

GOESR3 Periodic Reporting

Reporting Period: January 2019 – June 2019 (2nd half of FY18 funding cycle)

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Project Title: Improving the ABI Cloud Layers Product for Multiple Layer Cloud Systems and Aviation Forecast Applications

Project Number: 479

Executive Summary

This project seeks to improve the classification and categorization of multilayer cloud scenes by the GOES ABIs, while simultaneously improving the Cloud Cover Layers (CCL) product that identifies the height category of clouds in any given ABI pixel. The general methodology is threefold: (1) To investigate the usefulness of certain cloud proxies, such as layer relative humidity, by training on actively-sensed cloud layer boundaries; (2) To develop a new multispectral retrieval that uses ABI radiances to determine separation between cloud layers in known multilayer situations; and (3) To fuse this information together with our own statistical cloud base algorithm, which has been trained on radar and lidar-observed cloud boundaries.

In this reporting period, significant improvements were made in the construction of an algorithm to determine the presence of low clouds, having achieved approximately 84% accuracy in such prediction during our testing period. This algorithm consists of a machine learning implementation that trains on joint ABI and CloudSat/CALIPSO observations, combined with external information about low-level relative humidity (in this case, from a forecast model). This algorithm is the culmination of the lessons learned during the first 1.5 years of the project, including investigation of the behavior of low cloud clouds at a variety of wavelengths (including the 0.64 and 1.38 μm brightness temperature ratio, and 3.9 and 11.2 μm brightness temperature difference), and the utility of low-level atmospheric moisture as a predictor of low clouds.

Progress toward FY18 Milestones

This section will address overall progress toward FY18 milestones achieved, focusing mostly on the January through June 2019 reporting period (previous FY18 progress will be summarized as required). Milestones, bulleted and in italics, are referenced.

Overall, we are making rapid progress toward the goals of the project by making advances on two fronts. First, we continue to refine our cloud geometric thickness algorithm to directly improve the cloud cover layers (CCL) product with a threshold approach based on statistics of numerical weather prediction humidity data for multilayer scenes. Second, as described in the executive summary, a machine learning approach has been adopted that utilizes information from ABI channels (including various differences and ratios that are relevant for low cloud detection) as well as external information about layer moisture content. This machine learning model (based on the random forest) trains a set of decision trees that uses this physical information as inputs, and predicts whether low cloud is present in a given ABI scene. During training, CloudSat and CALIPSO observations of vertically resolved clouds serve as the truth that forms the basis for the model predictions.

- *Complete implementation of the statistical cloud base algorithm on ABI data.*

We have now completed an implementation of our statistical CCL implementation for the GOES-16/17 ABI. The code is submitted as part of the NOAA Enterprise cloud algorithm suite, providing an easy transition to operations.

We continue to refine the algorithm, and have experimentally implemented a version including five flight-levels rather than the traditional three pressure-based levels, with the encouragement of our operational partners. Our version of the product is disseminated in near real-time at CIRA through our SLIDER interface (<http://rammb-slider.cira.colostate.edu>). Figure 1 shows a four-panel display of a Pacific low pressure system from GOES-17 ABI on 4 March 2019, including the Geocolor image and corresponding representations of cloud top height, cloud geometric thickness, and the resulting cloud cover layers retrieval. The thickest clouds are located along the position of the warm and cold fronts, with a vast area of low cloud behind the system, consistent with our synoptic scale knowledge of these systems.

Figure 2 shows an observed CloudSat/CALIPSO cross section through a cyclone over the central U.S., and the corresponding CCL representation for GOES-16 ABI (1945 UTC on September 20, 2018). We have implemented a number of fixed low-level relative humidity (RH) thresholds to capture the “low plus high” cloud category as shown in the sample figure, which is not possible using only the cloud geometric thickness approach. As indicated in previous reporting periods, our research has shown that RH thresholds associated with the presence of low cloud vary in both time and space. The threshold approach shows a potential for CONUS cases but is not particularly useful outside the middle latitudes. We are therefore currently focusing on allowing our machine learning algorithm to itself determine where RH is useful as a predictor of low cloud, and where it is not, by learning the weighting based on events observed in the training.

- *Collect validation datasets (Active remote sensing products from CloudSat, CALIPSO, and EarthCare (if available); ARM site remote sensing products*

We continue to collect CloudSat and CALIPSO data and match it to ABI. This provides valuable training for our machine learning algorithm, and we are heavily utilizing these global-scale datasets for evaluation purposes. We note that CloudSat and CALIPSO are now in a new C-Train formation, consisting of only these two satellites, having left the A-Train during 2018.

- *Begin testing of daytime/nighttime lookup tables for determination of lower cloud boundaries (including high/low separation distance) in multilayer situations. Compare this physically based method to a statistically based method based on existing CloudSat/CALIPSO cloud boundaries.*

Although we will continue to explore a lookup table-type approach to low cloud height with radiative transfer modeling (see Figure 3), we are increasingly leaning on the machine learning results we have achieved using similar inputs. Figure 4 shows the hit rate and false alarm ratio for low cloud detection over a 10 day period in 2018 using our machine learning algorithm with ABI data, as verified through CloudSat/CALIPSO observations. The hit rate is the fraction of observed low clouds that are correctly forecast, while false alarm ratio is the fraction of incorrect low cloud forecasts made. In this figure we focus on some CLAVR-X cloud types where multiple layers are quite common and the existing CCL algorithm performs relatively poorly. Our initial results show a significant improvement in low cloud detection, at the expense of some false alarms. Later results (next reporting period) show a continuous and marked improvement over these results as we refine our implementation, increase our use of physics-guided training methods, and include more data in the training data set.

- *Present results at GOES-R meeting and at AMS or AGU.*

Our work was presented at the 15th Annual Symposium on New Generation Operational Environmental Satellite Systems at the American Meteorological Society (AMS) 2019 Annual meeting in Phoenix, Arizona.

Plans for Next Reporting Period

During the next reporting period we will continue development and implementation of our machine learning model for low cloud detection, and focus on combining these results with the cloud geometric thickness-guided results to produce a consistent combined cloud product that allows for multilayer scenes by supporting categories like “high and low” (or its equivalent in the five-layer model). Combining these two methods is an important step in the development of an algorithm that can be used operationally.

- *Extensively test and validate algorithm using CloudSat, CALIPSO, EarthCare, and ARM data, as availability allows.*

This task is ongoing, and we will continue to evaluate our product against a variety of observations (radar and lidar in particular).

- *Complete implementation of new algorithm into the CLAVR-x processing system (as a development/transition tool for NOAA operational algorithms).*

This work is ongoing.

- *Complete incorporation and display test of the product in AWIPS II or NAWIPS.*

We are currently working with Amanda Terborg of the Aviation Weather Center to implement cross sections of the CCL product in AWIPS-2. Aviation Weather Center has expressed interest in our product and has taken steps to aid us in developing an operational implementation of CCL as a cross-section product in AWIPS-2. This would allow a forecaster to click on two endpoints on a map and view the CCL product in vertical cross-section form along the line between these two points.

- *Complete VISIT module training module for AWC forecasters.*

This will occur in the latter half of the next reporting period, or the beginning of the following reporting period.

- *Visit Aviation Weather Center to deliver hands on training.*

We will visit the Aviation Weather Center in Year 3 to present our results and gather feedback on the product from operational forecasters.

- *Present results at GOES-R meeting and at AMS or AGU.*

We will present our results at the AMS/EUMETSAT joint satellite conference in Boston, Massachusetts in September 2019.

- *Publish results in a journal.*

We intend to submit a manuscript on our machine learning approach to low cloud detection in year 3 of the project.

Additional Information

1. Interaction with operational partners –

John Haynes arranged to visit the Aviation Weather Center in August, a trip that will be reported upon in the next semi-annual report.

2. Conference/workshop participation –

Haynes, J. M., Y. J. Noh, S. D. Miller, A. Heidinger, and J. M. Forsythe, 2019: Cloud geometric thickness and improved cloud boundary detection with the GOES ABI. 15th Annual Symposium on New Generation Operational Environmental Satellite Systems, American Meteorological Society 99th Annual Meeting, Phoenix, Arizona.

Noh, Y. J., S. D. Miller, J. M. Haynes, J. M. Forsythe, C. J. Seaman, A. Heidinger, and Y. Li, 2019: Improvement of nocturnal cloud base height and vertical layer retrievals in high latitudes, 99th AMS Annual Meeting/15th Annual Symposium on New Generation Operational Environmental Satellite Systems, 6-10 January 2019, Phoenix, AZ (Oral presentation at Session on Nighttime Environmental Monitoring)

Noh, Y. J., 2019: Satellite Cloud Base/Layer Product and Aviation Weather Applications, 4th KNU CARE conference on Aviation Weather, 23-24 Sept 2019, Gyeongju, South Korea (Invited talk)

3. Outside project publicity – none

4. Journal articles – none

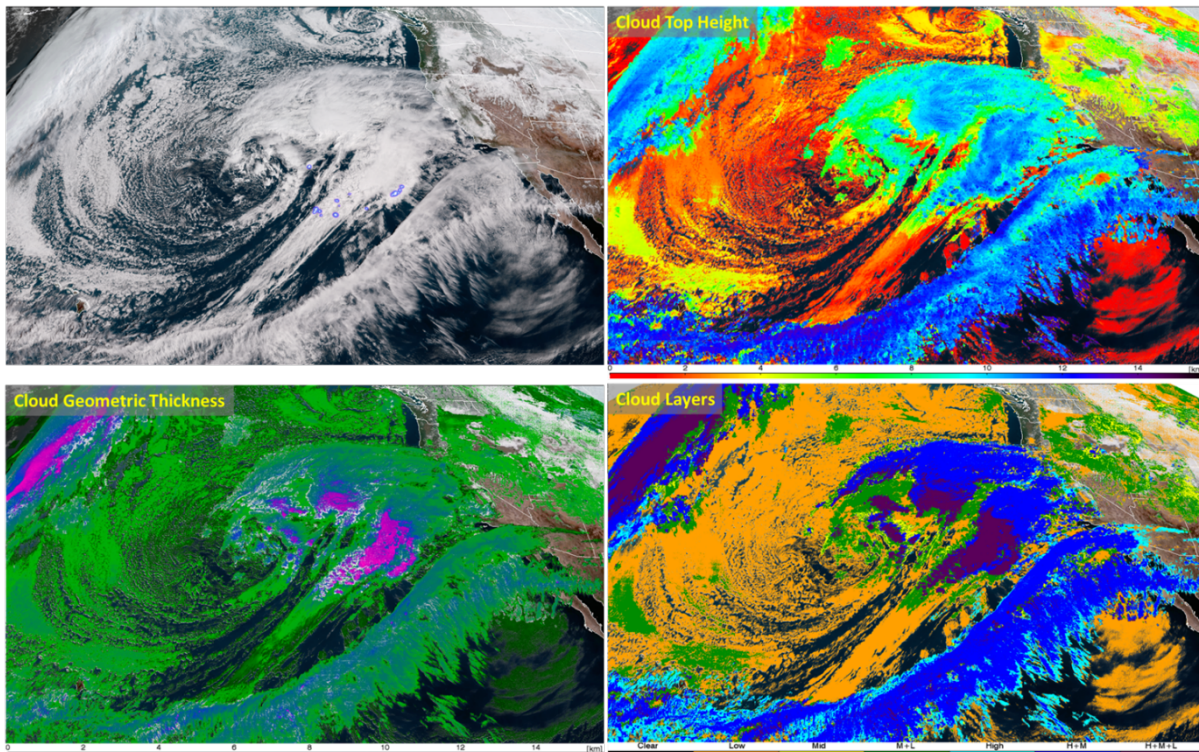


Figure 1. Sample GOES-17 cloud top height, geometric thickness, and layers over CONUS with the ABI GeoColor image (top left; GLM group energy overlaid in violet) produced from the CLAVR-x processing system at CIRA (1857 UTC on 04 March 2019). The cloud base and layer algorithm has been implemented for GOES-17 ABI in the CLAVR-x system. Cloud Layers and Cloud Geometric Thickness products are currently being displayed in CIRA's SLIDER (<https://rammb-slider.cira.colostate.edu>) with other cloud retrieval products and imagery for both GOES-16 and GOES-17 ABI for all four sectors in real time.

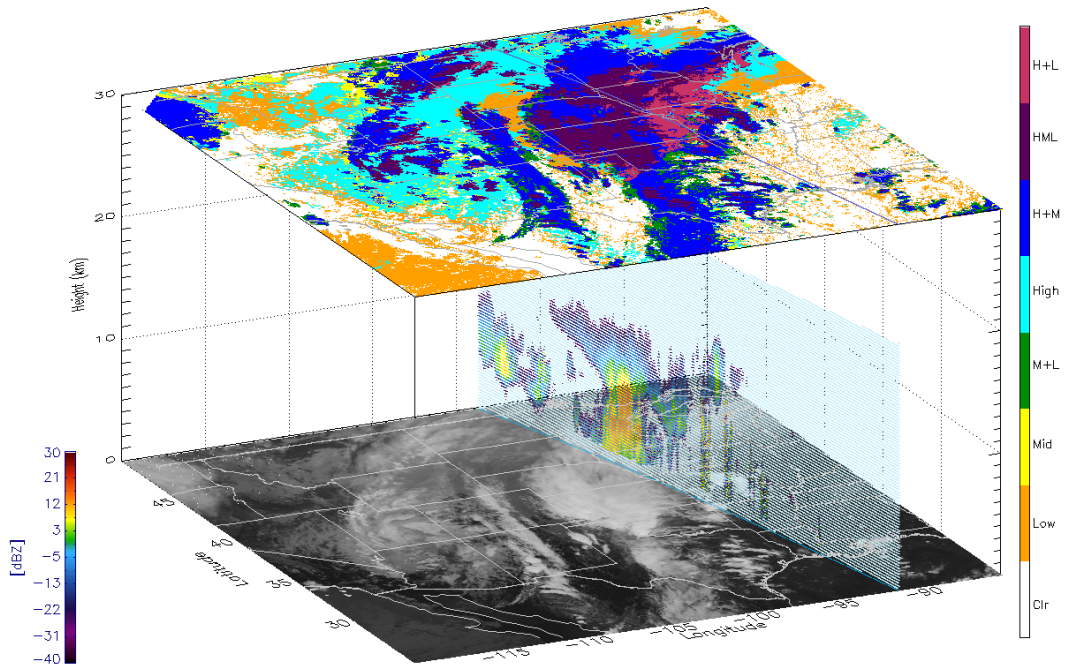


Figure 2. Improved Cloud Layers with CBH information over CONUS (top) for GOES-16 ABI at 1945 UTC on September 20, 2018. A preliminary result with ‘High + Low’ category (in magenta) using NWP surface humidity thresholds statistically derived for multi-layer scenes is shown at the bottom. An 80 % surface humidity threshold has been applied for cloudy pixels with ‘Overlap’ cloud type and high cloud fraction greater than 0.7 for the sample case. For comparisons, vertical cross-sections from CloudSat radar is also shown over the 11.2- μm IR image.

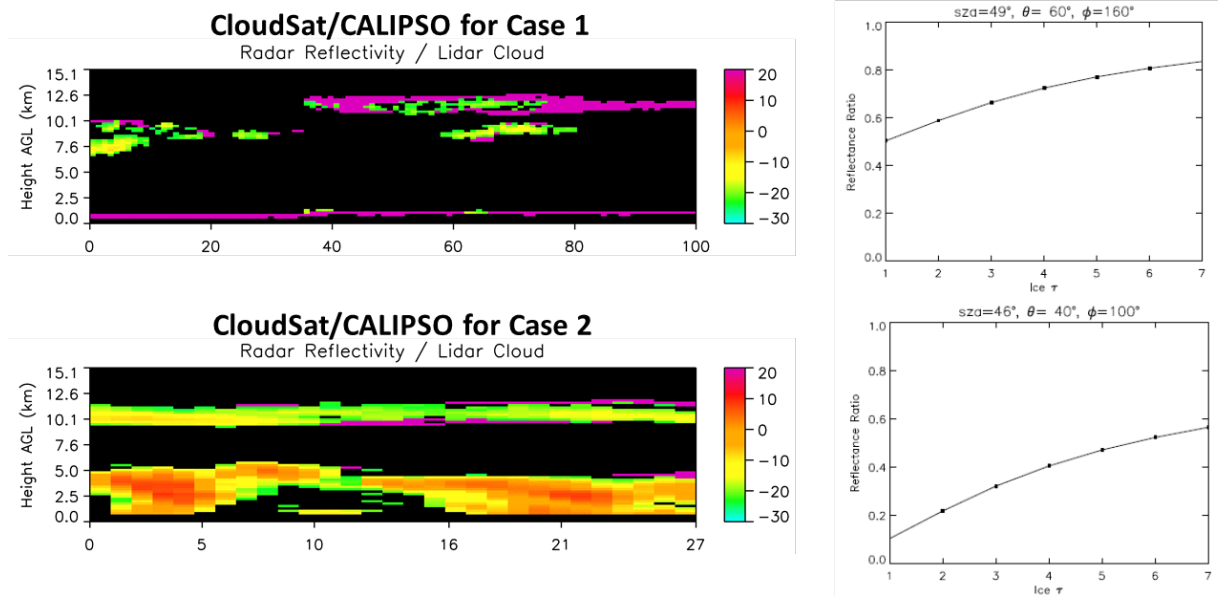


Figure 3. We created multispectral lookup tables of reflectance using radiative transfer code (0.64 and 1.38 μm for daytime and 3.9 and 11.2 μm for nighttime) by using the Santa Barbara DISORT Atmospheric Radiative Transfer (SBDART) with variations such as solar/sensor geometry angles and optical thickness to enrich the lookup table for multiple idealized cloud layer cases. For more realistic cloud simulation scenarios, we added input profiles obtained from co-locations between CloudSat/CALIPSO, ECMWF, and GOES-16 ABI as a baseline.

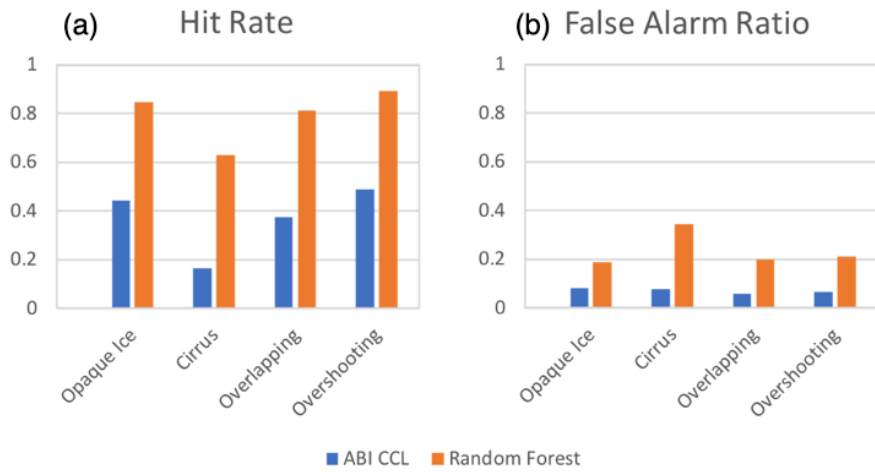


Figure 4. Hit rate and false alarm ratio for low cloud detection over a 10 day period in 2018 using our machine learning algorithm with ABI data, as verified through CloudSat/CALIPSO observations. The ordinate shows selected ABI/CLAVR-X cloud types. Hit rate is the fraction of observed clouds correctly forecast, and false alarm ratio is the fraction of incorrect low cloud forecasts made.