An Improved Cloud Classification Algorithm Based on the SGP CART Site Observations

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Introduction

Different types of clouds are usually governed by different cloud dynamics processes and have different microphysical properties, which results in different cloud radiative forcings (Hartmann et al. 1992; Chen et al. 2000). Climate changes can result in changing frequency of cloud type and changing properties of a cloud type. The combination of them determines the change of the role of clouds in the Earth water and energy cycles. We might face difficulties to accurate predict future climate change until climate models can properly represent the processes and feedback mechanisms of controlling different cloud types and their properties. Moreover, each of published cloud microphysical properties retrieval algorithms is only applicable to given type clouds because assumptions used in each algorithm are only valid for given type clouds. Therefore, cloud classification products not only supports cloud studies which need to group clouds according to cloud types, but also provides necessary information to implement different retrieval algorithms to generate integrated cloud microphysical products.

Classifying clouds into categories based on type is an important task for cloud remote sensing and global cloud climatology studies. Algorithms based on different cloud spectral, textural, and physical features from satellite passive sensors have been developed for cloud classification (Welch et al. 1992; Tovinkere et al. 1993; Bankert 1994; Luo et al. 1995; Rossow and Schiffer 1999). The International Satellite Cloud Climatology Project (ISCCP) approach (Rossow and Schiffer 1999) uses the combination of cloud top pressure and cloud optical depth to classify clouds into either cumulus (Cu), stratocumulus (Sc), stratus (St), altocumulus (Ac), altostratus (As), nimbostratus (Ns), cirrus, cirrostratus, or deep convective clouds. However, with more long-term ground-based remote sensing cloud studies underway, algorithms to classify cloud type using this approach are a necessity. Duchon and O'Malley (1999) studied the possibility of classifying clouds according to ground- based solar flux measurements. Their results show an accuracy of classification below 50%. Williams et al. (1995) developed an algorithm to classify precipitating clouds into either stratiform, mixed stratiform, convective, and deep or shallow convective clouds using 915-MHz wind profile data.

Wang and Sassen (2001) presented aalgorithm to classify clouds into either St, Sc, Cu, Ns, Ac, As, deep convective, or high cloud by combining ground-based active and passive remote sensing data. The class of high cloud includes cirrus, cirrocumulus, and cirrostratus, and deep convective cloud represents cumulus congestus and cumulonimbus.

Here, we present an improved cloud classification algorithm using active and passive remote sensing at the Southern Great Plains (SGP) Cloud and Radiation Testbed (CART) site. There are two main improvements on our published cloud type classification algorithm by including cloud phase determination and using fuzzy logic classification method. Cloud phase is an important cloud property, and an integrated cloud phase determination is implemented in the algorithm by combining atmospheric temperature, Raman lidar depolarization ratio, radar reflectivity factor, micropulse lidar (MPL) backscattering coefficient, and liquid water path (LWP) from microwave radiometer (MWR). To improve the flexibility of classification algorithm, we combine role-based and fuzzy logic classification methods, which allow the algorithm to output cloud type as well as the confidence level of cloud type, and is easy to modify for the Tropical Western Pacific (TWP) and the North Slope of Alaska (NSA) data streams.

Measurements Used for Cloud Classification

SGP CART site provides the best ground-based integrated observations in the world. The millimeter wave cloud radar (MMCR) provides radar reflectivity and mean Doppler velocity profiles for most of clouds in the troposphere. Raman lidar provide not only water vapor profile, but also cloud properties including backscattering coefficients and lidar linear depolarization ratio. MWR provides column-integrated water vapor and liquid water. IR radiometers measure the total T_b of the atmospheric column from gases and clouds combined. MPL measurements also can be used to estimate cloud backscattering coefficient.

We classify clouds by using vertical and horizontal cloud properties, the presence, or absence of precipitation, LWP, and downward IR brightness temperature (T_b). Vertically pointing lidar and radar provide a time series of vertical cloud profiles, and the vertical and horizontal extent of clouds represent important information for differentiating cloud types. In addition to active remote sensing data, IR radiometer and MWR measurements are also incorporated into our scheme. Although the T_b due to the cloud can be estimated from this and supplementary data, the standard deviation of T_b, which is calculated from high frequency (~0.05Hz) measurements, is found to be more useful for identifying cloud type. For clear-sky, T_b changes very slowly with time, primarily in accordance with column water vapor changes. However, it changes in a different manner for different types of clouds because of the fundamental horizontal inhomogeneities and fractional coverage of clouds, and the change of cloud base height with time. LWP retrieved from MWR measurements is another important layer-integrated cloud property.

Methodology

Role-based classification methods, which assign different threshold values to characteristic parameters, are simple and easy to use methods, but the results are sensitive to the selection of the thresholds. Instead of using Boolean logic, the proper use of fuzzy logic can improve the results of cloud classification (Penoloza and Welch 1996). The approach of using neural networks to classify cloud type in satellite imagery has shown recent success (Welch et al. 1992; Bankert 1994). The network is trained on selected spectral, textural, and physical features associated with expertly labeled samples. The trained network is subsequently applied to unknown cloud samples. However, these new classification techniques can not guarantee better performance, which depends on how properly designed the classifier is and the selection of features (Tovinkere et al. 1993). The rule-based classification method was selected in our initial study for its simplicity (Wang and Sassen 2001). However, it lacks flexibility to deal with some difficult situations and different measurement fields at different time (missing data issue). Here, we try to combine role-based and fuzzy logic-based classification method as schematically presented in Figure 1. Fuzzy logic-based classification also gives a chance to provide a measure for the quality of outputs during the defuzzifier process.

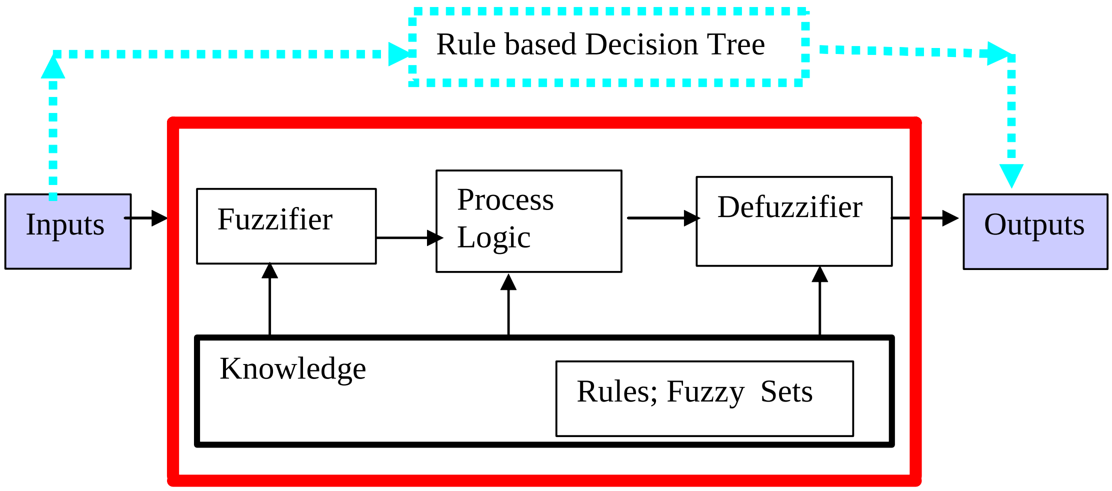


Figure 1. Schematic diagram for the combination of rule-based and fuzzy logical based classification.

Fuzzy sets are basics for fuzzy logic-based classification. Fuzzy set allows partial membership states. Ordinary, or crisp, sets have only two membership states: inclusion and exclusion; fuzzy states allow degrees of membership as well. Though there is an apparent external similarity between fuzzy logic and probability, their differences are distinct. Fuzzy logic is calculus of compatibility. Unlike probability, which is based on frequency distributions in a random population, fuzzy logic deals with describing the characteristics of properties. It describes properties that have continuously varying values by associating partitions of these values with a semantic label. Much of the descriptive power of fuzzy logic comes from the fact that these semantic partitions can overlap. This overlap corresponds to the transition from one state to the next. These transitions arise from the naturally occurring ambiguity associated with the intermediate states of the semantic labels. Examples of Fuzzy Sets related to cloud properties, such as cloud temperature, height, geometrical thickness, and cover are given in Figure 2.

We use the following strategy to classify clouds. First, cloud masks (from cloud boundaries) are used to find a cloud cluster according to their persistence in the horizontal (i.e., time) and vertical directions. A search will stop when a systematic change in cloud properties, such as cloud thickness, horizontal inhomgeneity, and cloud base or top height, is detected. To better consider the real situation, a 2-min

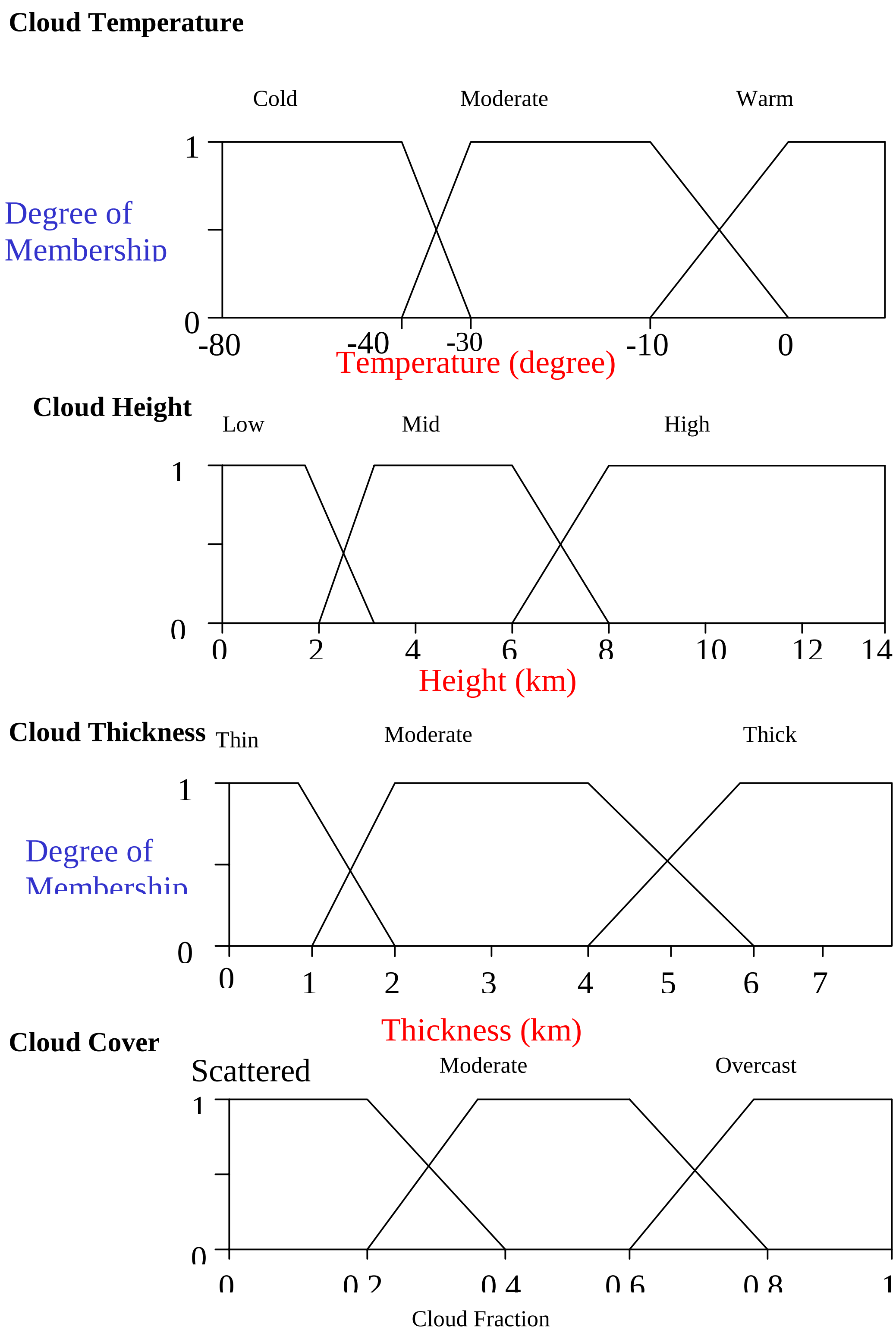


Figure 2. Examples of fuzzy sets.

break is allowed in a cluster. If a detected cloud cluster originally lasts less than 1-h, it will be forced to extend at the same height range until it is equal to or longer than 1-h to counting cloud horizontal inhomogeneity in ground-based measurements. Therefore, a cloud cluster permits spatially broken cloud fields.

Once a cloud cluster is found, the mean cloud base and top heights, cloud phase, horizontal extend, cloud fraction, as well as the occurrence and intensity of precipitation, are determined. Then these properties are inputed to a combined role-based and fuzzy logic-based classifier to provide a cloud type and confidence level for the cloud cluster. The flowchart of the method is given in Figure 3.

Cloud phase is an important cloud property and a very useful parameter for cloud classification. Nonetheless, it is difficult to provide in many circumstances. Lidar depolarization ratio is an effective measurement for cloud phase discrimination (Sassen 1991; Wang and Sassen 2001). One weakness of

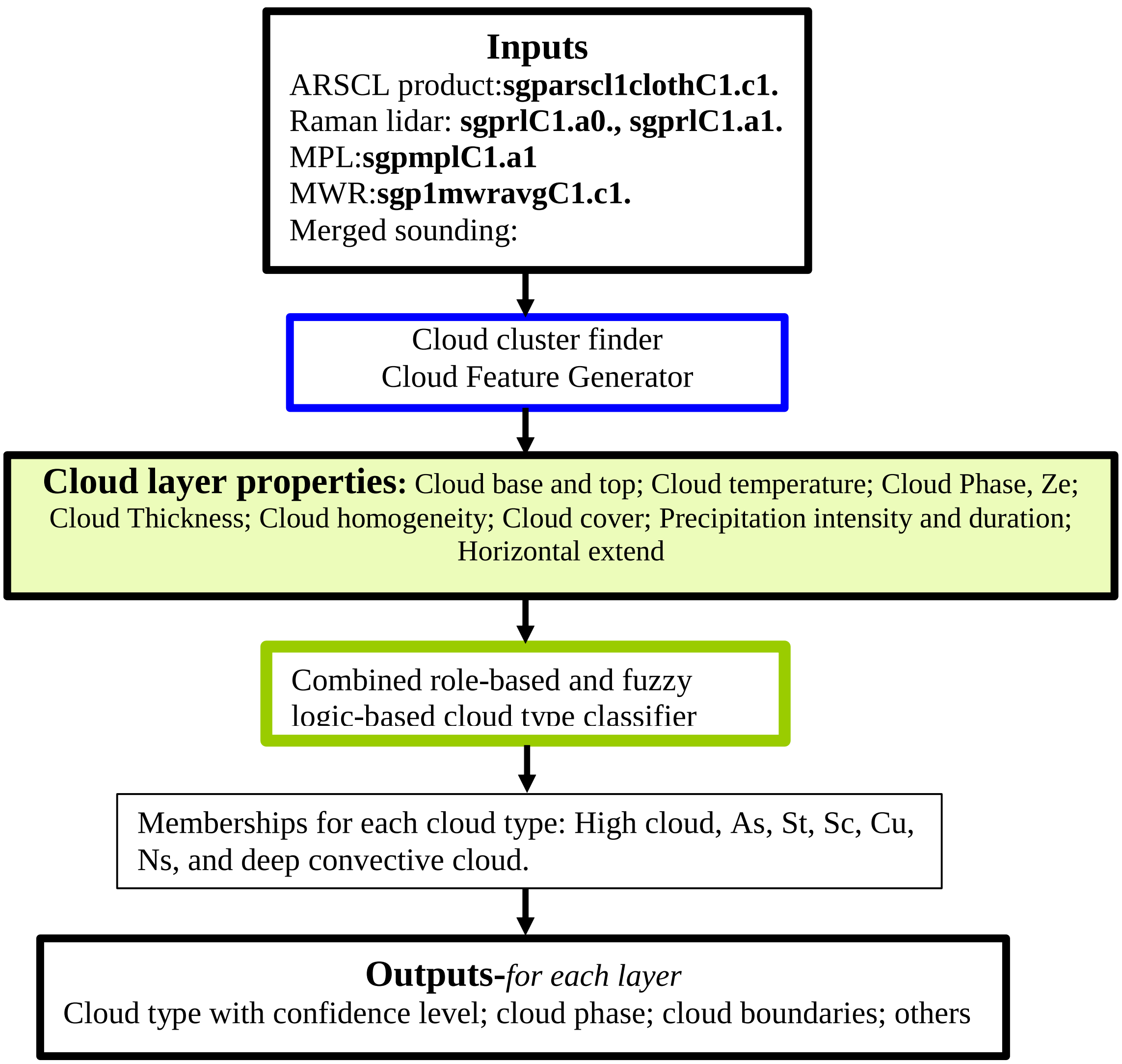


Figure 3. The general structure of cloud type classification algorithm.

lidar is that it can not penetrate optically thick clouds to provide measurements for upper cloud layers. To provide continuous cloud phase estimation, we are trying to develop an integrated cloud phase identification approach by combining atmospheric temperature, Raman lidar depolarization ratio, radar reflectivity factor, MPL backscattering coefficient, and LWP from MWR. The general steps are given in Figure 4. First, cloud temperature is used for the first cut. If cloud base temperature is colder than –40°C, it is ice cloud. On the hand, if cloud top temperature is warm than 0°C, it is water clouds for sure. The second step is to use available Raman lidar depolarization ratio measurements to discriminate cloud phase. Due to the limited penetration depth of lidar in the optically thick clouds, using LWP measurements to adjust cloud phase based on lidar depolarization measurements is important at some situations. For example of optically thick mixed-phase cloud, where optically thick ice layer below and water dominated mixed layer above, lidar may not be able to detect water signal, therefore, we may classify the layer as ice cloud. However, detectable LWP from MWR can provide information to identify water within the layer in these situations. Then, we can accordingly adjust the cloud phase as mixed-phase if water exists.

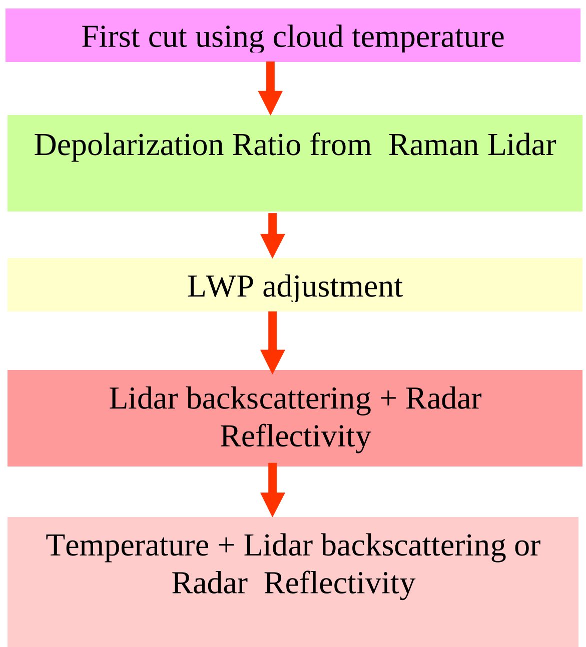


Figure 4. The general steps of integrated cloud phase identification.

For situations without lidar depolarization measurements, combining lidar backscattering and radar reflectivity factor give us some useful clues for cloud phase. Because of different microphysical properties (size and number concentration) for different phase clouds, lidar and radar signal show different characteristic features. For supercooled water clouds, lidar usually detect strong signal, but radar only has weak signal or fail to detect it because of small droplet size. For mixed-phase cloud, both lidar and radar detects strong signals. For ice clouds, lidar signal is weak or moderated, but radar signal may have a large variation. Based on a date set with cloud phase identified from Raman lidar measurements, we found these differences are statistically robust. When there is only lidar or radar measurement available, we only can combine it with temperature information for cloud phase determination. These five general steps are implemented in the code, but some details are still working issues. This approach will be improved by analysis more SGP data.

Examples of Classification

To give a more information about how fuzzy logical based classification works, the following tables gives two examples. Based on the inputs, we will have different memberships (between 0 and 1) for different fuzzy sets. The membership for different cloud type can be between 0 and 1 too. For the first case, we have membership 1 for high cloud, and 0 for the others. Therefore, we are confident about the output. The second case is more complicated as there are two cloud types with non-zero memberships. In the de-fuzzy process, we output a cloud type, which has the highest membership, and confidence level given by the moralized membership. However, there is option to output both cloud types with different confidence levels.

Inputs
Base_H Top_H dH Base_T Top_T Cloud Fraction Phase
8.52818 10.1073 1.57921 -53.0121 -63.0221 1.00000 3.00000

Member-ships of fuzzy sets
Base temperature : cold, moderate, warm 1.00000 0.000000 0.000000
Cloud base height: Low, Mid, High 0.000000 0.000000 1.00000
Cloud thickness: Thin, Moderate, Thick 0.000000 1.00000 0.000000
Cloud cover: Scattered, Moderate, Overcast 0.000000 0.000000 1.00000
Cloud horizontal extend : Isolated, Moderate, Extended 0.000000 1.00000 0.000000

Outputs
high_M, As_M, Ac_M, St_M, Sc_m, Cu_M, Ns_M, Deep_M
1.00000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000

Base_H Top_H dH Base_T Top_T Cloud Fraction Phase
7.47600 8.26350 0.787620 -38.8858 -43.7634 1.00000 3.00000
Base temperature : cold, moderate, warm 0.888580 0.111420 0.000000
Cloud base height: Low, Mid, High 0.000000 0.262000 0.738000
Cloud thickness: Thin, Moderate, Thick 0.589114 0.410886 0.000000
Cloud cover: Scattered, Moderate, Overcast 0.000000 0.000000 1.00000
Cloud horizontal extend : Isolated, Moderate, Extended 0.000000 1.00000 0.000000
high_M, As_M, Ac_M, St_M, Sc_m, Cu_M, Ns_M, Deep_M
0.738000 **0.262000** 0.000000 0.000000 0.000000 0.000000 0.000000 0.00000

The time-height display of inputs and outputs for April 12, 2000, is presented in Figure 5. For this case, we have all measurements from instruments we used.

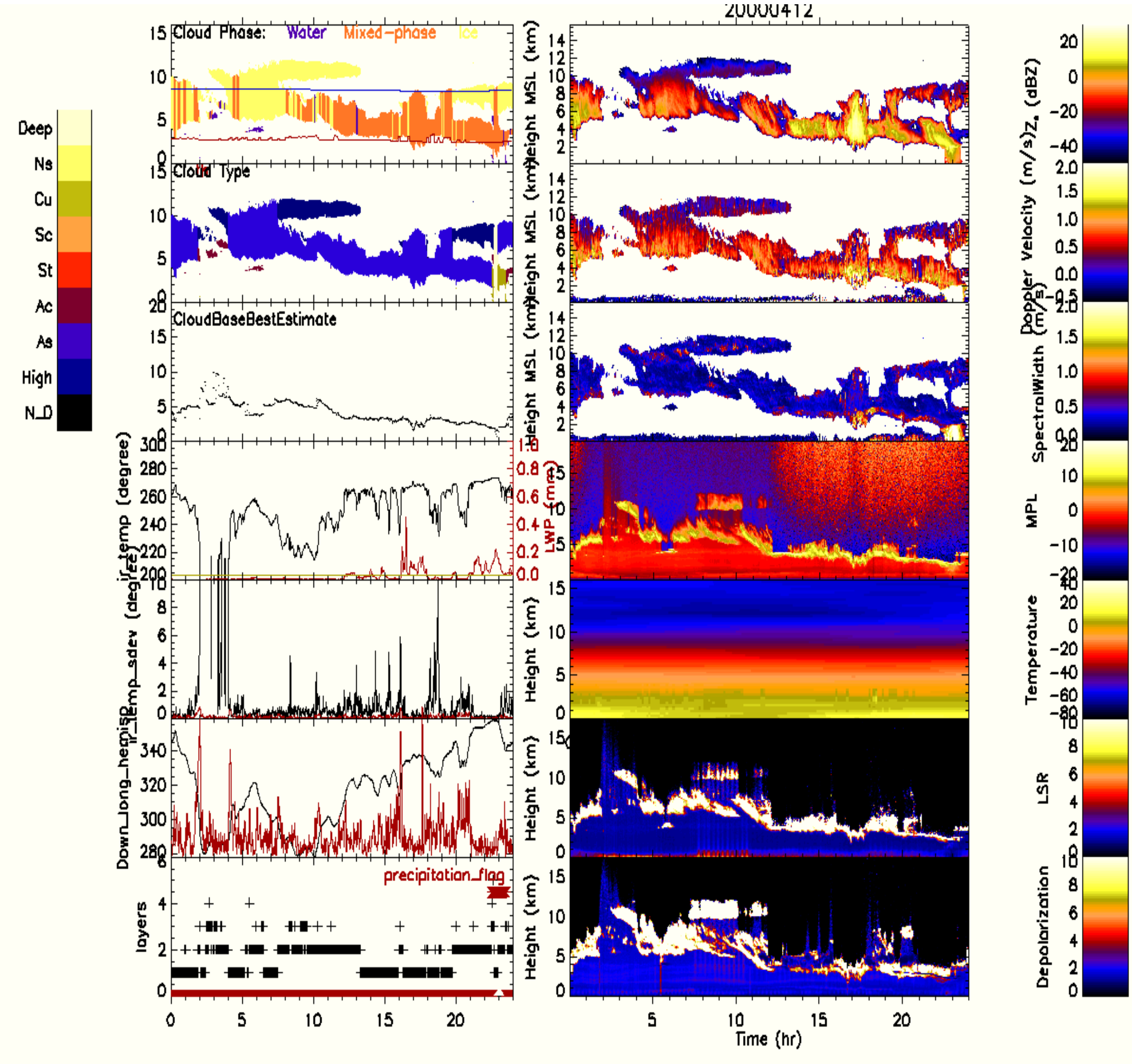
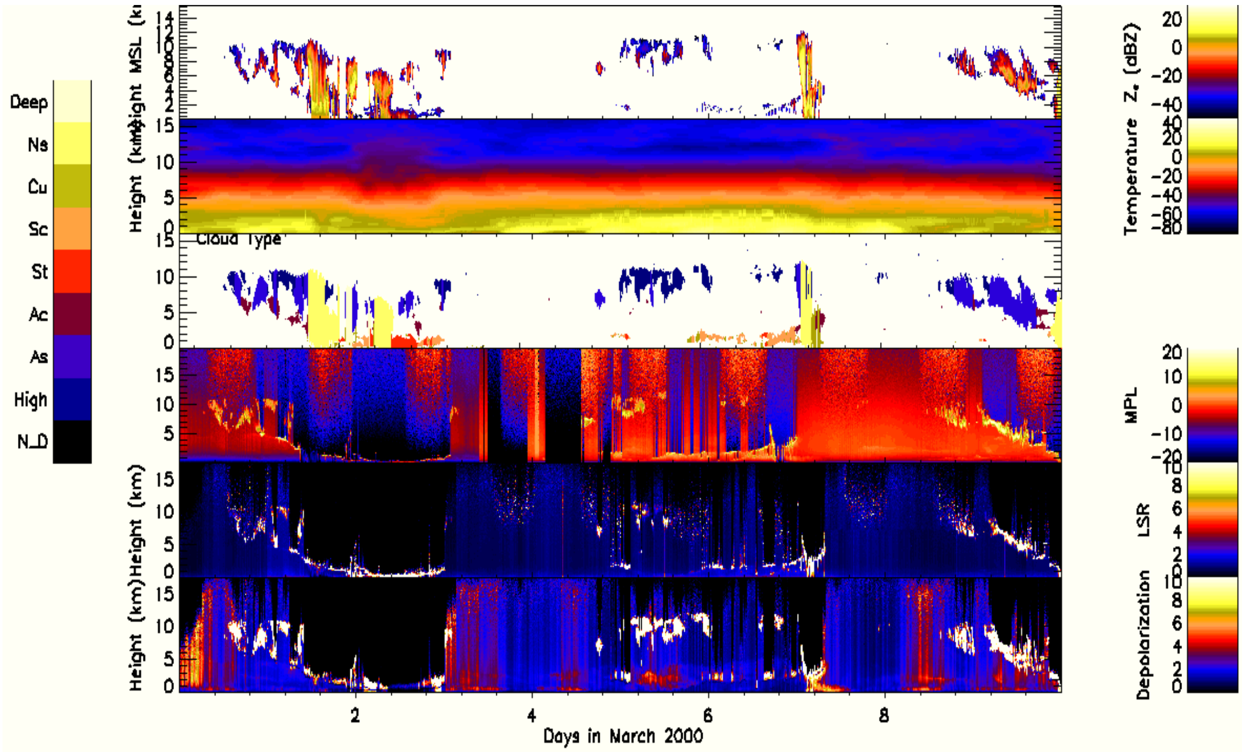
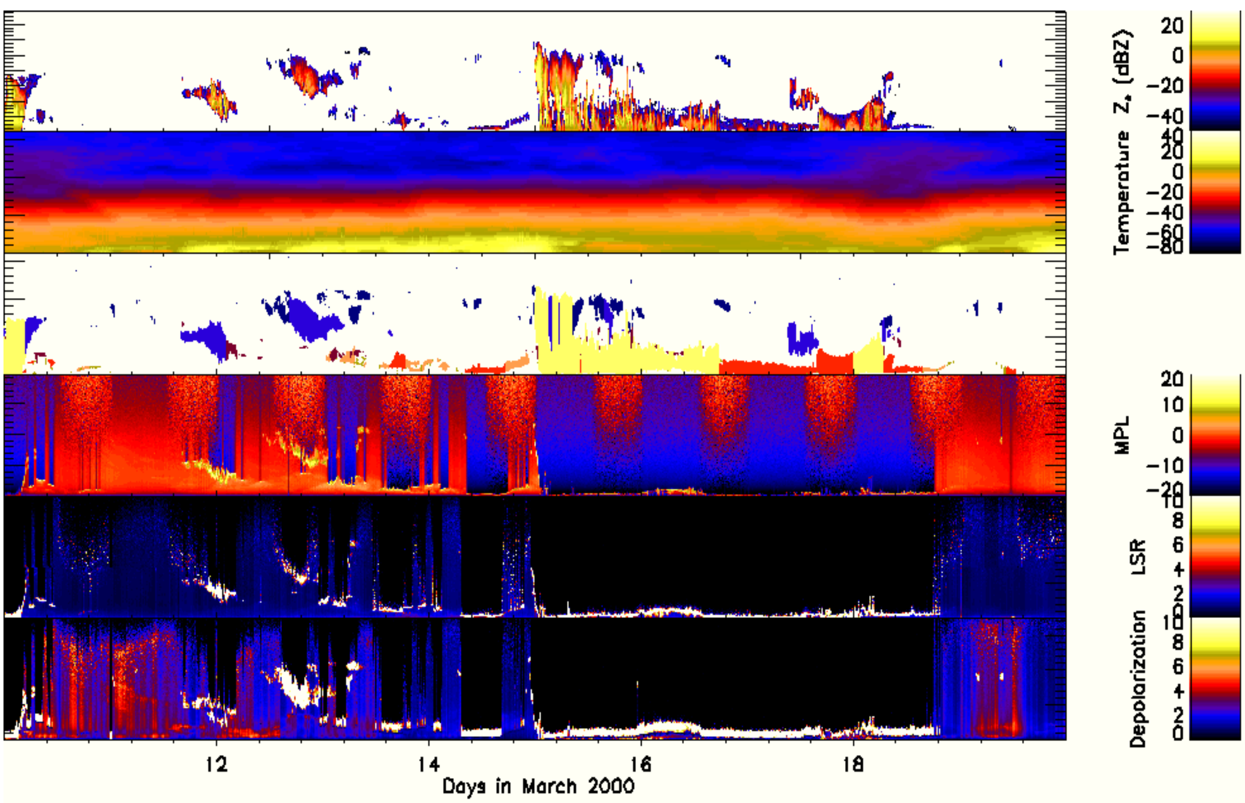


Figure 5. An example of inputs and outputs for cloud classifications on April 12, 2000.

Results for March 2000

The algorithm is tested based on the data of 2002 from SGP CART site. Results for March 2000 intensive observation period (IOP) are given in Figure 6, which show that the algorithm works reasonable well.


Deep
Ns
Cu
Sc
St
Ac
As
High
N_D
Height MSL (km)
Height (km)
Cloud Type
Height (km)
Height (km)
Days in March 2000
Z$_e$ (dBZ)
Temperature
MPL
LSR
Depolarization


Days in March 2000
Z$_e$ (dBZ)
Temperature
MPL
LSR
Depolarization

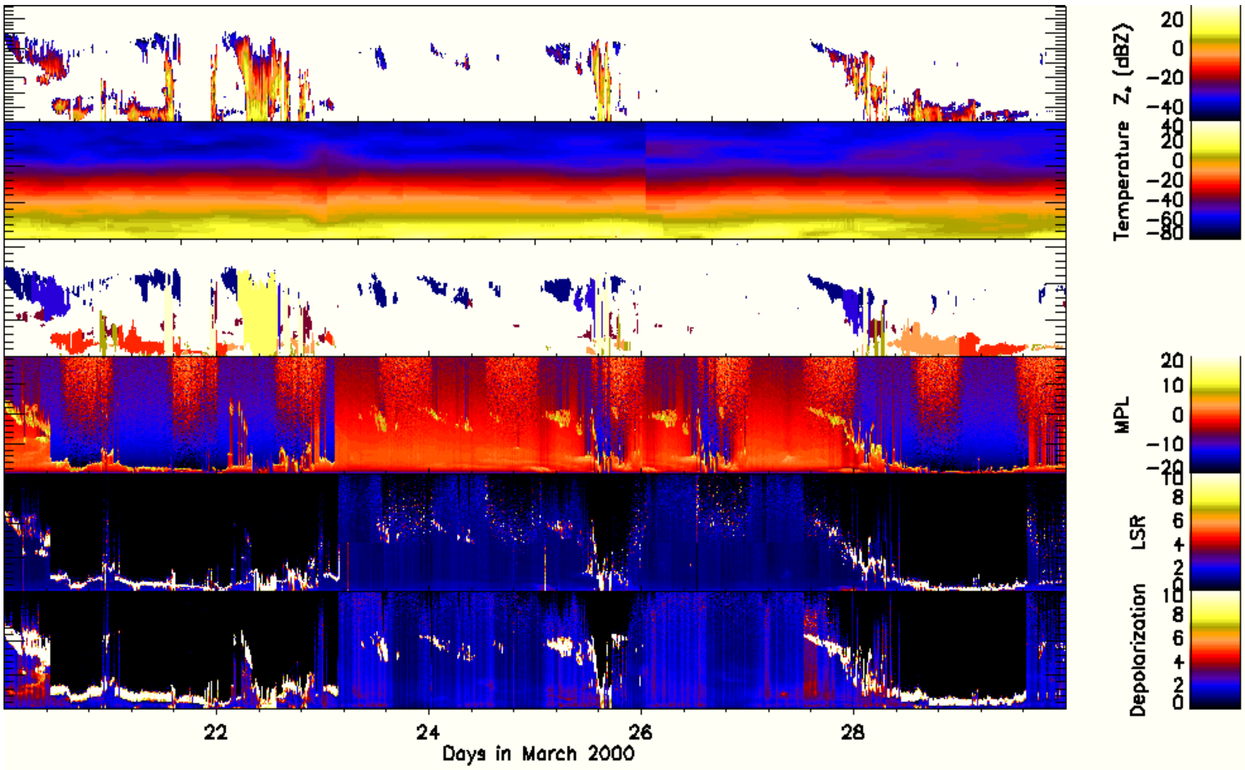


Figure 6. Time–height display of MMCR Ze, MPL return power, Raman lidar scattering ratio (LSR) and depolarization ratio, and classified cloud types for March 2000 IOP.

Summary

The cloud classification algorithm is improved by implementing a combined fuzzy logic based and role-based classification method and a better cloud cluster analysis. An integrated cloud phase identification is developed and tested to provide better cloud phase information. The vision 0 code is tested based on whole year data of 2000. But many improvements still are need, for example, we need to fine-tune the membership function of fuzzy sets based on more data at SGP CART site. Therefore, suggestions for improvements are highly welcome. The CD of initial results for year of 2000 was distribute during the meeting, and are available form authors upon request. The algorithm will test extensively with multiple-year SGP CART site data, and then it will be modified for TWP and NSA CART site data streams.

Acknowledgement

This research has been funded by DOE Grants DE-FG02-03ER63536 and DE-FG03-03ER63530 from the Atmospheric Radiation Measurement Program.

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