Response to Anonymous Referee #1

The article amt-2020-230 entitles 'A robust low-level cloud and clutter discrimination method for ground-based millimeter-wavelength cloud radar' by Xiaoyu Hu, Jinming Ge, et al., (2020).

General Comment:

The research article mainly uses the measurements of groundbased 35-GHz cloud radar. The authors propose a clutter or biota discrimination method under the presence of low-level clouds. A Multi-dimensional PDF approach effectively has been utilized for Cloud and Clutter identification. Further, the obtained PDFs are used to train the AI-/ML-based Bayesian classifier for the classification mask generation. The scientific results and conclusions presented in a clear, concise, and well-structured way with number and quality of figures/tables, appropriate use of the English language. However, one specific primary concern is as below:

Response: We thank the reviewer very much for his/her positive comments and suggestions on this manuscript, which are very helpful for improving the quality of our paper. Our detailed responses to the comments are listed below.

Specific Major Concern:

Authors mainly showcase shallow layer clouds' persistently long presence whose flat horizontal cloud base was found using collocated ceilometers based cloud base observation (fig 8-10). Moreover, all the presented cloud and clutter discrimination cases have more apparent boundary discrimination between clutter and cloud, the meteorological target. Fig. 8 is a broken cumulus case, but the cloud base is elevated above 1.5 km, just above the clutter. Please include few shallow convective cloud cases surrounded by dense biota/insect clutter and cloud base having biota (near similar to authors fig 4, but here cloud is not weak because it possesses strong dBZ values above 10). The reason for asking it because it is interesting to see the performance of the proposed method under a dense clutter crowded the broken cumuli with duration may be less than a few minutes (e.g., see referred Luke et al., (2008) & Kalapureddy et al., AMT,(2018) within Fig 13-14 and A3).

Response: Thanks for this important comment. We have added another two cases in the manuscript following the reviewer's suggestion. One is shallow convective cloud cases with clutter near cloud base in Fig. 1, another is a case of low-level clouds surrounded by dense clutters as shown in Fig. 2 below. These two cases show that the method can successfully discriminate most shallow convective cloud from dense clutter, although a few cloud droplets are misclassified as clutters. We have added the description for these two more cases and marked them as Fig. 11 and 12 in the revised manuscript.

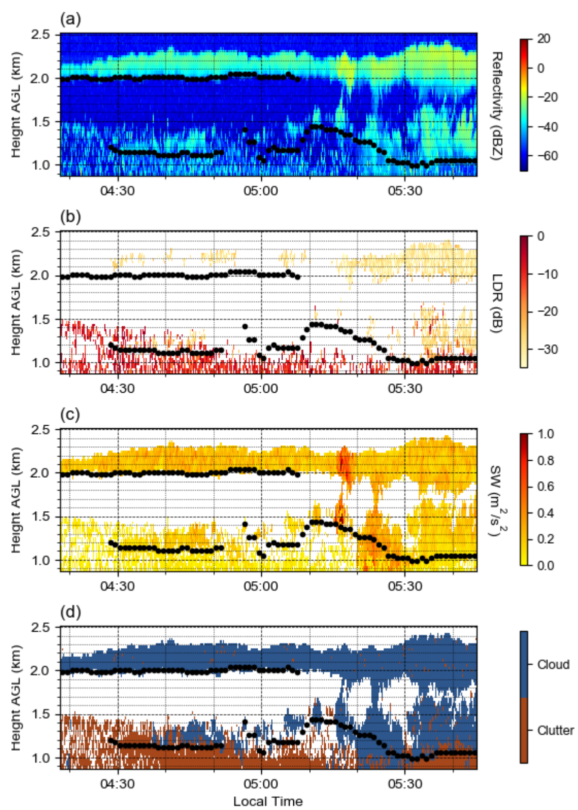

Figure 1. (Figure 11 in the revised manuscript). Same as Figure 8 in the original manuscript, except from local time 04:18 to 05:45 on July 20th, 2014.

Figure 1 shows a case of broken cumulus and shallow convective clouds under stratus. One can see a few thin clouds (less than 300 m) below 1.5 km AGL during 04:30 to 05:10 and some broken cumulus from 04:30 to 04:50, which are like the case shown in Figure 8 but with lower cloud top and base heights ("more deeply buried" in the clutter layer). There may be many insets in the cloud, causing the large radar observed LDR, e.g., from 04:30 to 04:40 (greater than −15 dB, Fig. 1b), therefore, these range gates are classified as clutter by our algorithm (Fig. 1d). The clouds, where are less effected by insects from 04:40 to 04:50 (lower LDR than −15 dB and higher SW than 0.4 m^2/s^2), are identified as cloud no doubt. Note that the occurrence of interlaced blocky appearance of classification masks around 04:40 (Fig. 1d). There are only little available LDR range gates there (Fig. 1b), meaning the classification masks are mostly contributed by the spatial filter (Sect. 3.4), which causes some misclassification (e.g., from 04:30 to 04:40) because the spatial correlation of clouds is reduced since they are largely contaminated by clutter. During 04:55 to 05:15, a few broken clouds higher away from the clutter layer are successfully identified by the algorithm, which is in accordance with the MPL lidar detections, indicating the spatial filter does work well when clouds are not adjacent to falsely identified masks. The shallow convective clouds after 05:15 are more turbulent (SW greater than 0.6 m^2/s^2, Fig. 1c) than these broken cumuli, thus are effectively identified as cloud even with dense clutter layer below. We believe the identified cloud mask below lidar cloud base from 05:15 to 05:30 are drizzle particles because of the virga reflectivity during that time (Fig. 1a).

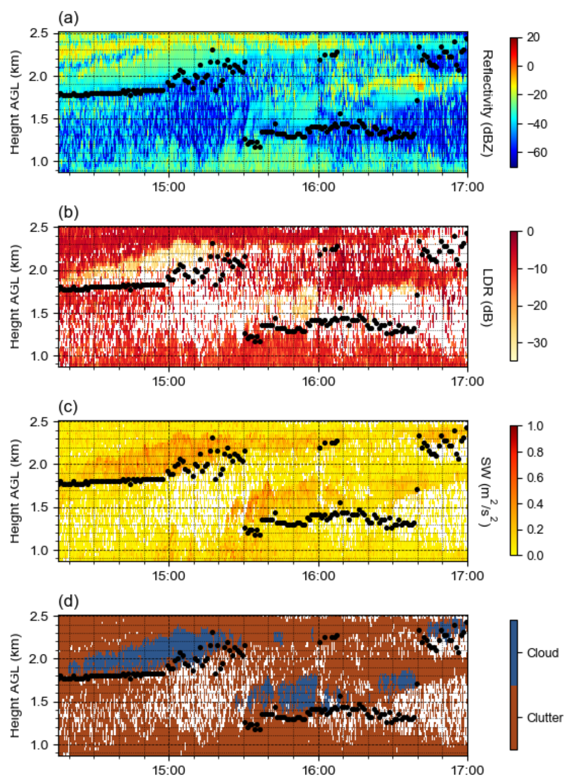

Figure 2. (Figure 12 in the revised manuscript). Same as Figure 8 in the original manuscript, except from local time 14:15 to 17:00 on August 19th, 2013.

Figure 2 shows a case of low-level clouds completely surrounded by intense insets. This is the most difficult case to discriminate cloud and clutter, because cloud signals are heavily contaminated by clutters. Figure. 2d shows that the identified cloud masks correspond well with lidar cloud base during 14:15 to 16:00, due to lower LDR (less than −15 dB, Fig. 2b) and higher SW (greater than 0.4 m^2/s^2, Fig. 2c) of the cloud particles. However, the algorithm misses some clouds with low SW (around 0.2 m^2/s^2, Fig. 2c) during 16:00 to 16:40. Note that large amount of LDRs are unavailable for this cloud (Fig. 2b) and its structure is loose (Fig. 2a), especially around cloud edges where clutter signals are even stronger than cloud. In this circumstance, the algorithm can only identify part of the cloud.

For the better flow of the manuscript, immediately after Sec 3.3's Bayesian method, the method's functional performance can start directly with Sec. 3.4 by shifting the First Para in Pg.10 suitably after ending part of line number 217 (i.e.,'....near-surface in Figure 7c).'

Response: We have modified this paragraph in Sect. 3.4.

All figures from 7-11 need to modify and extend the height (y-axis) up to 3.6 km as per multi-dimensional PDFs maximum height discussed with figures (5-6) and the probability of detecting height with figure 12e.

Response: We modified the height scale in Figures 7-11 up to 3.6 km as shown below (Figs. 3-7) and can see large blank areas above 3 km, which might reduce the readability for these figures. Thus, we believe the original figures are much clear for the details. In addition, the probabilities of detection (P_D) and false alarm rate (P_{FA}) as a function of height are shown in Fig. 12e. That gives info for the reader to see the algorithm’s performance with height. So, we kept the original figures unchanged in the revised version.

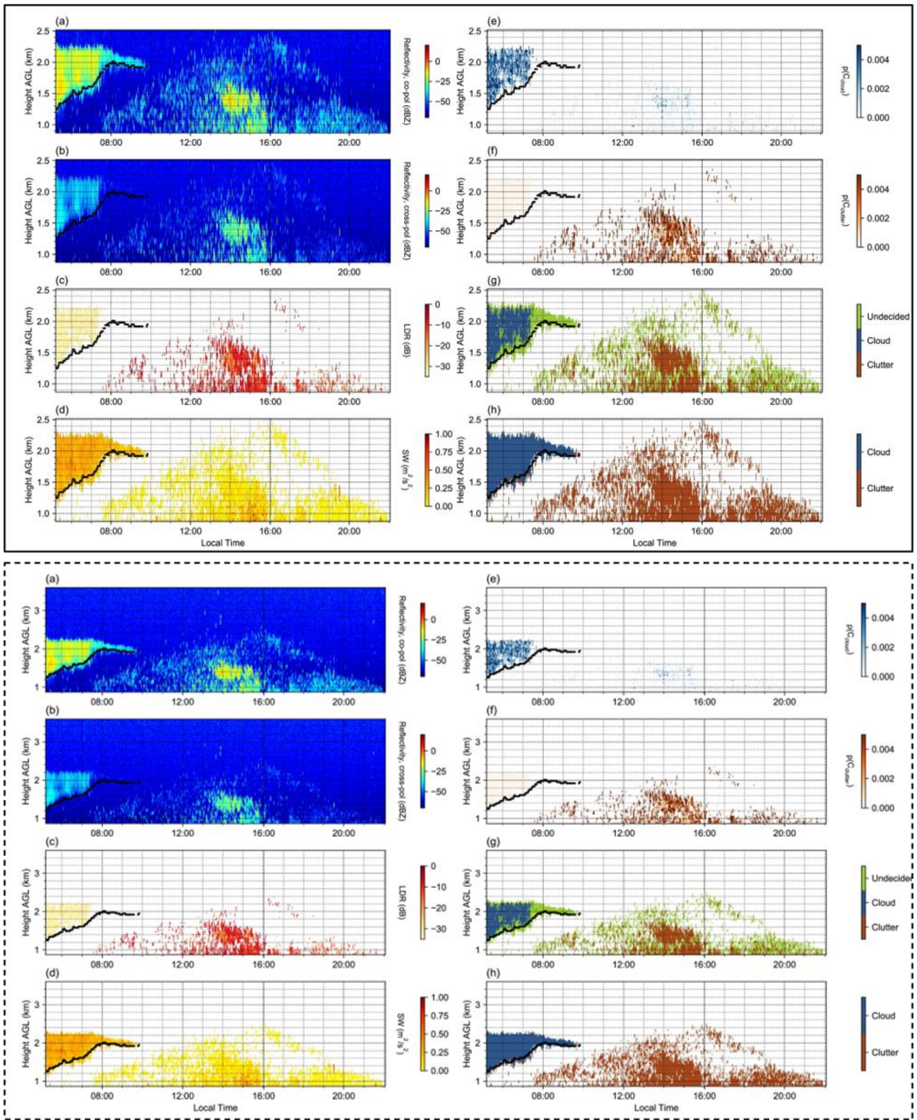

Figure 3. Original figure 7 in the manuscript (top panel within solid line box), and modified figure with extending y-axis (bottom panel within dashed line box)

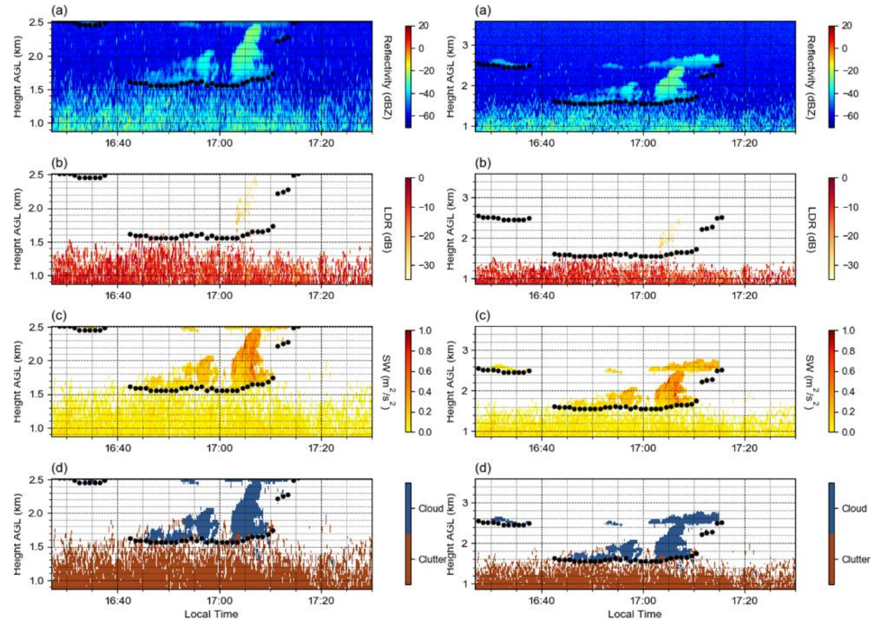

Figure 4. Original figure 8 in the manuscript (left panel), and modified figure with extending y-axis (right panel)

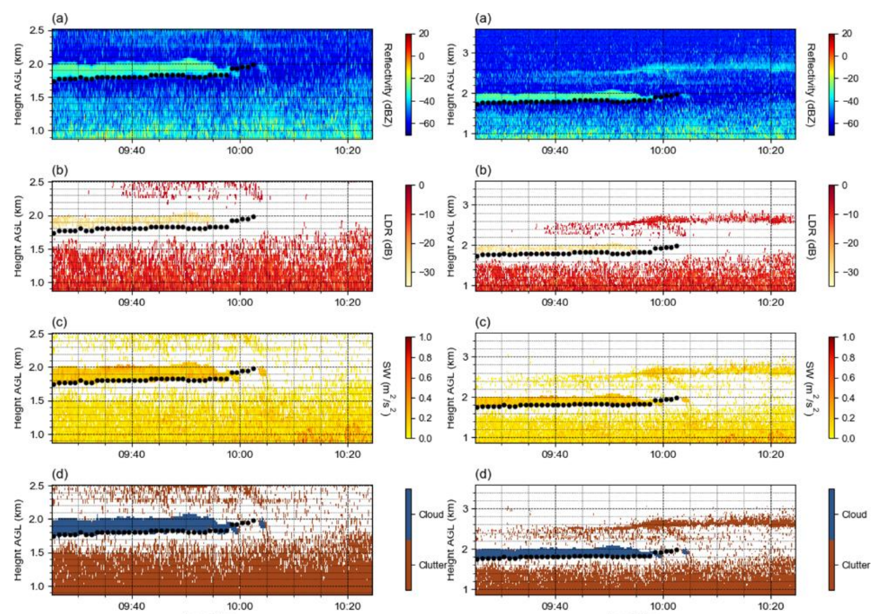

Figure 5. Original figure 9 in the manuscript (left panel), and modified figure with extending y-axis (right panel)

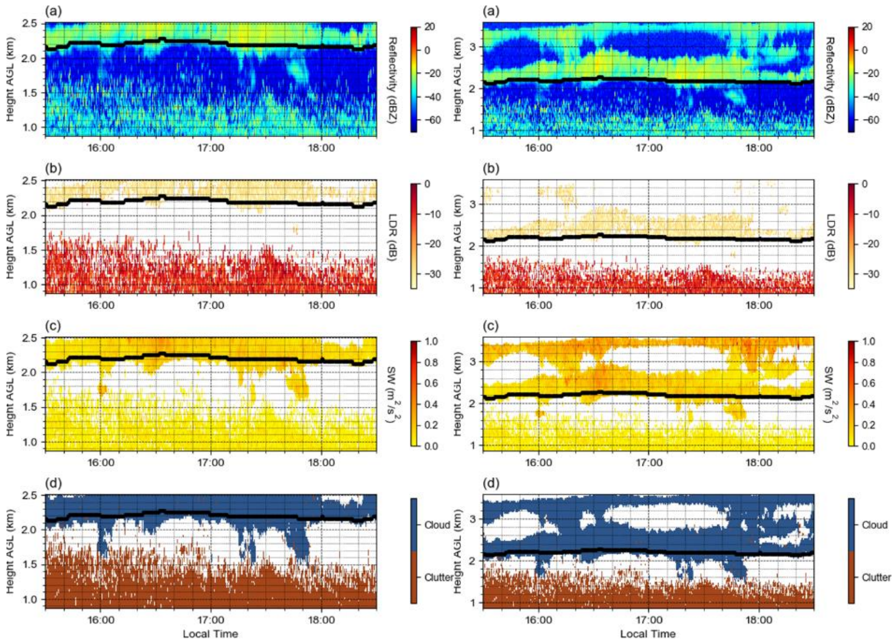

Figure 6. Original figure 10 in the manuscript (left panel), and modified figure with extending y-axis (right panel)

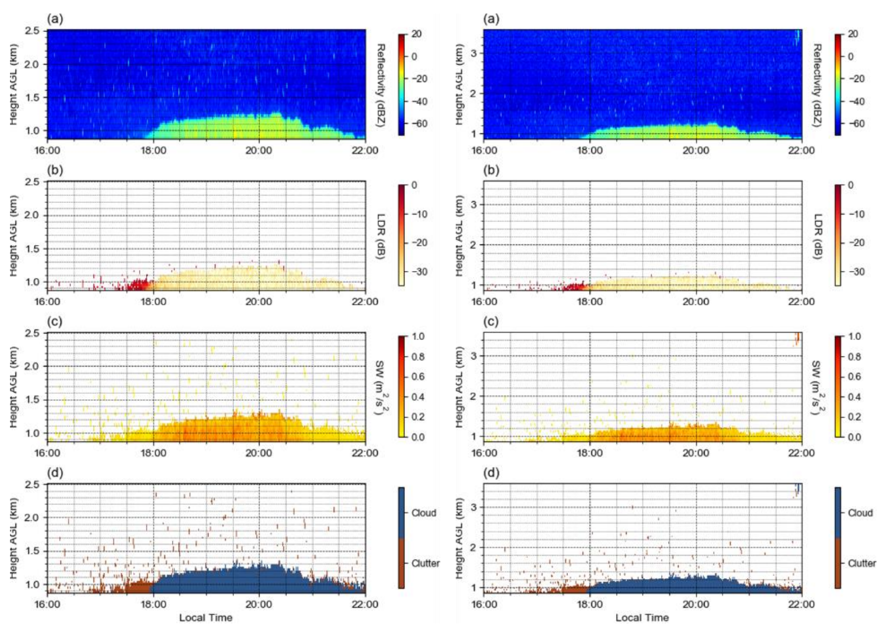

Figure 7. Original figure 11 in the manuscript (left panel), and modified figure with extending y-axis (right panel)

Page 12, Line 53 & Fig.10: How the precipitating drizzle droplets kept as clouds? Is it done manually or taken care of through the spatial filter? Because initially stated (at line no. 119), the non-cloud meteorological targets need to remove with the low-level atmosphere for the created

PDFs' better accuracy to characterize cloud from clutters.

Response: The precipitating drizzle droplets are kept as clouds by the method. Yes, we stated that the non-cloud meteorological targets, including precipitation, melting layer and drizzle, are removed before creating PDF from the training data. However, note that both precipitation and melting layer are merely identified by radar, while drizzle is distinguished from the MPL derived cloud base. That means we can identify precipitation and melting layer before the process of separating cloud from clutter by using the test data, but cannot classify drizzle only using the KAZR observation. Thus, the drizzle is kept as cloud by the method. We think it is acceptable because clutter can be removed on which we mainly focused, and preserving drizzle as cloud rather than clutter, like Luke et al. (2008) explained.

Minor technical corrections:

1. Pg2 Line no. 37: modify the sentence '.....of ground-based millimeter-wavelength cloud radars (MMCR) being……….'? This inclusion is the prerequisite for the Pg3 Line no. 48, an acronym MMCR?

Response: This has been corrected.

2. Pg6 Ln114: '….the flat cloud boundary around 4.5 …' it is not flat but slant.

Response: We have changed “flat” to “slanted”.

3. Pg7 Ln146 & (Fig 4e): '.....the height of maximum (Z' x V') up to 500 m above (below) the peak ….. ' In fact, it is five range gate spacing (of each 30 or 25 m) from the peak (see Fig 4e there are 11 dots between two red dots that is spread in 300 m height (3100-2800). Please check it?

Response: You are right about the depth of the melting layer in the Fig. 4e (11 dots and 300 m). Here, by “500 m”, we don’t mean the real depth, but the “maximum” half depth of melting layer (top to middle, or middle to bottom), that is a threshold of melting layer in the identification algorithm, which was modified from Khanal et al. (2019). The main steps are:

a. Compute the reflectivity', velocity', |reflectivity'|×|velocity'|, and (|reflectivity'|×|velocity'|)''. (The sign of absolute value was missed in the original manuscript and has been added now.)

b. Find the altitude with maximum |reflectivity'|×|velocity'|, which is the middle of melting layer.

c. Search for top of melting layer as maximum (|reflectivity'|×|velocity'|)'' up to 500 m above middle of melting layer.

d. Search for bottom of melting layer as maximum (|reflectivity'|×|velocity'|)'' up to 500 m below middle of melting layer.

We have changed some statements in the manuscript. It should be less confusing now.

4. Fig.4: (a) what is the reason not extending the identified black dots bottom and top portion of the melting layer before 20:24-20:27 LT (where high LDR at ~3 km with yellow backdrop seen)?

Response: It is true that there is still undetected melting layer around 20:24-20:27. This is because the melting layer identification algorithm only works for precipitation profile. No precipitation is detected during that time, so does the melting layer. We tried to develop an independent melting layer identification method from precipitation, but that caused some false detections. Since the undetected melting layer is quiet few by our manual scanning, we think it is acceptable to get the PDF.

5. Fig.4 caption needs to recheck, especially correctness with 2nd line '.....Black dots and gray shading area in the left panels.....' unable to locate the gray shading in left panel except with (b) due to noise (may be removed by the NER with dBZ).

Response: The precipitation is the shaded area after 20:27 and below 2.8 km, which may be not clear in the original manuscript. We modified the figure as shown below.

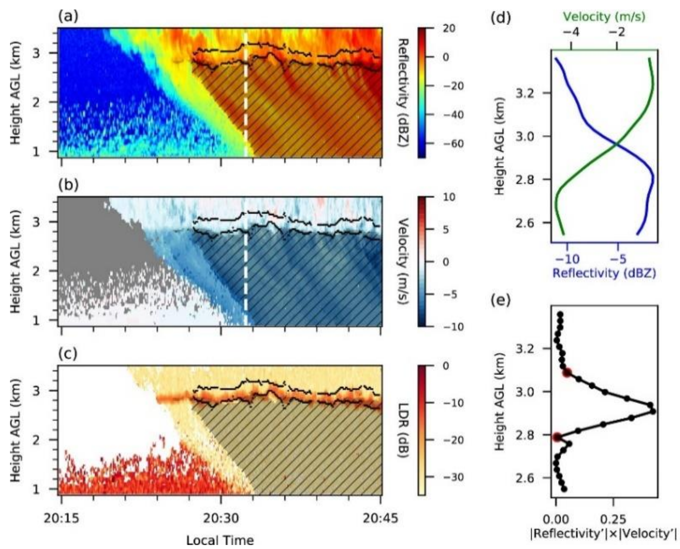

Figure 8 Modified Fig 4 in the original manuscript

6. Pg11 Ln225: Please provide clarity on the used '…spatial filter with 'five range bins in vertical' do you mean with respect to 'height' and 'five range bins in the horizontal' do you mean 'concerning time'??

Response: Yes. "Vertical" refers the height and "horizontal" is time. We have change it as "spatial filter with five range bins respecting to heigh (150 m) and five range bins concerning time (21.4 s)".

7. Pg11 Ln239 end: delete 'is also'.

Response: We think keeping the "is also" is more easily understandable. So, we kept the original sentence unchanged in the revised version.

8. Pg 12 Ln250 & 267: it is confusing to read …lower SW values (below 0.4 m^2 s^{-2}) & higher SW values (around 0.3 m^2 s^{-2}).

Response: We have changed the "around 0.3 m^2/s^2" to "around 0.6 m^2/s^2 in the cumulus from 18:00 to 20:30" in Line 267. The original "0.3 m^2/s^2" is calculated from the whole identified cloud. However, the SW of cumulus during 18:00-20:30 is obviously higher than that during 20:30-22:00. We recalculate the SW during that time, it should be "around 0.6 m^2/s^2".

9. Typo with Equation 4 where ',' read as FN'.

Response: We have deleted the ",".

10. Pg 13 Ln283: modify sentence for completeness '……small portions of the data that overlaps.'

Response: We have rewritten this sentence as "……, however, which are only small portions of the whole data as shown in Figures 5 and 6".

11. Pg 13 Ln289: I agree with the statement '….less fluctuating with time (Fig. 12d) and ' but not for height (Fig.12e) where P_D shows significant changes above 2 km, especially in the cold season after 3.2 km altitude.

Response: Yes, we have explained this in the end of the sentence (which is in the next page that may be missed). It was "except for P_D above 3.2 km, where the clutter is extremely rare (fewer samples)". We changed the original number of "3.5 km" to "3.2 km".

12. Fig. 11 caption should have mentioned reason for missing lidar cloud base.

Response: The lidar observation was not available that day. However, the different LDR values before and after 18:00 help to distinguish cloud from clutter reliably. We have added the expiation in the caption.

Reference:

Khanal, A. K., Delrieu, G., Cazenave, F., & Boudevillain, B. (2019). Radar Remote Sensing of Precipitation in High Mountains: Detection and Characterization of Melting Layer in the Grenoble Valley, French Alps. *Atmosphere, 10*(12).

Luke, E. P., Kollias, P., Johnson, K. L., & Clothiaux, E. E. (2008). A technique for the automatic detection of insect clutter in cloud radar returns. *Journal of Atmospheric and Oceanic Technology, 25*(9), 1498-1513.

Response to Anonymous Referee #3

The authors developed a cloud and clutter discrimination algorithm for a ground-based millimeter-wave cloud radar system collocated to an MPL. The methodology to separate cloud from clutter is based on multivariate histograms that are used in a Bayes classification approach to provide categorical separation. Spectral width (SW), reflectivity, and linear depolarization ratio (LDR) are used to create joint histograms for cloud and insect clutter. The methodology is tested with a few case studies including shallow cumulus in the warm and cold seasons, uniform stratus embedded within insect layers, and precipitating stratocumulus. Comparisons are made to the MPL cloud base and show generally good agreement in the case studies. The approach is extended to one year of data and a probability of detection of 98% is obtained.
The methods, approach, and use of data all appear sound and the manuscript is organized well. The use of English could be improved in places. The novelty of the methods used in this manuscript should be more clearly called out when compared to previous works. These comments should be considered minor in scope, however.

Response: We thank the reviewer very much for his/her positive comments and suggestions on this manuscript. We have carefully read through the manuscript and corrected some grammar errors, including those pointed out by the reviewer. The novelty compared to previous works has also been described more clearly in the revised manuscript.

Detailed comments:
Overall the manuscript could use a thorough edit for the use of English. One example is the use of 'clutters' rather than 'clutter'

Response: We have carefully edited the use of English in the manuscript, including changing "clutter" into "clutters".

In the Introduction, some clearer description of how this approach follows from, or is different from previous literature, should be added. It appears similar approaches exist in the literature but perhaps in pieces. For instance, insect detection with KAZRs may be better handled in spectra *domain as by [1, 4], and LDR statistics with [2], and a similar but more comprehensive dual pol approach in [3] for scanning radars. Generally, LDR based estimates are widely used in the field as well.*

[1] Luke, E. P., P. Kollias, K. L. Johnson, E. E. Clothiaux, A Technique for the Automatic Detection of Insect Clutter in Cloud Radar Returns. J. Atmos. Oceanic Technol. 25, 1498-1513, doi:10.1175/2007JTECHA953.1 (2008). (this is already cited); [2] Martner, B. E., and Moran, K. P. (2001), Using cloud radar polarization measurements to evaluate stratus cloud and insect echoes, J. Geophys. Res., 106(D5), 4891–4897, doi:10.1029/2000JD900623. (not cited); [3] M. A. Rico-Ramirez and I. D. Cluckie, "Classification of Ground Clutter and Anomalous Propagation Using Dual-Polarization Weather Radar," in IEEE Transactions on Geoscience and Remote Sensing, vol. 46, no. 7, pp. 1892-1904, July 2008, doi: 10.1109/TGRS.2008.916979. (not cited); [4] Williams, C. R., Maahn, M., Hardin, J. C., & de Boer, G. (2018). Clutter mitigation, multiple peaks, and high-order spectral moments in 35 GHz vertically pointing radar velocity spectra. (not cited)

Response: We thank the reviewer for providing these relevant references, and we have cited these in the revised manuscript. We agree that the insect detection with KAZR is well handled in spectra domain as by Luke et al. (2008) and Williams et al. (2018). We think some other methods still have scientific significance, like the TEST algorithm proposed by Kalapureddy et al. (2018), which uses reflectivity measurements to characterize irregular echoes associated with clutter returns. Such methods do not require huge spectral data and the analysis processes are relatively simpler. The LDR statistic methods, such as proposed by Martner and Moran (2001) and Rico-Ramirez and Cluckie (2008), are for sure widely used in the field, but they can only be applied when both co- and cross-polarized reflectivities are available, which may be not the case at low signal-to-noise ratio conditions as mentioned by Luke et al. (2008). That is why we use LDR statistics to create the PDFs and use a spatial filter to deal with these range gates when LDR measurements are unavailable. We have added these descriptions in the revised manuscript.

Lines 90-91 are repetitive

Response: We have deleted the second half of this sentence.

Lines 97-100, it appears the entire basis for the cloud and clutter histograms derives from the use of the MPL cloud base product. Are there other discriminants? How these histograms were obtained should be clearer. Furthermore, how do aerosols (e.g., dust) impact the histograms? Is there any dust in the case studies shown, and would the authors expect dust to hinder the discrimination of clouds and clutter in the algorithm itself?

Response: Yes, the histograms derived from the MPL cloud base product are the basis for the cloud and clutter separation. There is no other discriminant. The histograms are derived through the following steps: (1) we first collect all the reflectivity, LDR, SW data for cloud and clutter at different height and season based on MPL cloud base product; (2) we then divide all the samples into 12 panels according to their time and height ranges for warm and cold seasons separately (as shown in Fig. 5 and 6); (3) in each panel, the probability is calculated by $p(\boldsymbol{X}=\boldsymbol{X}^O|C_i) = n(\boldsymbol{X}=\boldsymbol{X}^O|C_i)/\sum n(\boldsymbol{X}=\boldsymbol{X}^O|C_i)$, where $p(\boldsymbol{X}=\boldsymbol{X}^O|C_i)$ is the conditional probability of discriminants being $\boldsymbol{X}^O$ for class C_i, $n(\boldsymbol{X}=\boldsymbol{X}^O|C_i)$ is the number of samples of discriminants being $\boldsymbol{X}^O$ for class C_i, $\sum n(\boldsymbol{X}=\boldsymbol{X}^O|C_i)$ is the number of discriminant samples being $\boldsymbol{X}^O$ for all classes. We have added the details of calculation in Sect. 3.2 (Line 175) in the revised manuscript, as "……, which is calculated as the number of samples in each discriminant range for each class (clouds or clutters), divided by the total number of samples in each discriminant range for all classes."

For the impact of aerosols on the histogram, since MPL is not susceptible to the clutters, we use its cloud base product to separate cloud and clutter samples. All the non-cloud features identified from MPL, which are measured as significant echoes by KAZR, are considered as clutters, including insects, dust aerosols, pollen, or dry leaves. In other words, the clutter type is not the main concern of this study. Here, the MPL cloud base is derived from a feature detection using continuous wavelet transform analyses (Xie et al., 2017) that can well separate cloud and dust aerosols. Based on our current algorithm, we can not identify the clutter type (insect or dust), so we are not sure if there is any dust shown in the case studies. However, we do not expect that the dust would hinder the discrimination of clouds and clutters.

Line 157, not sure if 'discrepant' is the right word

Response: We have changed it to "distinct"

Lines 173-174, while the literature describes the number density and height of insects are temperature-dependent, do the species of insects themselves differ with season? Could a seasonal species dependence of insects have some bearing on the characteristics of the pdfs?

Response: Thanks for this interesting comment. Yes, the insect migration can cause seasonal variation of insect species. Note that cotton bollworm emerging in the far northeast of China would migrate into northern China in autumn, changing the local species of insect (Feng et al., 2007). The species of insects do affect the radar observation, due to their various shape, length, and wing-beat frequency, generating different morphology on spectra domain (Wang et al., 2017). However, such difference normally doesn't affect the reflectivity, LDR or SW (Wainwright et al., 2020), or the created PDF, consequently. Despite that, the difference of radar measurements between various insect species is smaller than that between insects and cloud droplets. Thus, we ignore the seasonal variation of insect species which may have a very small impact on the created PDFs.

Reference:

Feng, H. Q., Wu, K. M., Ni, Y. X., Cheng, D. F., and Guo, Y. Y.: Return migration of Helicoverpa armigera (Lepidoptera: Noctuidae) during autumn in northern China, Bulletin of Entomological Research, 95, 361-370, 10.1079/ber2005367, 2007.

Kalapureddy, M. C. R., Sukanya, P., Das, S. K., Deshpande, S. M., Pandithurai, G., Pazamany, A. L., Ambuj K, J., Chakravarty, K., Kalekar, P., Devisetty, H. K., and Annam, S.: A simple biota removal algorithm for 35 GHz cloud radar measurements, Atmospheric Measurement Techniques, 11, 1417-1436, 10.5194/amt-11-1417-2018, 2018.

Wainwright, C. E., Reynolds, D. R., and Reynolds, A. M.: Linking Small-Scale Flight Manoeuvers and Density Profiles to the Vertical Movement of Insects in the Nocturnal Stable Boundary Layer, Scientific Reports, 10, 10.1038/s41598-020-57779-0, 2020.

Wang, R., Hu, C., Fu, X., Long, T., and Zeng, T.: Micro-Doppler measurement of insect wing-beat frequencies with W-band coherent radar, Scientific Reports, 7, 10.1038/s41598-017-01616-4, 2017.

Xie, H., Zhou, T., Fu, Q., Huang, J., Huang, Z., Bi, J., Shi, J., Zhang, B., and Ge, J.: Automated detection of cloud and aerosol features with SACOL micro-pulse lidar in northwest China, Optics Express, 25, 10.1364/oe.25.030732, 2017.

A robust low-level cloud and clutter discrimination method for ground-based millimeter-wavelength cloud radar

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Abstract. Low-level clouds play a key role in the energy budget and hydrological cycle of the climate system. The accurate long-term observation of low-level clouds is essential for understanding their climate effect and model constraints. Both ground-based and spaceborne millimeter-wavelength cloud radars can penetrate clouds but the detected low-level clouds are always contaminated by clutters, which need to be removed. In this study, we develop an algorithm to accurately separate low-level clouds from clutters for ground-based cloud radar using multi-dimensional probability distribution functions along with the Bayesian method. The radar reflectivity, linear depolarization ratio, spectral width, and their dependences on the time of the day, height and season are used as the discriminants. A low pass spatial filter is applied to the Bayesian undecided classification mask by considering the spatial correlation difference between clouds and clutters. The final feature mask result has a good agreement with lidar detection, showing a high probability of detection rate (98.45%) and a low false alarm rate (0.37%). This algorithm will be used to reliably detect low-level clouds at the Semi-Arid Climate and Environment Observatory of Lanzhou University (SACOL) site for the study of their climate effect and the interaction with local abundant dust aerosol in semi-arid region.

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1. Introduction

Clouds play a crucial role in the Earth-atmosphere system by reflecting solar radiation back to space and trapping outgoing terrestrial radiation (Bony et al., 2015; Fu et al., 2000, 2018; Quaas et al., 2016). Clouds also produce precipitation to release large amounts of latent heat into the atmosphere, compensating the atmospheric radiative cooling, which is consequently closely related to the hydrological cycle and global distribution of water resources (Bala et al., 2010; Fu et al., 2002; Nuijens et al., 2017). Low-level clouds are primarily composed of water droplets and have an overall cooling effect on the climate system. In the context of global warming, tropical low-level cloud amount decreases because of stronger surface turbulent fluxes and dryer planetary boundary layer, generating a positive climate feedback through a reduction in the reflection of short-wave radiation (Brient and Bony, 2012; Zhang et al., 2018); While the liquid water path of low-level clouds over mid- to high-latitude tends to increase due to a reduced conversion efficiency of liquid water to ice and precipitation, which leads to a negative feedback (Ceppi et al., 2016; Terai et al., 2016). However, the magnitude of these low-level cloud feedbacks responds inconsistently in different climate models, producing a wide range of equilibrium climate sensitivity (Mace and Berry, 2017; Watanabe et al., 2018; Zelinka et al., 2020). To reduce this uncertainty, accurate long-term observations are important to characterize low-level clouds and understand their climate feedbacks (Garrett and Zhao, 2013; Toll et al., 2019; Turner et al., 2007).

The ground-based cloud radars can probe the vertical structure of low-level clouds in high temporal-vertical resolution, including multi-layer clouds (Kim et al., 2011; van der Linden et al., 2015). Due to substantial progress in the development and application of ground-based radars, there are increasing numbers of ground-based millimeter-wavelength cloud radars (MMCR) being deployed all over the world (Arulraj and Barros, 2017; Huo et al., 2020; Kollias et al., 2019). Their short wavelengths allow the radars to detect clouds with small droplets and infer the microphysical and dynamical cloud processes (Kollias et al., 2007a). A Ka-band zenith radar (KAZR) has been continuously running at the Semi-Arid Climate and Environment Observatory of Lanzhou University (SACOL) since 2013 (Ge et al., 2018, 2019; Huang et al., 2008b) to investigate cloud properties over the site. SACOL is located in the downwind dust transport path about 2000 km to the east of the Taklimakan Desert (i.e. one of the most important global sources of atmospheric dust) (Ge et al., 2014; Huang et al., 2007; Su et al., 2008). Low-level clouds in this semi-arid region with abound dust aerosols acting as cloud condensation nuclei may contain a larger number of small droplets (Givati and Rosenfeld, 2004; Huang et al., 2006), which may reflect more short-

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wave radiation, merge more slowly to fall as precipitation (Huang et al., 2014; Xue et al., 2008), and thus affect regional energy budget and water cycle in specific ways. Therefore, cloud observations are vital to understand their effects on the local fragile dryland ecosystem (Fu and Feng, 2014; Huang et al., 2017, 2018, 2020). MMCR-observed cloud echoes in the lowest 3 km above ground level (AGL) are often contaminated by unwanted clutters, mostly insects for midlatitude continent (Clothiaux et al., 2000), presenting non-Rayleigh scattering at millimeter wavelength with their large physical size, which need to be removed for the low-level cloud research.

Clouds and clutters show distinguishable morphologies in radar spectra because insects are point targets with wing beat, while clouds are distributed targets. Accordingly, they can be well detected with the radar spectral processing (Luke et al., 2008; Williams et al., 2018). Clutters are generally more non-spherical than cloud droplets that can lead to a relatively larger linear depolarization ratio (LDR) value comparted to clouds, and thus LDR is also a widely used variable in moment data to separate clouds from clutters (Görsdorf et al., 2015; Martner and Moran, 2001; Oh et al., 2018; Rico-Ramirez and Cluckie, 2008). Although a simple LDR threshold can remove a large part of the clutters, not all the radar range bins with high LDR are clutters. For example, the non-spherical melting hydrometeors also generate a significant LDR peak in the melting layer (Kowalewski and Peters, 2010). Furthermore, the threshold fails to separate clutters from hydrometeors when their LDR probability density function (PDF) curves are in the overlapping area. Instead of a single LDR threshold, using more attributes to build multi-dimensional PDFs can adequately describe the different properties of clouds and clutters in multi-dimensional space, thereby decrease the overlapping region and reduce the fraction of ambiguous classifications. For instance, Golbon-Haghighi et al. (2016) used three-dimensional PDFs and two-days training data to successfully identify fixed clutters such as buildings and trees for weather radar. The latest CALIPSO cloud aerosol discrimination algorithm uses five different parameters to build multi-dimensional PDFs and improves the previous classifications (Liu et al., 2019). However, samples are more scattered in higher-dimensional space and are less likely to capture the characteristics of various insect clutters, for examples, which have unique yet complicated behaviors, using short-term data. To clearly characterize the insect's behaviors, a large amount of long-term training data is required to build an accurate multi-dimensional PDF for such clutters.

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In this study, we develop a robust algorithm to distinguish low-level clouds from clutters. We first remove the background noise, precipitation and melting layer from radar measurement. We then examine cloud radar observations and select discriminants using radar reflectivity, LDR, and spectral width (SW). Next, we utilize one-year micro pulse lidar (MPL) data to establish the multi-dimensional PDFs for clouds and clutters by noting that lidar is not susceptible to clutters and therefore can provide accurate cloud base measurements. The obtained PDFs are used to train the Bayesian classifier which can determine whether a radar range gate is a cloud or clutter, by comparing their estimated probabilities. Finally, a low pass time-spatial filter is applied to the radar range gates where the Bayesian classifier does not work. Section 2 illustrates radar and lidar observations. The details of the algorithm are described in Sect. 3. Using the presented method, in Sect. 4, several case studies and one-year evaluation are showed. Finally, the summary and discussion are provided in Sect. 5.

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2. Instruments and datasets

The KAZR at SACOL site (35.57° N, 104.08° E) is a zenith-pointing dual-polarization cloud radar operating at 35 GHz. It uses an extended interaction Klystron (EIK) amplifier with a peak power of 2.2 kW. KAZR has a narrow (0.3°) antenna bandwidth and high temporal (4.27 s) and vertical (30 m) resolutions. The cloud radar has been running continuously since 2013 and provides radar reflectivity, doppler vertical velocity, and SW in each radar range gate from 0.9 km to 17.6 km AGL. The LDR is derived as the ratio of cross-polarized reflectivity to co-polarized reflectivity. More details about the KAZR are described in (Ge et al., 2017). In this study, we use radar reflectivity, LDR and SW as discriminants to separate low-level clouds and clutters. The vertical velocity is also used to identity precipitation and melting layer to reduce the potential misclassification. A MPL working at 527 nm wavelength with 1-min temporal and 30-m vertical resolution, is simultaneously running nearby the KAZR (Huang et al., 2008a; Xie et al., 2017; Xin et al., 2019). Since lidar is not susceptible to the clutters, the lidar-measured cloud base is accurate, which can be used to establish dependable multi-dimensional PDFs for both clouds and clutters. We use one-year lidar data (August 2014 to July 2015) to build the multi-dimensional PDFs to train the Bayesian classifier (in Sect. 3.2), and another year data (August 2013 to July 2014) to evaluate the algorithm (in Sect. 4.2). We choose

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the latter year to build the PDFs because there are more observations available in that year.

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3. Low-level cloud and clutter discrimination algorithm

The algorithm uses radar-observed variables to describe the different characteristics of clouds and clutters. A probability of a radar range gate to be a cloud or a clutter is estimated based on the Bayesian method using the pre-established multi-dimensional PDFs. The step-by-step procedure of the algorithm is summarized in Figure 1. Before constructing multi-dimensional PDFs of cloud and clutter, the radar echoes including background noise, precipitation and melting layer need to be removed from radar measurement (Sect. 3.1). We then use the simultaneous lidar measurement to distinguish clouds and clutters (Sect. 3.2). Any radar echoes above the lidar cloud base height are considered to be clouds, and below are clutters. After the multi-dimensional PDFs are created, the Bayesian method is used to estimate the probability of any given radar observation being a cloud or a clutter (Sect. 3.3). Although the multi-dimensional PDFs do provide a more comprehensive description of the difference, the Bayesian classifier can only discriminate cloud from clutter when all radar discriminants (radar reflectivity, LDR and SW) are available. The fact that LDR measurement can merely be derived when both co- and cross-polarized reflectivities are available, causes a non-negligible amount of undecided classification. A final time-spatial filter is therefore used to identify these radar range gates, considering that clouds are more spatially correlated than clutters (Sect. 3.4).

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3.1. Removing noise and non-cloud meteorological target

The radar background noise is firstly removed using the noise equivalent reflectivity (NER) (Kalapureddy et al., 2018), that is $r^2 \times Z_{start\ range}$, where r is height and $Z_{start\ range}$ is the noise equivalent reflectivity of the first range gate from the bottom. Here we use a $Z_{start\ range}$ of $-60 dBZ$, because it fits the radar noise level well after several trials. Figure 2 shows an example of raw and noise-removed reflectivity from local time 12:08 to 12:29 on May 28th, 2014. The reflectivity is irregularly dispersed below 2.6 km, which is caused by flying insects, while it is distributed more homogeneously inside the cloud layers above 2.6 km (Figure 2a). This is because clutter reflectivity is determined by the size and number of individual insects in a radar range gate and is little relevant to its surrounding insects. But the reflectivity inside a cloud is largely controlled by environmental variables which is highly spatially correlated. The NER curve (blue dashed line in Figure 2b) fits well with the background noise, and almost all the background noise is removed (Figure 2c). Additionally, the slanted cloud boundary around 4.5 km, the fluctuant cloud boundary that may be caused by gravity wave around 6.4 km, and the broken thin cirrus boundary around 9.2 km are all kept (Figure 2a and c). It is obvious that the clutter reflectivity is not necessarily less than the cloud reflectivity (Figure 2b). A single threshold of reflectivity cannot adequately separate clouds from clutters, and therefore multi-dimensional PDFs are needed to describe their differences.

The non-cloud meteorological targets in the low-level atmosphere, such as precipitation and melting layer, usually have different features from cloud droplets. If we put them into the cloud category, it would affect the accuracy of the created PDFs to characterize clouds and clutters. Thus, these non-cloud meteorological targets need to be removed before establishing the multi-dimensional PDFs. Rain drops are normally larger than cloud droplets and have fast fall velocity, thus radar reflectivity and vertical velocity can be used to identify precipitation (Shupe, 2007). In some cases, the radar-measured velocity may be erroneously aliased (Kollias et al., 2007b; Zheng et al., 2017) when the naturally occurring velocity is larger than the maximum unambiguous velocity (V_{max}, ±10.38 m/s for KAZR at SACOL), as shown in Figure 3. From this heavy precipitation event, one can see that the radar reflectivity is attenuated above 3 km (Figure 3a). The velocity aliasing happens at the lower level of atmosphere where radar measured velocity suddenly reverses from large downwards to large upwards (harsh red area in Figure 3b and blue dots near the right gray line in Figure 3d). The absolute value of the gate-to-gate velocity difference is used to check if velocity is aliased. For aliased velocity, that is when absolute velocity difference exceeds $1.5 \times V_{max}$, $2 \times V_{max}$ is subtracted from (or added to) the aliased velocity if the velocity difference is positive (or negative) (Johnson et al., 2017; Sokol et al., 2018). The adjusted velocity is shown in Figure 3c, where the upwards velocity at the lower level of atmosphere is de-aliased to downwards (smooth blue region in Figure 3c and orange dots in Figure 3d). The de-aliased velocity and reflectivity are then averaged over 1 minute to reduce the effect of wind drift effects to identify precipitation. These range bins with averaged reflectivity greater than 10 dBZ and averaged velocity lesser than −3 m/s are identified as precipitation (Chandra et al., 2015). However, the drizzle with smaller sizes and lower velocity (Kollias et al., 2011; O'Connor et al., 2005) may not be identified by the above method. Thus, the radar echoes that below the lidar detected cloud base, while still being connected to the cloud, are marked as drizzle (Wu et al., 2015; Yang et al., 2018), and removed from the training data.

Water coating ice particles inside the melting layer are largely non-spherical, therefore have high LDR values, similar with insects (Brandes and Ikeda, 2004; Islam et al., 2012). This can be seen from Figure 4c. The melting layer around 2.8 km has relatively higher LDRs than the precipitation below and the ice particles above. Clutters near the surface before the precipitation reaching the surface at about 20:30 have similar high LDR values. Clutter layer can appear as high as 3 km AGL during daytime in warm season at SACOL site, which is close to or even higher than melting layer height. In order to avoid wrongly identifying the melting layer with high LDR as clutters, the melting layer is recognized by analyzing the gradient of reflectivity and velocity that has a large value associated with the melting layer (Baldini and Gorgucci, 2006; Matrosov et al., 2007; Perry et al., 2017). The peak of $|\text{reflectivity}'| \times |\text{velocity}'|$ (Figure 4e) is located as the middle of melting layer for each identified precipitation profile, then the height of maximum $(|\text{reflectivity}'| \times |\text{velocity}'|)''$ up to 500 m above (below) the peak are defined as the top (bottom) of melting layer as shown in Figure 4e with red dots (Devisetty et al., 2019; Khanal et al., 2019). The identified melting layer and precipitation are plotted in Figure 4a-c as black dots and slashed shading area.

3.2. Creating multi-dimensional PDFs

To capture the differences between clouds and clutters as accurately as possible, we need to choose the appropriate discriminants before creating the PDFs for both. From a statistical point of view, the description of differences in higher-dimensional space is generally more complete than in lower-dimensional space. Increasing the number of discriminants could decrease the overlapping region of the two PDFs, thereby reducing the fraction of ambiguous classifications (Liu et al., 2004). However, only when the added discriminant is largely independent of the other used, can it improve the classification significantly (Liu et al., 2009). After carefully examining all radar variables for many specific clutter and cloud cases, we chose

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radar reflectivity, LDR, SW along with their time-height and seasonal dependence as discriminants. LDR is chosen because it has distinct distributions for clouds and clutters due to their shape difference (cloud droplets are largely spherical while clutters are non-spherical). Insects' number density and sizes make them often generate low radar reflectivity, which has a similar range with strati and broken cumuli (Luke et al., 2008), but is commonly higher in warm seasons when they swarm (Abrol, 2015). The seasonal dependence of radar reflectivity is considered as a factor to build the PDFs. Clutters also generally have lower SW and lower vertical velocity because insects may actively oppose environmental vertical motion and control their own flying behavior, while cloud particles are more vulnerable to small-scale local turbulence and entrainment processes (Geerts and Miao, 2005). Yet after checking both variables, we found that distributions of SW for clouds and clutters are more discrepant than that of vertical velocity, thus SW is used to build the PDFs rather than using vertical velocity directly. One distinctive character of insects that differs from other fixed clutters is that their behaviors are influenced by many natural factors (Chapman et al., 2015; Johnson et al., 2016; Thomas et al., 2003). For example, insects' number density has a high correlation with surface temperature (Luke et al., 2008), thus the maximum height and radar echo intensity of insects have strong diurnal cycles (Hubbert et al., 2018; Wood et al., 2009). The time and height variations of radar echoes are thereby considered in the construction of multi-dimensional PDFs.

Once the discriminant factors are selected, the cloud and clutter samples need to be extracted for building the multi-dimensional PDFs. The radar echo above the lidar cloud base height after removing noise and non-cloud meteorological targets are considered to be clouds, otherwise are clutters. Based on the lidar auxiliary data, all the radar echoes below 3.6 km from August 2014 to July 2015 are separated into cloud or clutter samples. Figs. 5 and 6 show the multi-dimensional PDFs for different local time and heights for warm and cold seasons, respectively, which is calculated as the number of samples in each discriminant range for each class (clouds or clutters), divided by the total number of samples in each discriminant range for all classes. After examining one-year data, it is found that 3.6 km AGL is the highest level that clutters can reach at the SACOL site. As expected, clutters tend to have lower reflectivity (lower density), larger LDR (non-spherical shape) and lower SW (less turbulent motion) compared with cloud (Figure 5 and Figure 6). Insect activities are largely influenced by temperature, thus

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the clutters appear mostly during daytime and their height has an obvious diurnal cycle. It is also notable that there are no clutters above 2.7 km during the nighttime (Figure 5c1 and d1, Figure 6c1 and d1). The three radar variables for clouds and clutters still have contrasting distributions during cold season. Nevertheless both clouds and clutters occur less frequently compared to warm season (Zhu et al., 2017). Note that some overlapping regions of cloud and clutter PDFs still occur (e.g. Figure 5b3). However, the multi-dimensional PDFs made the ambiguity area much smaller compared with the results by only using a single discriminant. The significant differences between clutter and cloud PDFs (Figs. 5 and 6) can be used to adequately separate them more accurately.

3.3. Generating classification mask based on Bayesian method

The obtained multi-dimension PDFs are then used to train the optimal Bayesian classifier to separate clouds and clutters for any observed discriminants ($\boldsymbol{X}^O$). According to Bayesian method, the probability of a radar range gate with discriminants $\boldsymbol{X} = \boldsymbol{X}^O = Reflectivity^O, LDR^O, SW^O, Time^O, Height^O, Season^O$ being class $C_i, (i \in [cloud, clutter])$ can be estimated as:

$$p(C_i|\boldsymbol{X} = \boldsymbol{X}^O) = \frac{p(\boldsymbol{X} = \boldsymbol{X}^O|C_i)p(C_i)}{p(\boldsymbol{X} = \boldsymbol{X}^O)} \quad (1)$$

where the priori probabilities are assumed to be equal for all classes (Golbon-Haghighi et al., 2016; Ma et al., 2019), which means $p(C_{cloud}) = p(C_{clutter}) = 1/2$. Furthermore, as $p(\boldsymbol{X} = \boldsymbol{X}^O)$ is the same for all classes, hence Eq. (1) can be rewritten as

$$p(C_i|\boldsymbol{X} = \boldsymbol{X}^O) = Kp(\boldsymbol{X} = \boldsymbol{X}^O|C_i) \quad (2)$$

where K is constant for all classes

$$K = \frac{1}{2p(\boldsymbol{X} = \boldsymbol{X}^O)} \quad (3)$$

and $p(\boldsymbol{X} = \boldsymbol{X}^O|C_i)$ is the conditional probability of discriminants being $\boldsymbol{X}^O$ for each class, which has been derived from one-year training data as descript in Sect. 3.2.

For any given observation of discriminants, the posterior probability for each class $p(C_i|\boldsymbol{X} = \boldsymbol{X}^O)$ is estimated

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3.4. Applying low pass spatial filter to undecided mask

Bayesian classifier is able to separate clouds and clutters in most cases when all the radar discriminants as described in Sect. 3.2 and 3.3 are offered. Figure 7 shows such a case from local time 05:00 to 22:00 on September 24th, 2013. Unsurprisingly, these radar range bins with low reflectivity (Figure 7a), high LDR (Figure 7c), and low SW (Figure 7d) are considered more likely to be clutters rather than clouds (Figure 7e, f and g), while high reflectivity, low LDR and high SW have higher probability to be clouds (Figure 7a-g). When the individual three radar variables disagree on the classification, for example, these clutters from 12:00 to 16:00 near the surface with high reflectivity and high SW (likely to be clouds) and high LDR (also likely to be clutters), the Bayesian classifier can still correctly separate them as shown in Figure 7g. However, the cloud radar may not always provide valid observations. For example, LDR can only be computed when both co- and cross-polarized reflectivities are available. Figure 7a and b show the reflectivities of co- and the cross-polarized channels, respectively. There are some range gates where co-polarized reflectivity detects signal (cloud or clutter) while no signal is detected in cross-polarized channel, which causes the missing LDR in these radar range gates (e.g., the rightmost range bins above the lidar cloud base and some bins scattering near-surface in Figure 7c). Without the LDR input data, Bayesian classifier fails to work (green dots in Figure 7g), because no conditional probability was established for an incomplete $\boldsymbol{X}^{O}$. Mathematically, there are several approaches to deal with missing data for Bayesian method, such as assuming a distribution of them (Linero and Daniels, 2018). However, in practice, we find it is uneconomical to solve such an issue. Rather, we utilize the spatial correlation difference between clouds and clutters to process the Bayesian undecided classifications, which is more effective and simpler. As mentioned earlier, cloud droplets are highly correlated in time and space, while clutters do not have the same feature. For those radar bins that cannot be identified as clouds or clutters from the probability estimate, we use their

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neighboring range gates to provide information to help make the final decision. A spatial filter with five range bins respecting to heigh (150 m) and five range bins concerning time (21.4 s), which is centered at each undecided classification bin, is employed here (Hu et al., 2020; Marchand et al., 2008). Following Ge et al. (2017), if the number of cloud range bins in the box is less than 13, this range bin is considered to be clutter, otherwise it will be marked as a cloud bin. The final classification mask result is shown in Figure 7h. Comparing with lidar observation on the same day, the undecided range bins are correctly categorized into clutters (green dots turned to brown), and clouds (green dots turned to blue above lidar cloud base) after applying the low pass spatial filter. It is clear from Fig. 7h that clutter layer height has an apparent diurnal cycle and the insects' number density is much stronger in the early afternoon near the surface (patchy high reflectivity rather dotted low reflectivity). This is why time and height are also chosen as the discriminants.

4. Result

4.1. Case study

We apply the identification algorithm to a whole year of radar data to discriminate low-level clouds and clutters. The results are compared with the simultaneous lidar cloud base to demonstrate the performance of the algorithm.

Figure 8 shows a case of broken cumulus from local time 16:27 to 17:30 on April 15^{th}, 2014. During this period, a substantial presence of insects is observed below the broken cumulus. The top of the insect layer is around 1.6 km, where is also the cloud base height detected by lidar and our algorithm (Figure 8d). From the radar reflectivity image in Figure 8a, the cloud droplets begin to dissipate due to entrainment (Chernykh et al., 2001; Pinsky and Khain, 2019) and have similar reflectivity values as clutters (around −50 dBZ) around cloud base. As shown in Figure 8b, clutters have the LDRs mostly greater than −15 dB but clouds have relatively smaller LDR values. The high SW above the cloud base (more than 0.4 m^2/s^2) indicates strong turbulence inside the cumulus. Combining all these radar variables together, our clutter identification algorithm shows a great agreement with lidar detection (Figure 8d).

Figure 9 shows a case of stratus clouds embedded in insect layers. The reflectivity inside cloud is similar to the clutter

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reflectivity (between −40 to −20 dBZ), but is distributed more homogeneous in time and space (Figure 9a). Note that for these flat clouds, Kalapureddy et al. (2018) used the standard deviation of reflectivity to remove clutters. However, this method causes some false positives (cloud is wrongly identified as clutter) around fuzzy cloud edges. The stratus cloud is typically more featureless than cumulus (Figure 8) due to the absence of active convective elements (Harrison et al., 2017), and it has lower SW values which may fall within the same range as clutters (below 0.4 m^2/s^2, Figure 9c). Thus, in this case, the LDR (Figure 9b) and spatial filter in our method made the major contribution to separate them.

Figure 10 shows a case of precipitating stratocumulus. The drizzle droplets that fall from the cloud base are kept as clouds (Figure 10d), since they have relatively small falling velocity and reflectivity, and cannot be recognized as precipitation by the algorithm. The edge between clutter and drizzle are blurry in radar reflectivity and SW (Figure 10a and c). Under this circumstance, the algorithm identifies the clutters near the surface with large LDR (larger than −15 dB), but keeps the drizzle as hydrometeors with low pass filter since they are temporal and spatial correlated (Figure 10b). Note that although the bottom of identified hydrometeors is coincidental with the top height of clutter layer (Figure 10d), it does not mean that the drizzle droplets "suddenly" all evaporate when they fall into the insect layer. The drizzle may still fall toward the ground, however the signals are much smaller than that from the insect layer. In other words, the clutter mask does not necessarily mean only clutter being in this range bin, rather the backscattered power is largely dominated by insects.

Figure 11 shows a case of broken cumulus and shallow convective clouds under stratus. One can see a few thin clouds (less than 300 m) below 1.5 km AGL during 04:30 to 05:10 and some broken cumulus from 04:30 to 04:50 like the case shown in Figure 8, but with lower cloud top and base heights ("more deeply buried" in the clutter layer). There may be many insets in the cloud, causing the large radar observed LDR, e.g., from 04:30 to 04:40 (greater than −15 dB, Figure 11b), therefore, these range gates are classified as clutters by our algorithm (Figure 11d). The clouds, where are less affected by insects from 04:40 to 04:50 (lower LDR than −15 dB and higher SW than 0.4 m^2/s^2), are identified as cloud no doubt. Note that the occurrence of interlaced blocky appearance of classification masks around 04:40 (Figure 11d). There are only little available LDR range gates there (Figure 11b), meaning the classification masks are mostly achieved by the spatial filter (Sect. 3.4), which causes some misclassification (e.g., from 04:30 to 04:40) because the spatial correlation of clouds is reduced since they are largely contaminated by clutters. During 04:55 to 05:15, a few broken clouds higher away from the clutter layer are successfully identified by the algorithm, which is in accordance with the MPL lidar detections, indicating the spatial filter does work well when clouds are not adjacent to falsely identified masks. The shallow convective clouds after 05:15 are more turbulent (SW greater than 0.6 m^2/s^2, Figure 11c) than these broken cumuli, thus are effectively identified as cloud even with dense clutter layer below. We believe the identified cloud mask below lidar cloud base from 05:15 to 05:30 are drizzle particles because of the virga reflectivity during that time (Figure 11a).

Figure 12 shows a case of low-level clouds completely surrounded by intense insects. This is the most difficult case to discriminate each other, because cloud signals are heavily contaminated by clutters. Figure 12d shows that the identified cloud masks correspond well with lidar cloud base during 14:15 to 16:00, owing to lower LDR (less than −15 dB,Figure 12b) and higher SW (greater than 0.4 m^2/s^2, Figure 12c) of the cloud particles. However, the algorithm misses some clouds with low SW (around 0.2 m^2/s^2, Figure 12c) from 16:00 to 16:40. Note that a large amount of LDRs are unavailable for this cloud (Figure 12b) and its structure is loose (Figure 12a), especially around cloud edges where clutter signals are even stronger than cloud. In this circumstance, the algorithm can only identify a part of the cloud.

Figure 13 shows a case of shallow cumulus near the surface in cold season. Compared with the earlier cases (Figure 8-12), the clutters in this case are less organized. There is no dense insect layer gathering near the surface. The different behaviors of insects in warm and cold seasons are why seasonal variation is chosen as a discriminant. The radar reflectivity in the cumulus is more homogenous than that from the scattering clutters (Figure 13a) and can easily be identified even though human eyes. Shallow cumulus have LDR less than −20 dB whereas clutters have higher LDR greater than −15 dB (Figure 13b). Higher SW values (around 0.6 m^2/s^2, Figure 13c) in the cumulus during 18:00 to 20:30 indicate that the cloud droplets are more affected by small-scale local turbulence and entrainment processes. The algorithm can screen out the shallow cumulus in cold season and filter out the clutters (Figure 13e).

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4.2. One-year evaluation

To further objectively demonstrate the performance of this algorithm, probability of detection (P_D) and false alarm rate (P_{FA}) are calculated using one-year data (August 2013 to July 2014) that are defined as:

$$P_D = \frac{TP}{TP + FN}$$
$$P_{FA} = \frac{FP}{FP + TN} \tag{4}$$

where the number of TP (true positives), TN (true negatives), FP (false positives) and FN (false negatives) are based on our algorithm identified clutter ("positive" of "negative") validated by lidar detection ("true" or "false" of clutter classification mask). Note that the evaluation is focused on the identified clutters rather than low-level clouds, because lidar power is often attenuated by optically thick low-level water clouds, leading to a significant discrepancy between radar- and lidar-measured low-level clouds, while the "true" or "false" of clutter only relies on lidar cloud base height, which would cause less uncertain in the assessment.

Figure 14 illustrates the P_D and P_{FA} as functions of reflectivity (a), LDR (b), SW (c), time (d) and height (e). The P_D (solid lines) is usually above 98%, except when reflectivity is larger than −10 dBZ (Figure 14a), LDR lower than −15 dB (Figure 14b), or SW larger than 0.2 m^2/s^2 (Figure 14c), where clutters have similar properties as clouds, however, which are only small portions of the whole data as shown in Figure 5 and Figure 6. So the seasonally- and yearly-averaged P_D are all above 98% (Figure 14f). Similarly, for the cloud with reflectivity lower than −30 dBZ (Figure 14a), LDR larger than −20 dB (Figure 14b), and SW lower than 0.1 m^2/s^2 (Figure 14c), there are chances that clouds are falsely identified as clutters (higher P_{FA}, dashed lines). The P_{FA} are below 0.5% in all seasons (Figure 14f). Using a single LDR threshold to filter out clutter would induce a sharp increase of P_D from 0% to 100% at the threshold point. Very different from that, by using multi-dimensional PDFs with the Bayesian method, it can correctly identify cloud-like clutter and clutter-like cloud, thus increase the accuracy of the classification mask. Both P_D and P_{FA} are less fluctuating with time (Figure 14d) and height (Figure 14e) compared with the three radar variables (Figure 14a-c), except for P_D above 3.2 km, where the clutter is extremely rare (fewer samples). This indicates that the time and height variations of cloud and clutter features are well captured by the multi-dimensional PDFs. The P_D and P_{FA} of whole year (black lines) are more consistent with that of warm season (red line), because clutters are more frequently appear in warm season. Overall, the one-year evaluation shows that the algorithm can successfully filter clutter out with a high value of P_D (98.45%) and a very low value of P_{FA} (0.37%) as shown in Figure 14f.

5. Summary and discussion

We develop a low-level cloud and clutter discrimination algorithm for a ground-based cloud radar based on multi-dimensional PDFs with the Bayesian method using cloud radar reflectivity, LDR, SW and their time of the day, height, and season dependences as discriminants. A low pass spatial filter is applied to the Bayesian undecided classification mask, considering the spatial correlation difference between clouds and clutters. The case studies indicate the algorithm can filter out most of the clutters while still maintaining the low-level clouds (including drizzle), even when they are embedded in clutter layer. Unlike the traditional way by selecting a single LDR threshold to remove the clutter, this algorithm particularly shows higher accuracy for clutter-like clouds or cloud-like clutters. The one-year evaluation demonstrates a good performance of this algorithm (98.5% detection rate and 0.4% false alarm rate). For the quantitative evaluation, the lidar detected cloud base is assumed to be perfectly correct, and the small temporal and spatial offsets between the radar and lidar are assumed to have a small impact. We conclude that this algorithm satisfactorily retains low-level clouds and removes radar clutter at SACOL site.

For the non-cloud low-level meteorological target, such as precipitation and melting layer, we use radar observation itself to identify them (Chandra et al., 2015; Matrosov et al., 2007). Although it might not be as reliable as the method by combining the radar with other instruments such as rain gauge, it would still be enough to effectively reduce the misclassification of clutters and clouds. The more accurate estimation of rain rate will be carried out in our future work, along with this algorithm, used to provide more reliable low-level cloud and precipitation radar data to study its climate effect and the interaction with local abundant dust aerosol in semi-arid region.

Data availability

Both the lidar and radar data used in this study can be acquired from the SACOL site (http://climate.lzu.edu.cn).

Author contributions.

XH and JG designed the study. XH, JD and QL performed the cloud and clutter discrimination. XH and JG prepared the manuscript with significant contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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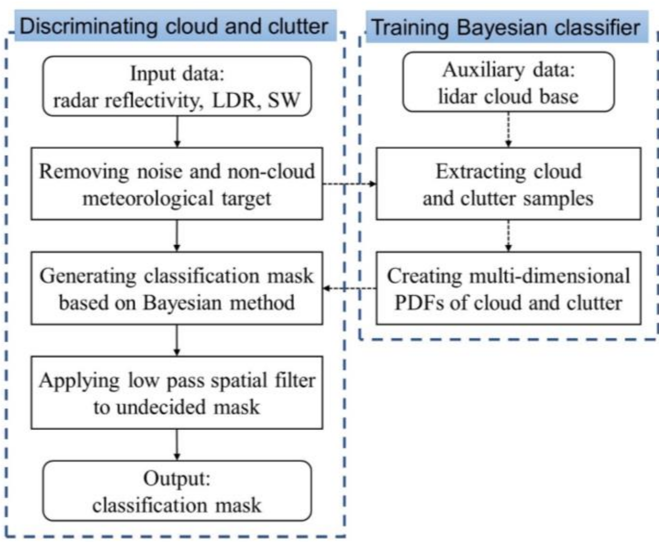

655 Figure 1. Schematic flow diagram for cloud and clutter discrimination. The right panel (connected by dashed arrow) is only executed once to train the Bayesian classifier.

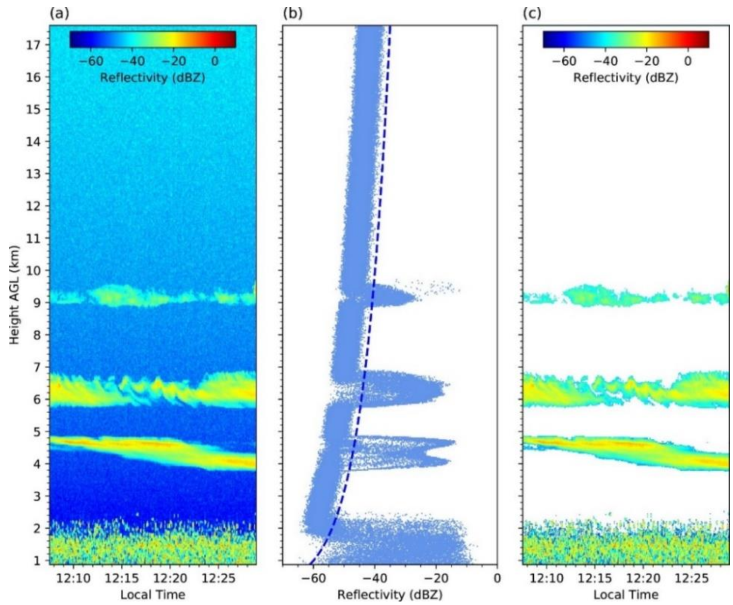

Figure 2. (a) Raw reflectivity and (c) noise-removed reflectivity from local time 12:08 to 12:29 on May 28th, 2014. (b) 300 reflectivity profiles of the same duration, the blue dashed line is noise equivalent reflectivity curve.

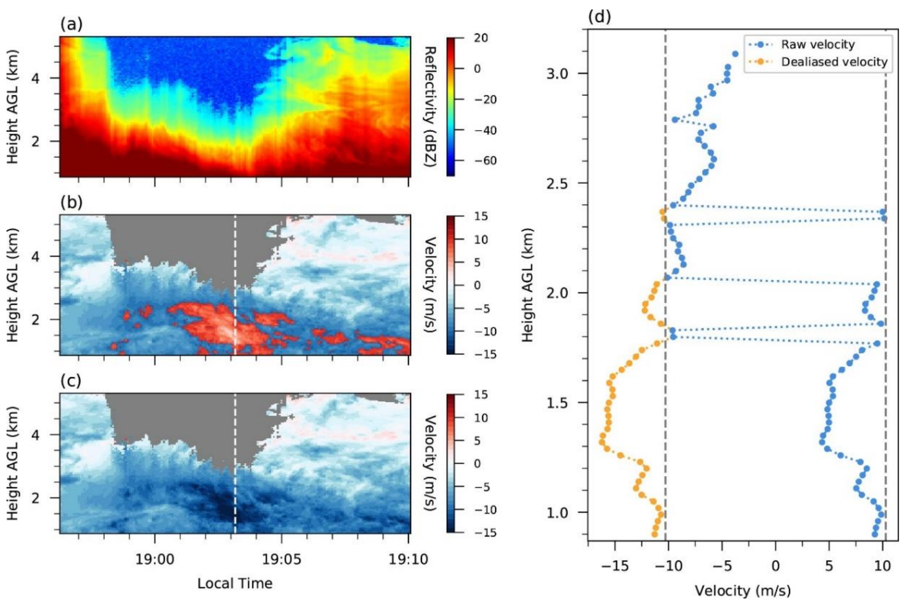

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Figure 3. (a) Reflectivity, (b) radar measured doppler velocity and (c) de-aliased velocity from local time 18:56 to 19:10 on August 30th, 2013. (d) Raw and de-aliased velocity profile of the white dashed line in left panels, the gray dashed line is the maximum unambiguous velocity (±10.38 m/s for SACOL KAZR). Positive velocity represents upwards velocity.

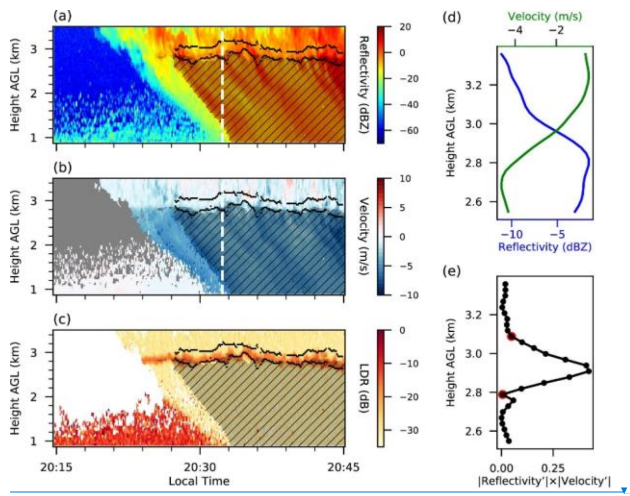

Figure 4. (a) Reflectivity, (b) velocity, and (c) LDR from local time 20:15 to 20:45 on August 10th, 2013. (d) Reflectivity and velocity, and (e) |reflectivity'| × |velocity'| profile of the white dashed line in left panels. Black dos and slashed shading area in left panels are identified melting layer and precipitation. Red dots in (e) are the identified bottom and top of melting layer.

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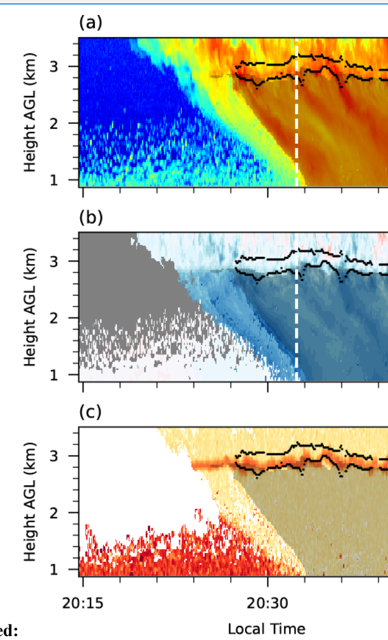


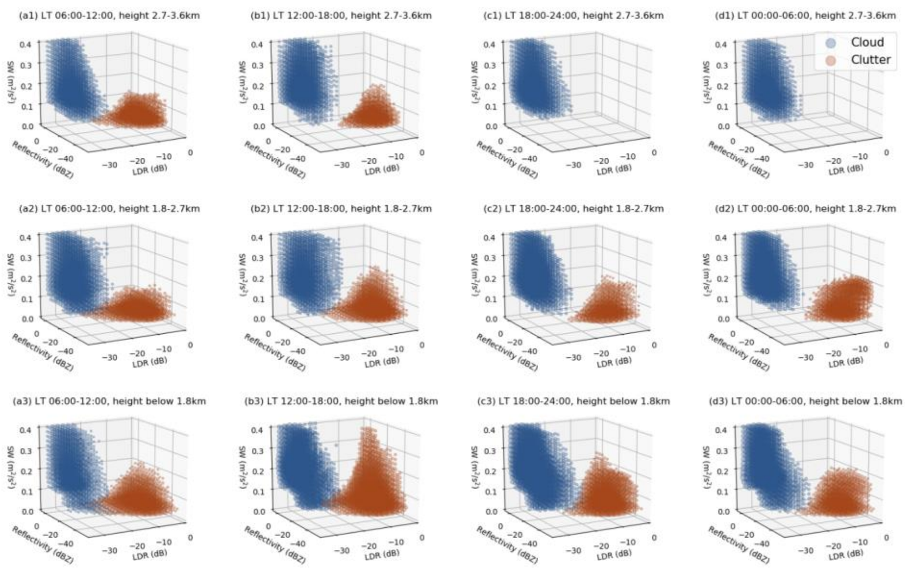


Figure 5. The multi-dimensional PDFs of clutters (brown dots) and cloud droplets (blue dots) at local time 06:00-12:00 (column a), 12:00-18:00 (column b), 18:00-24:00 (column c) and 00:00-06:00 (column d), and height below 1.8 km (row 3), 1.8-2.7 km (row 2) and 2.7-3.6 km (row 1) in warm season (April to September). The size of dots represents the value of probability density.

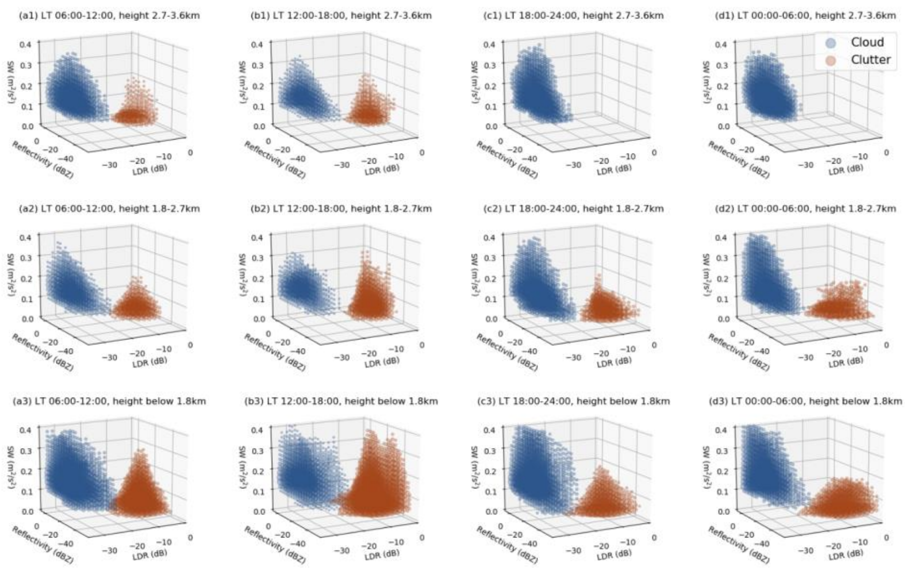


Figure 6. Same as Figure 5, except for cold season (October to March).

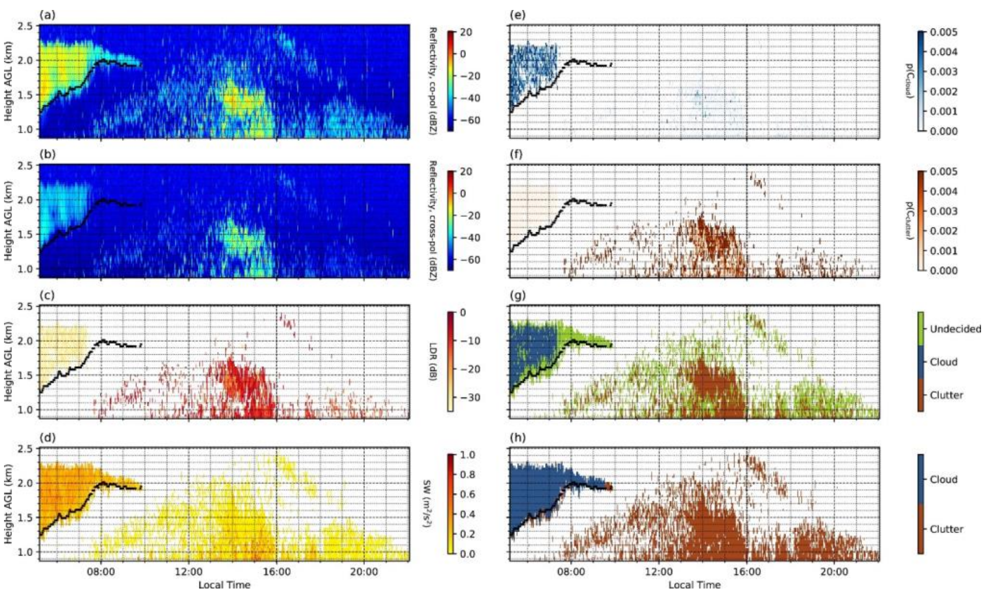


Figure 7. (a) Reflectivity of co-pol, (b) reflectivity of cross-pol, (c) LDR, (d) SW, (e) estimated probability of cloud, (f) estimated probability of clutter, (g) classification mask using Bayesian method and (h) classification mask after the spatial filter from local time 05:00 to 22:00 on September 24th, 2013. The black dots represent lidar detected cloud base height.

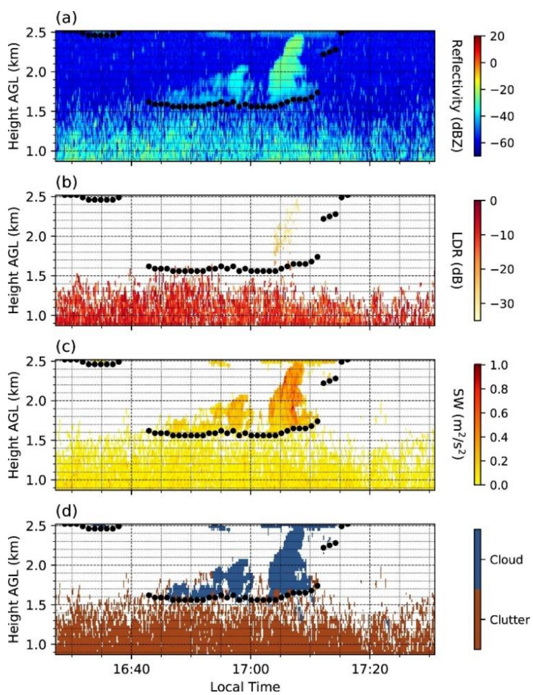
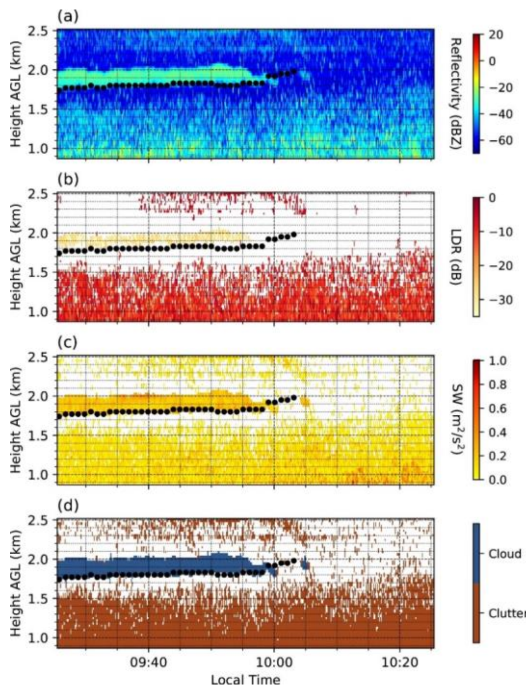


Figure 8. (a) Reflectivity, (b) LDR, (c) SW and (d) classification mask from local time 16:27 to 17:31 on April 15th, 2014. The black dots are lidar detected cloud base.



685 Figure 9. Same as Figure 8, except for local time 09:25 to 10:25 on October 12th, 2013.

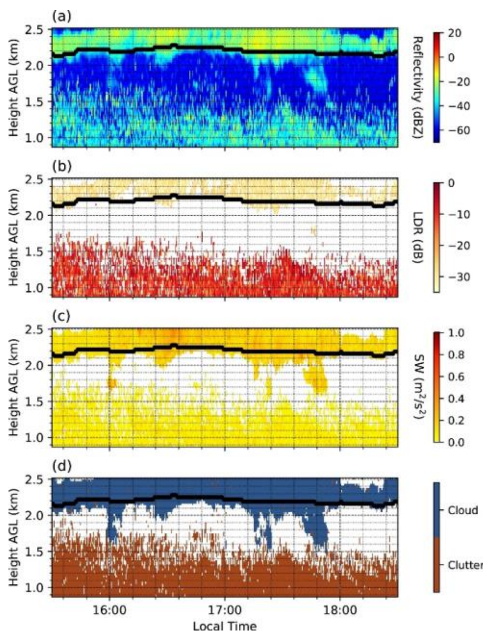
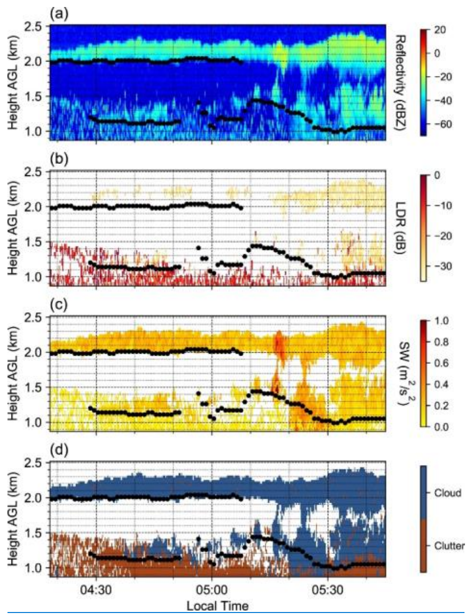


Figure 10. Same as Figure 8, except from local time15:30 to 18:30 on July 7th, 2014.



690 Figure 11. Same as Figure 8, except for local time 04:18 to 05:45 on July 20th, 2014.

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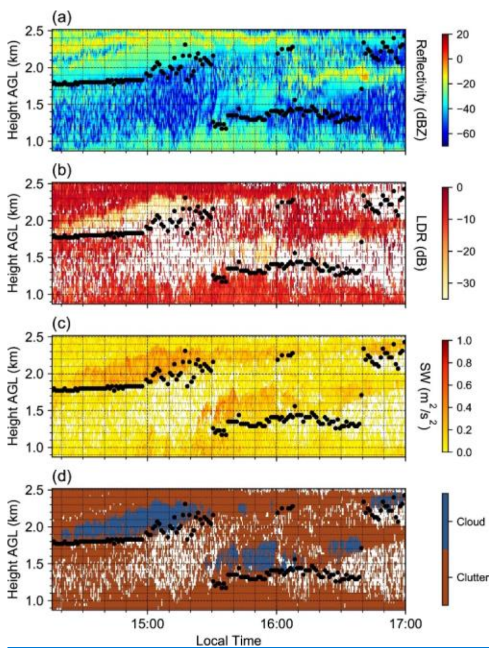

Figure 12. Same as Figure 8, except for local time 14:16 to 17:00 on August 19th, 2013.

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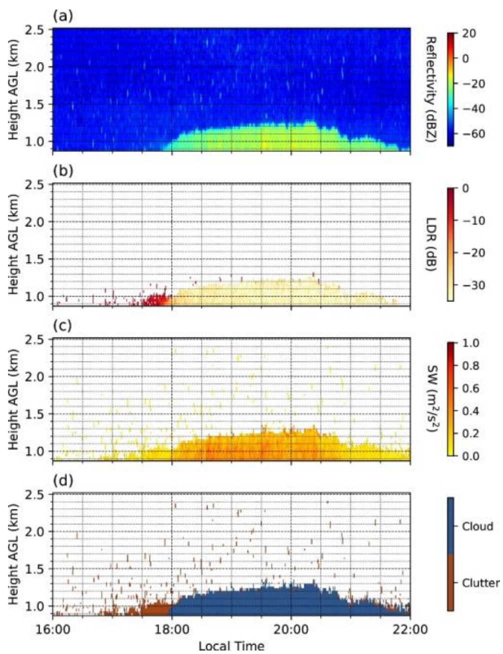

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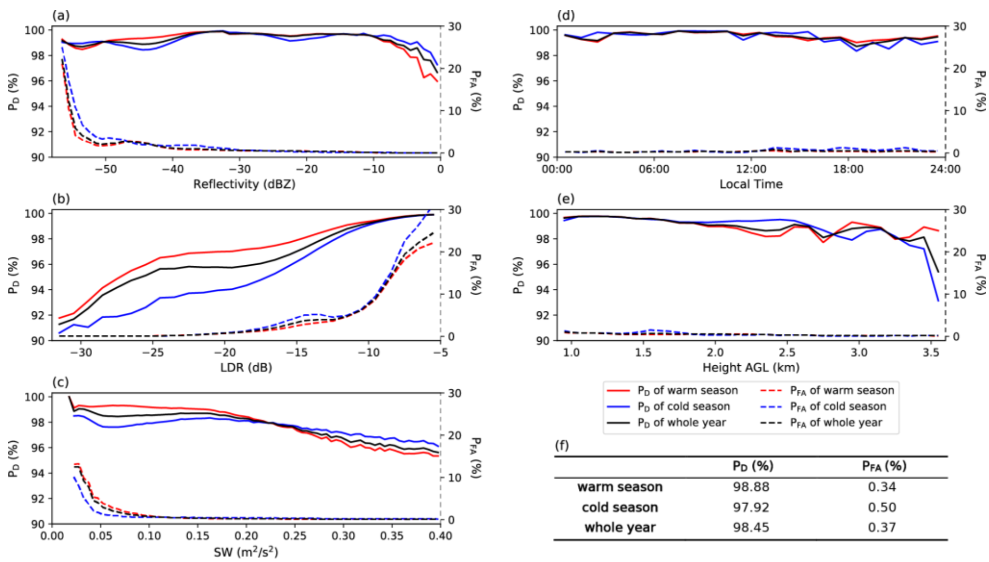
Figure 13. Same as Figure 8, except for local time 16:00 to 22:00 on February 4th, 2014. Note that the lidar observation is missed that day.



	P_D (%)	P_{FA} (%)
warm season	98.88	0.34
cold season	97.92	0.50
whole year	98.45	0.37

Figure 14. Probability of detection (P_D, solid line) and false alarm rate (P_{FA}, dashed line) as function of reflectivity (a), LDR (b), SW (c), time (d) and height (e) for warm season (red line), cold season (blue line) and whole year (black line). The values of P_D and P_{FA} for warm season, cold season and whole year are shown in (f).