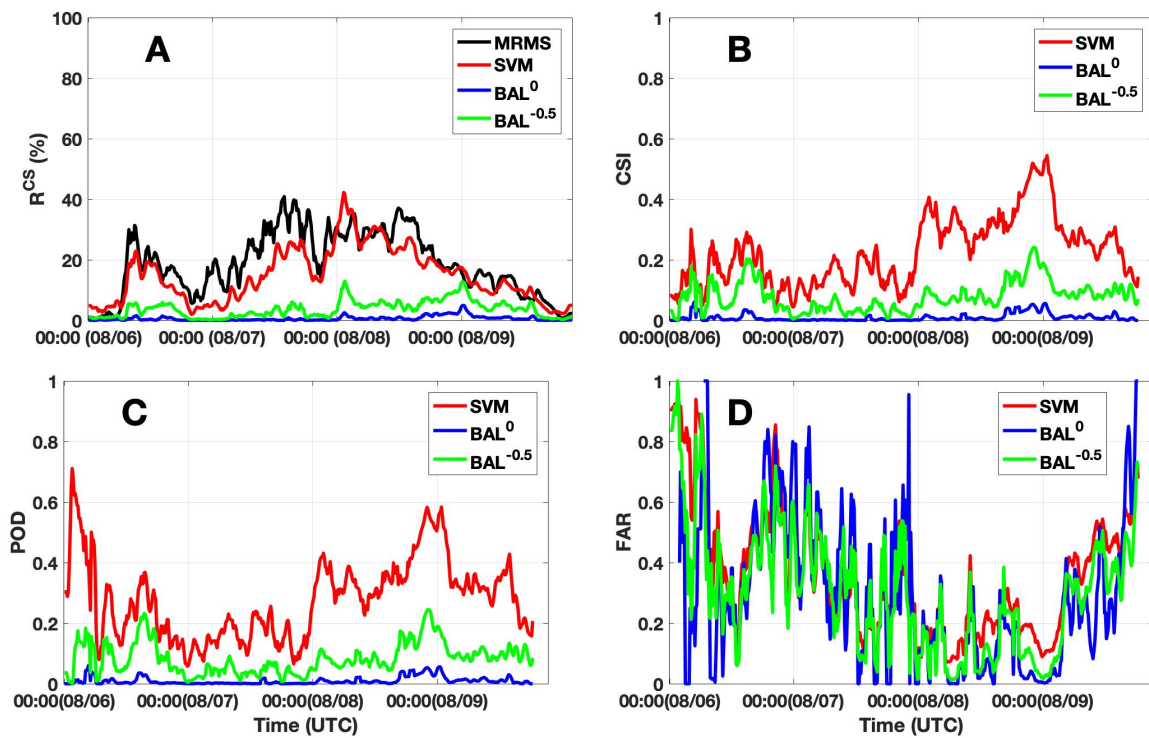**Figure 7.** Similar to Figure 5, results are from 0650 UTC.

Figure 8. The time series plot of R^{CS}(A), CSI(B), POD(C), and FAR(D) from 06~09 August 2009. 96-hours data are used in each case. The results from BAL with threshold T_0 = -0.5, BAL with threshold T_0 = 0, SVM, and MRMS are indicated by green, blue, red and black lines, respectively.
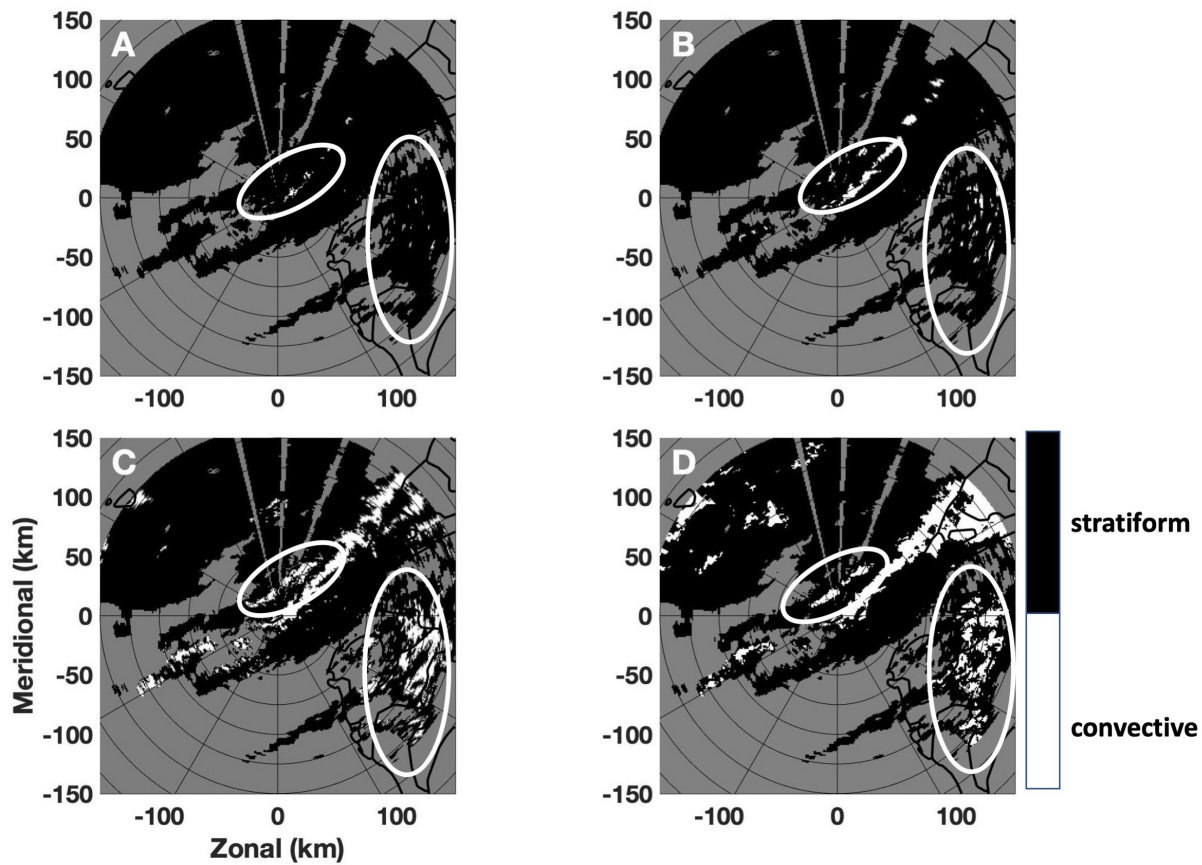
Figure 9. The classification results from BAL^0(A), $BAL^{-0.5}$(B), SVM(C), and MRMS(D). The time stamp for BAL^0, $BAL^{-0.5}$, and SVM is 0402 UTC 9 August 2009, and time stamp for MRMS is 0400 UTC 9 August 2009.
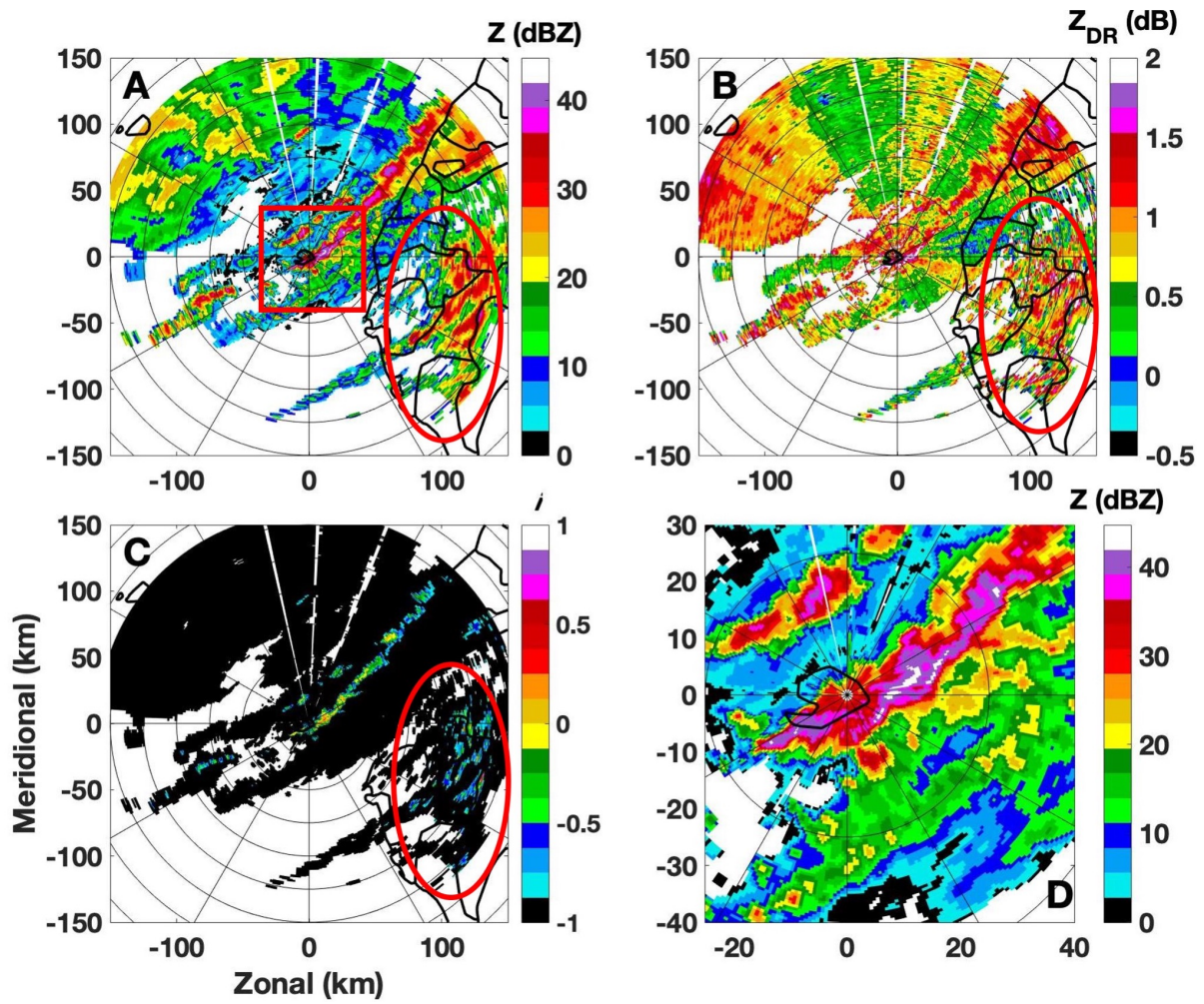
Figure 10. Radar variables of reflectivity(A), differential reflectivity(B), separation index(C), and reflectivity within the red rectangular box in A(D). The radar data was collected by RCMK at 0402 UTC 9 August 2009.