How NASA's Spaceborne Active Sensors Have Contributed to Operational NOAA 3D Cloud Products for Aviation

John M. Haynes

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Work supported by NOAA GOES-R and JPSS Program Offices • john.haynes (@colostate.edu/@noaa.gov)

Motivation

- Most cloud information from passive remote sensing instruments is limited to the tops of clouds, or the top of the topmost cloud layers.

- But information on what's happening closer to the surface is valuable for aviation and other real-time applications

- Using CloudSat/CALIPSO data, CIRA has been developing cloud products to estimate the *vertical distribution of clouds* from operational, passive satellite observations

Outline

I. Cloud Vertical Structure
   - Why is this important to operational users, and how do measure it?

II. Cloud Base / Vertical Structure from Passive Sensors
   - An improved cloud base algorithm
   - Applications to ABI and VIIRS, including customizable cloud vertical cross sections

III. A machine learning application to improve detection of difficult-to-retrieve clouds

IV. Towards the future

I. Cloud Vertical Structure

Why is this important, and how do we measure it?

- Cloud base / ceiling is particularly important for aviation, especially for *general aviation*
    - Instrument Flight Rules (IFR)
    - Mountain obscuration
    - Aerodrome forecasting
- How can we *operationally* measure/infer cloud base?

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Aviation Weather Center

abdallahh (CC BY-SA 2.0)

Cloud Vertical Structure for Operations

- We can get cloud bases from ceilometers, where available

FAA/NWS Ceilometer Network

Alaska

Hawaii

Jk047

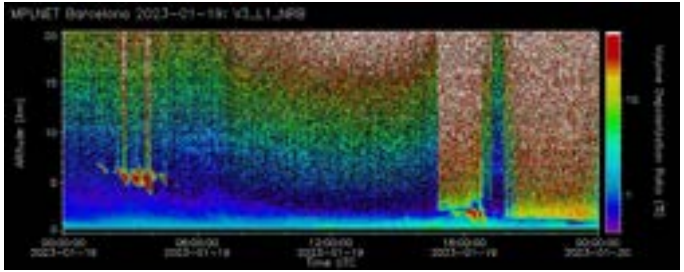
Pros: High vertical and temporal resolution, automated obs
Con: Limited distribution and representativeness

Cloud Vertical Structure for Research

- Ground-based millimeter wavelength radars; lidars – ARM Sites, MPLNET

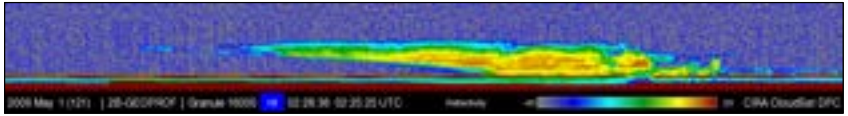
KAZR: KA band radar (ARM)

MMCR: Ka band radar (ARM)



MPLNET (NASA)

- CloudSat and CALIPSO (future AOS / EarthCARE)



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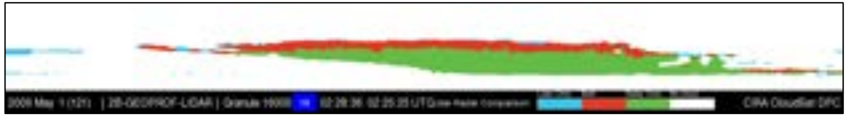
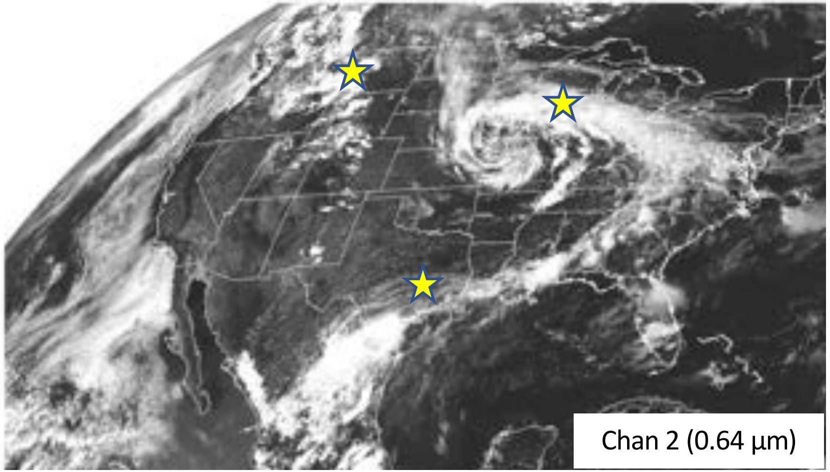
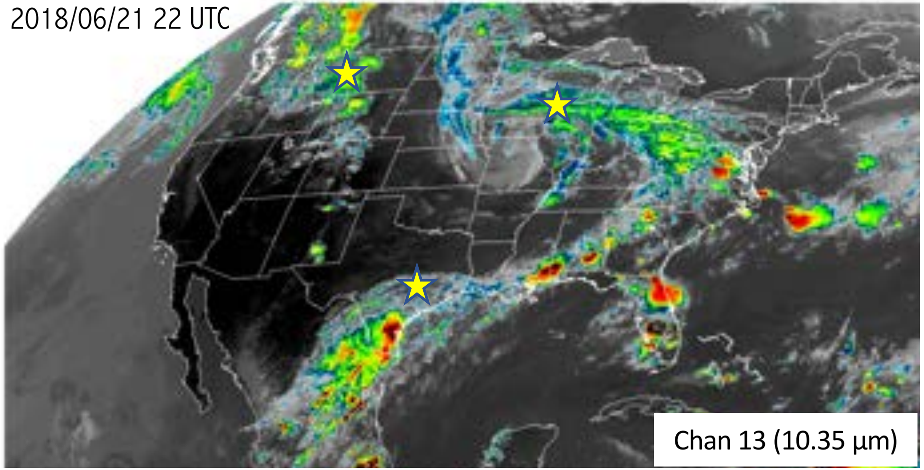


Pros: High vertical resolution, high temporal resolution (ground sites)
Con: Low temporal resolution (C/C), lack of global applicability; costly

Cloud Vertical Structure from Space

We are all familiar with using passive satellite imagery to locate clouds in time and space… but by *space* we usually mean *horizontal space*.





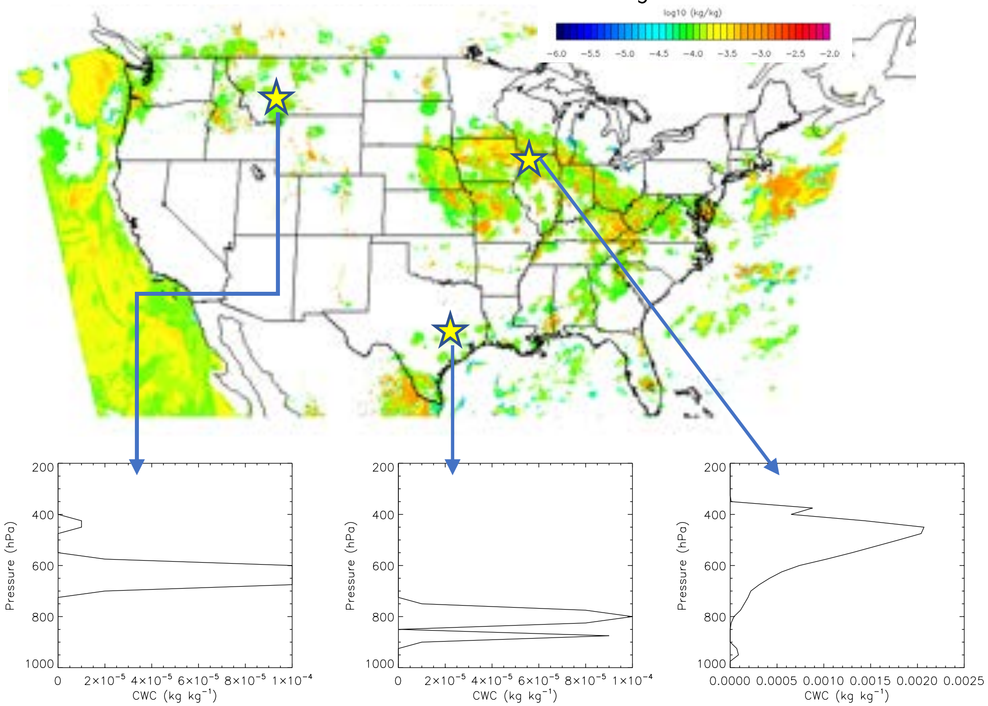
What does the vertical profile of cloudiness look like at the ★ locations?

By using a combination of different channels, combined with surface observations, we might make some guesses – but can we do this operationally?

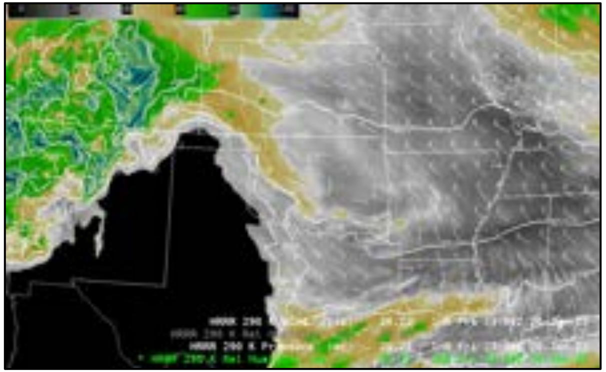
Cloud Vertical Structure from Models

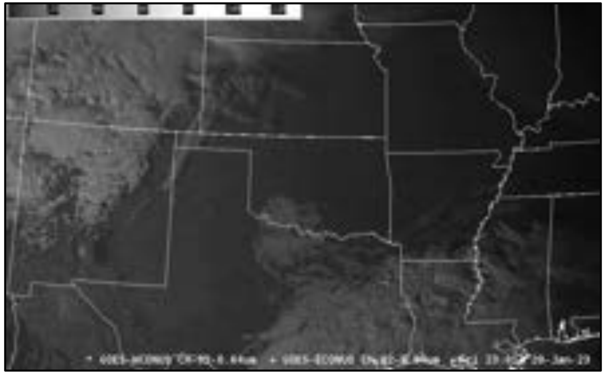
Another option is to appeal to high resolution forecast models (NWP)…

2018/06/21 22 UTC F00 HRRR cloud mixing ratio



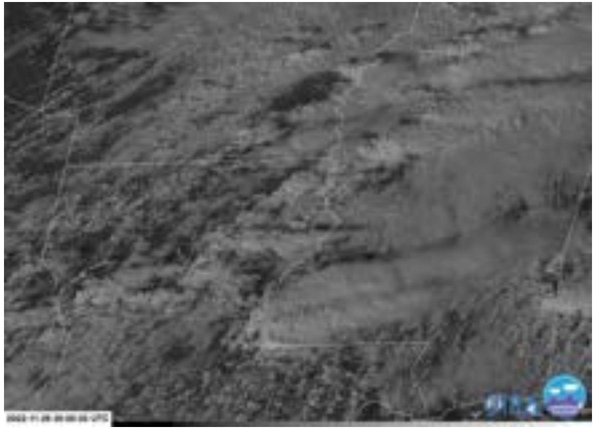
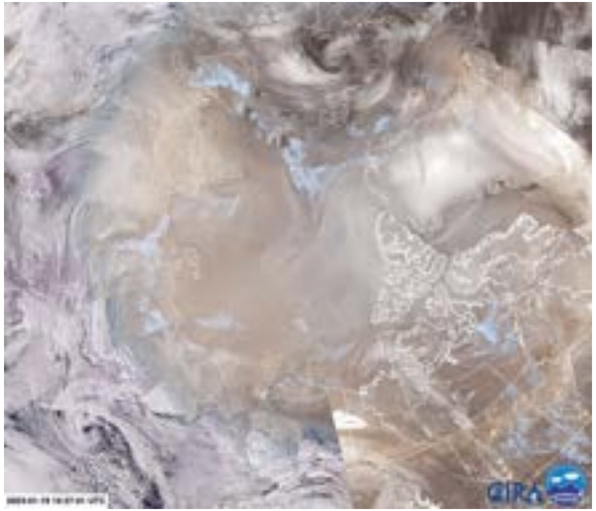
In practice, forecasters often use relative humidity (RH) from NWP as a proxy for cloud cover…





… back to satellites!

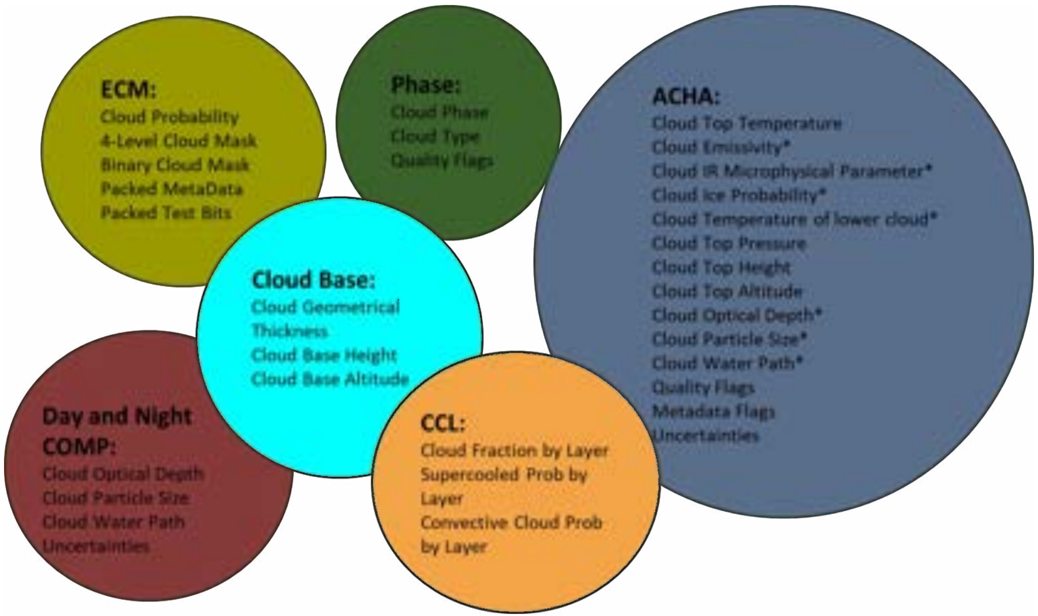
- Satellites sensors like the GOES Advanced Baseline Imager (ABI) or JPSS Visible Infrared Imaging Radiometer Suite (VIIRS) have some distinct advantages…
    - ABI: 10 minute CONUS refresh rate; 1 minute (or 30 seconds) for meso sectors
    - VIIRS: Frequent monitoring for high latitude regions
- BUT these are passive sensors…
    - Most information content is near cloud top
    - Multilayer clouds obscure information about low levels
- Can we use them to say something useful about cloud vertical structure?

II. Cloud Base / Vertical Structure from Passive Sensors

NASA

Cloud Top and Base



Enterprise Cloud Product Package

From 2020 EPS-SG STAR Product Requirements Review by A. Heidinger

- Cloud top height is a key operational product produced by the NOAA Enterprise Cloud product suite.
- Our focus has been on the two circles at left feature cloud base height (CBH) and cloud geometric thickness (CGT)…
- … and this is where CloudSat/CALIPSO have been instrumental

The “Old” VIIRS CBH algorithm

Credit: Curtis Seaman

- Originally, VIIRS utilized a cloud base height (CBH) algorithm for liquid clouds as follows:

$$CBH = CTH - \left(\frac{LWP}{LWC}\right) \qquad LWP = \frac{2\tau\rho r_e}{3}$$

Red variables from upstream retrievals

LWC is pre-defined average value based on cloud type; cloud type comes from upstream retrieval

(*) Ice retrieval is similar, but assumes IWC is function of temperature

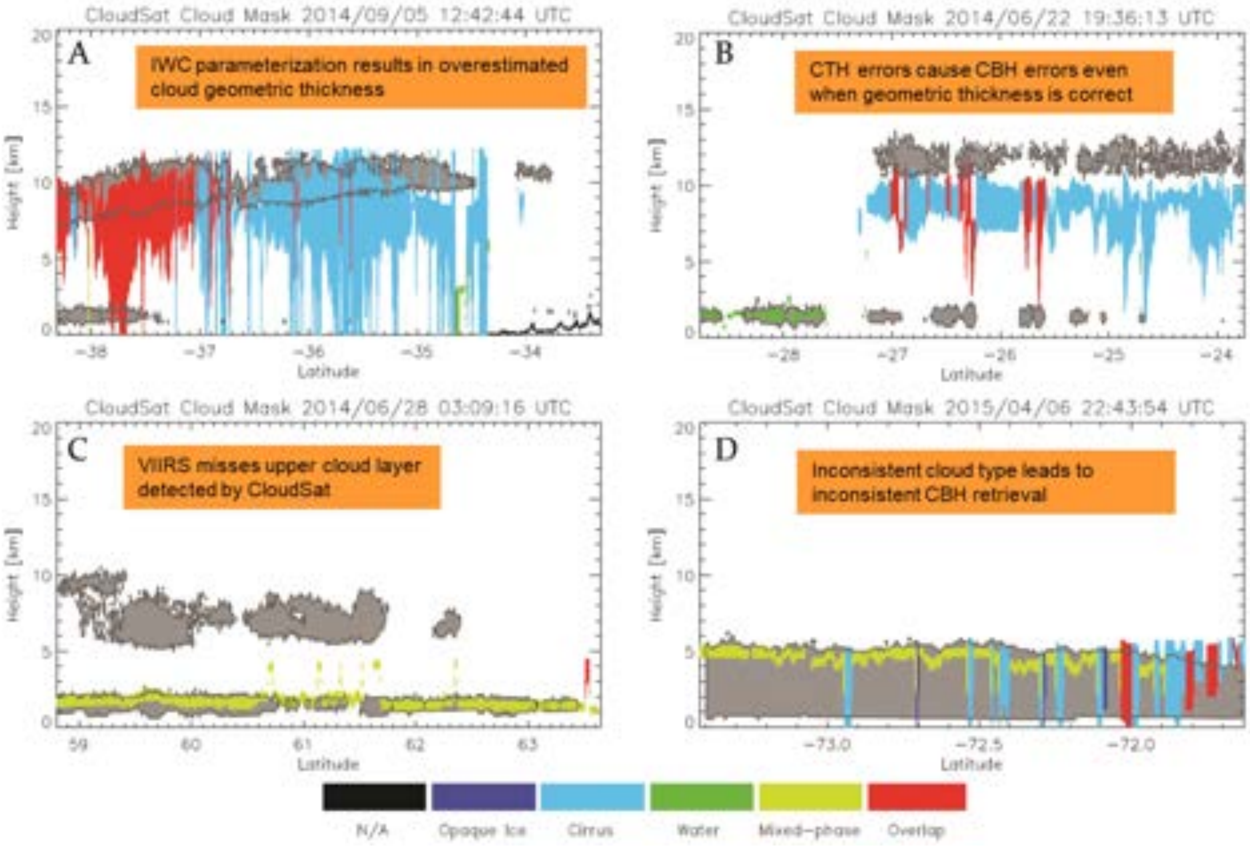
- The fact that LWC was a mean dependent on cloud type was extremely problematic

- Seaman et al. (2017) used matchups between JPSS and CloudSat (overlap ~4.5 hours every 2-3 days, resulting in 11-12 overlap periods per month) to evaluate the performance of the algorithm described above
  - Daytime only
  - Excluding precipitation
  - Require CBH,CTH above 1 km

The “Old” CBH algorithm

Credit: Curtis Seaman
Seaman et al. (2017)

CloudSat (gray)
VIIRS cloud bounds (colors)



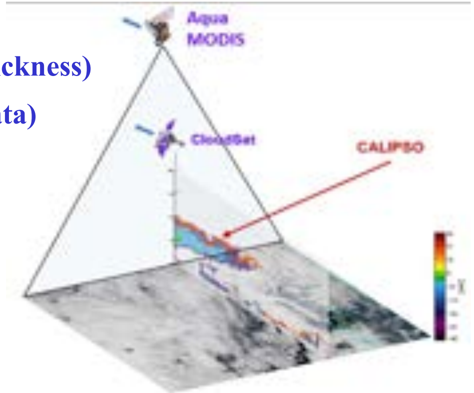
RMSE ~ 2.7 km
$r^2 = 0.452$

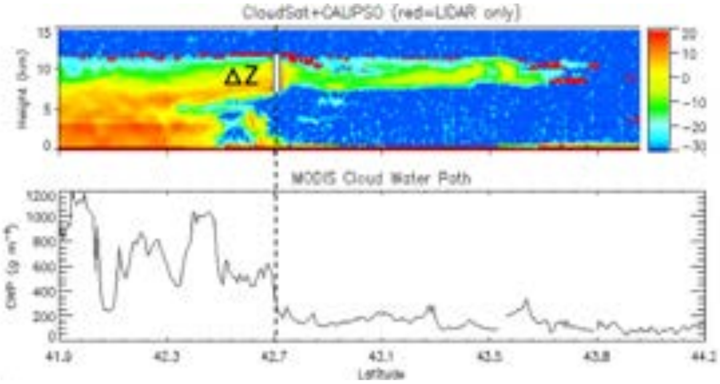
"New" CBH algorithm

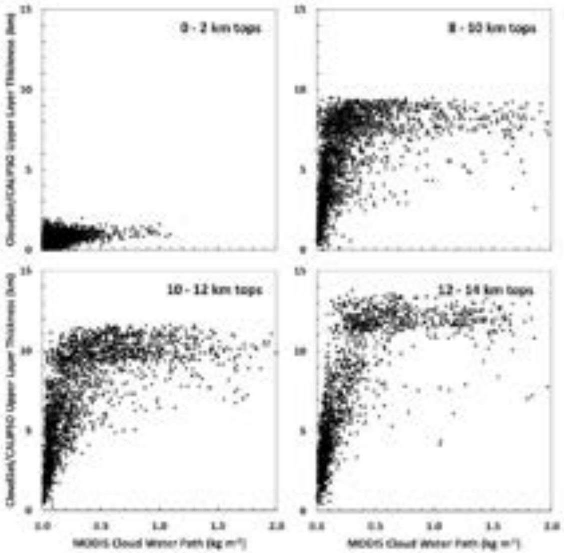
- We developed a cloud base height / cloud geometric thickness algorithm using NASA A-Train satellite data, and then applied it to VIIRS and then ABI (Noh et al. 2017, JTECH)

***CBH (*) = CTH – ΔZ* (CGT; Cloud Geometric Thickness)**

where *ΔZ = a(CWP)+b* (*a, b* based on A-Train data)







(*) Special considerations for optically thin clouds and optically thick clouds

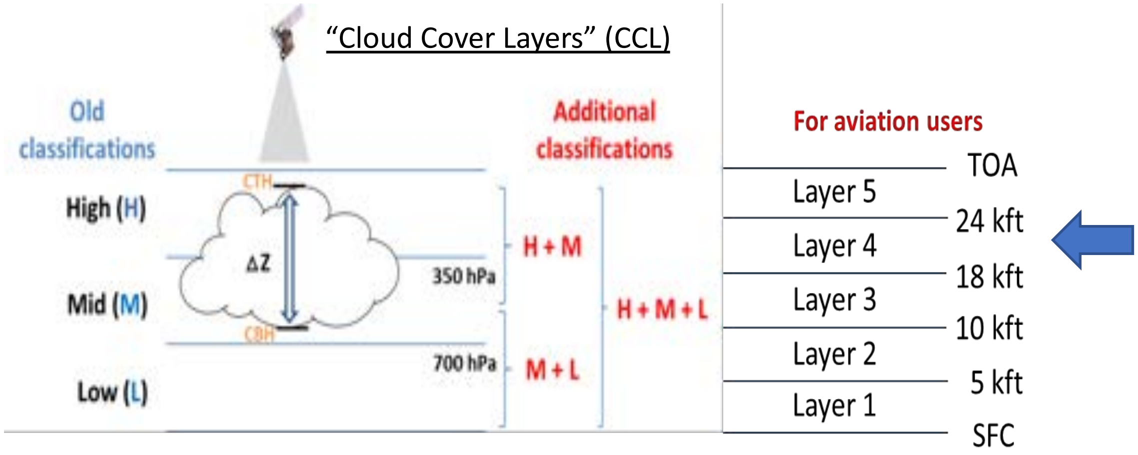
No more cloud type dependency!

“New” CBH algorithm

- Having developed these coefficients, we can now apply them to *any data* source that provides CTH and CWP

- Optimal for single layers – more on this later

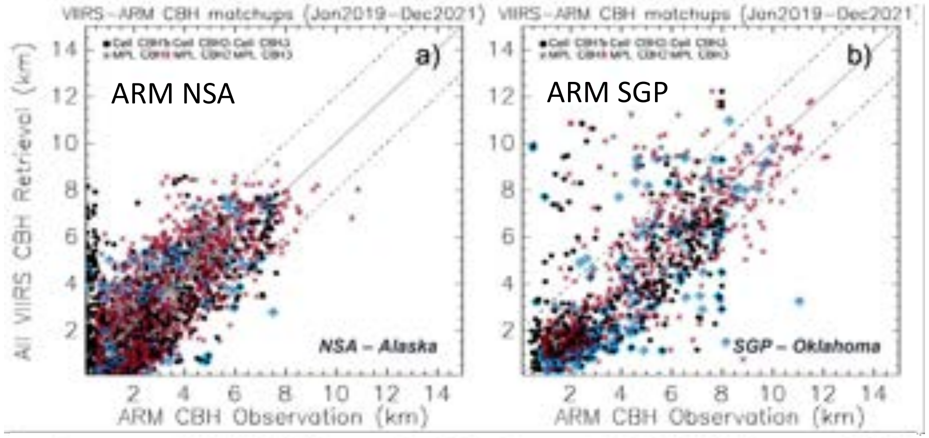
- Retrieving geometric thickness means a better Cloud Cover Layers product:



Cloud Base Validation

Cloud Base Height:

ARM Ceilometer / MPL
vs.
VIIRS

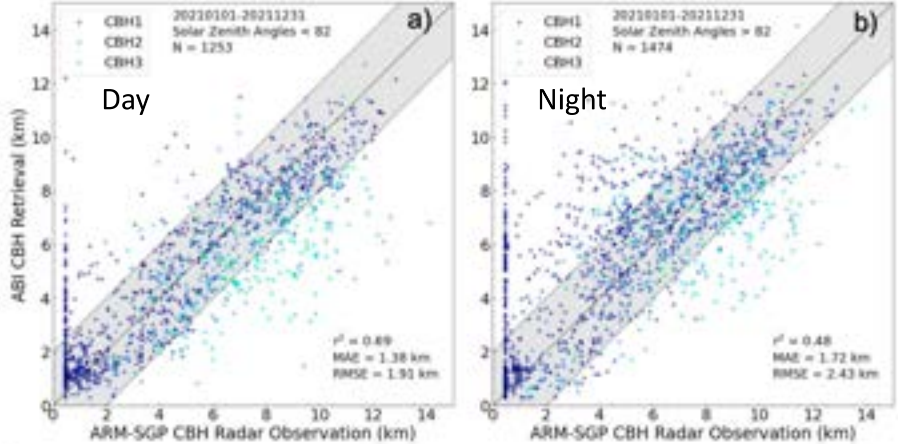


Samples where VIIRS cloud base heights are within 2 km of..

Ceilometer / MPL:
- 89% / 82% (NSA)
- 85% / 68% (SGP)

Cloud Base Height:

ARM SGP KAZR radar
vs.
ABI



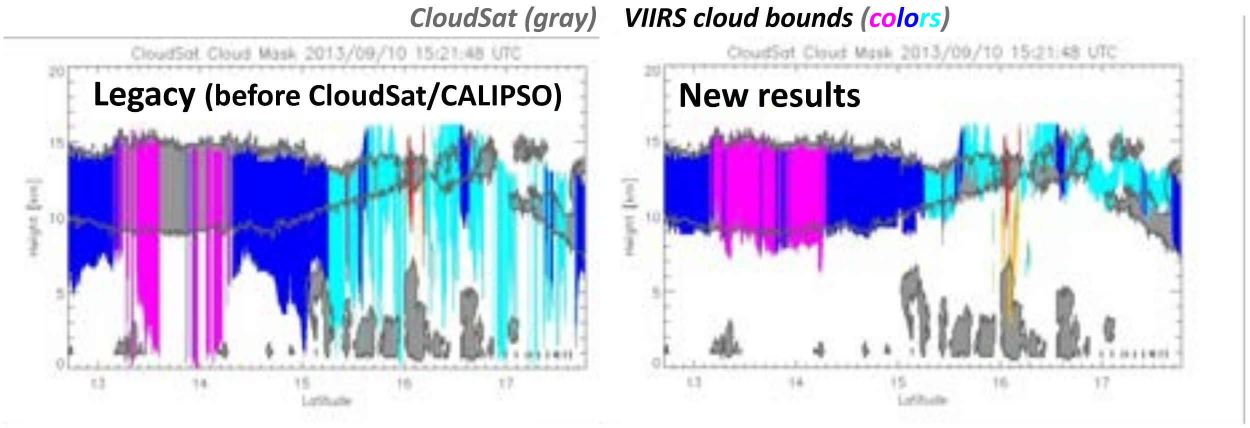
KAZR radar:
- 80% (day) / 70% (night)

Yoo-Jeong Noh
Brandon Daub

Cloud Base Validation

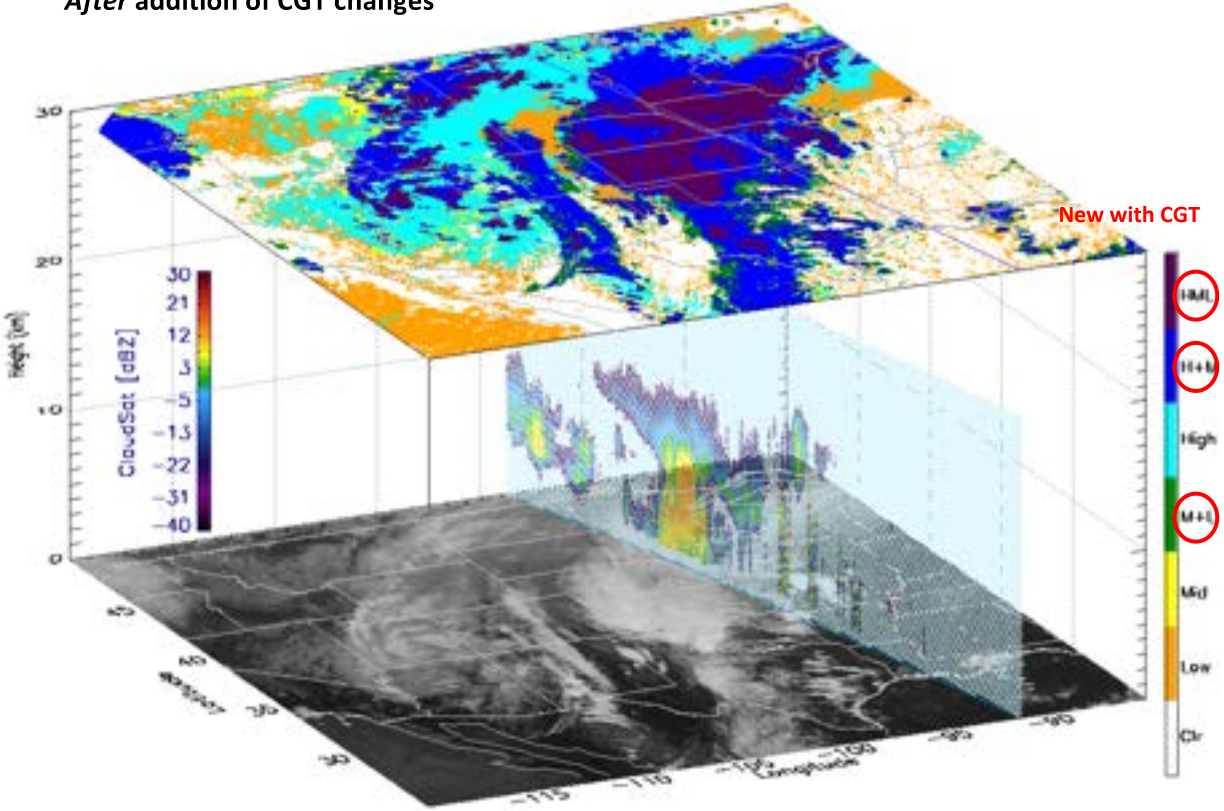
CBH comparison: “in-spec” results for VIIRS
relative to CloudSat/CALIPSO

	RMSE	r^2
Legacy algorithm	2.7 km	0.452
New algorithm	1.7 km	0.791



Cloud Base / Geometric Thickness

GOES-16 ABI
***After* addition of CGT changes**



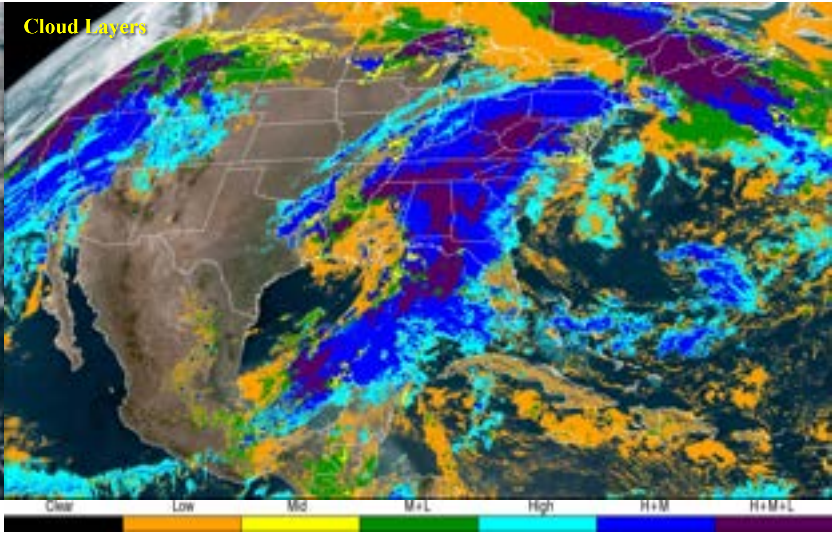
Cloud Base / Geometric Thickness

- Now applicable to polar and geostationary satellite sensors (JPSS VIIRS and GOES ABI, AHI, …)
- Real-time display for the products available in CIRA's SLIDER - http://rammb-slider.cira.colostate.edu
- May be particularly useful for oceanic flight routing when combined with GLM

GOES-16 ABI GeoColor
with GLM overlay (L2 group energy)

Cloud Cover Layers

1806 – 2106 UTC (per 15 min) 08 April 2019

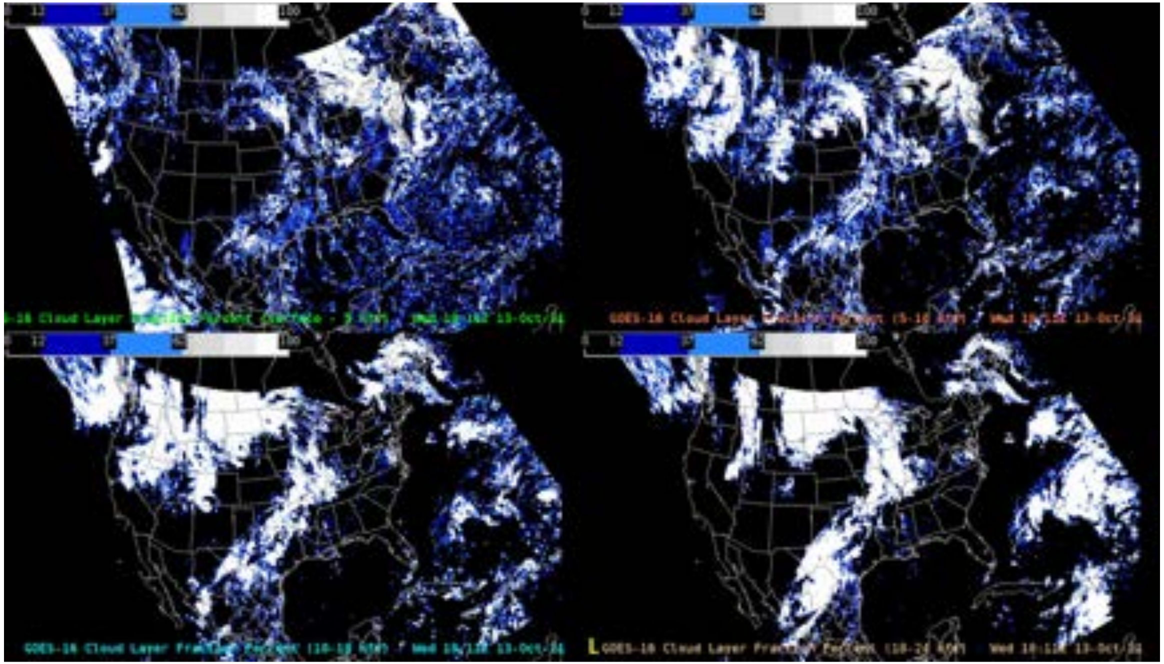


GOES-16 ABI CONUS

AWIPS II Display

< 5 kft

5-10 kft



10-18 kft

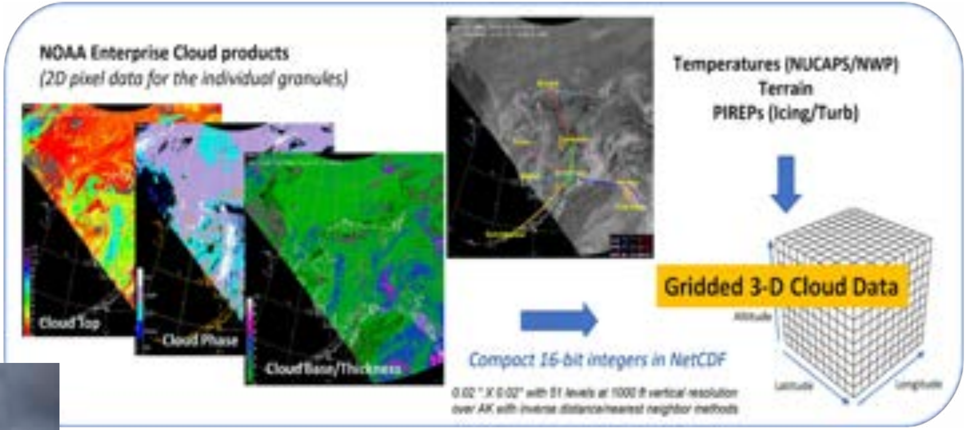
18-24 kft

Debra Molenar
Ty Higginbotham
Amanda Terborg

- Layer cloud fractions improved with Cloud Base in AWIPS II at the Aviation Weather Center
- Provisional review this Spring
- Current work: Development of volume browser display

Gridded 3D Cloud Data

- Working with the JPSS Aviation Initiative, we have developed real-time VIIRS-based cloud vertical cross sections for Alaska
- Goal is to enable production of an "active sensor-like" cloud mask between arbitrary locations



- Aviation is critical for health and safety in remote regions of Alaska, and to economy
- Large number of aircraft based in AK!

Zachary Perras

Aviation Cross Sections: Alaska

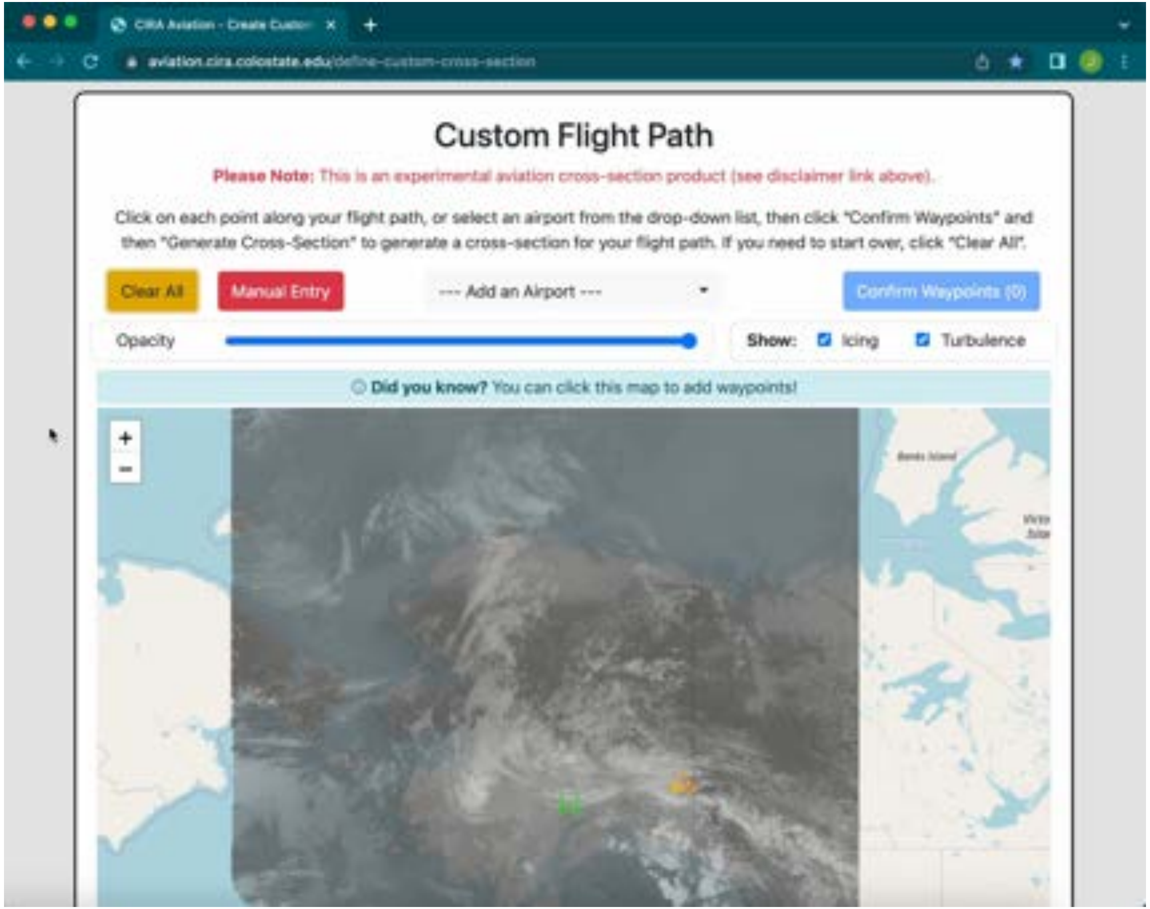
https://aviation.cira.colostate.edu

(Click at right for demo)

- ”Active sensor-like” cloud vertical cross sections…
- … without the active sensors! (*)

(*) but impossible w/o them!

- Let’s take a tour…



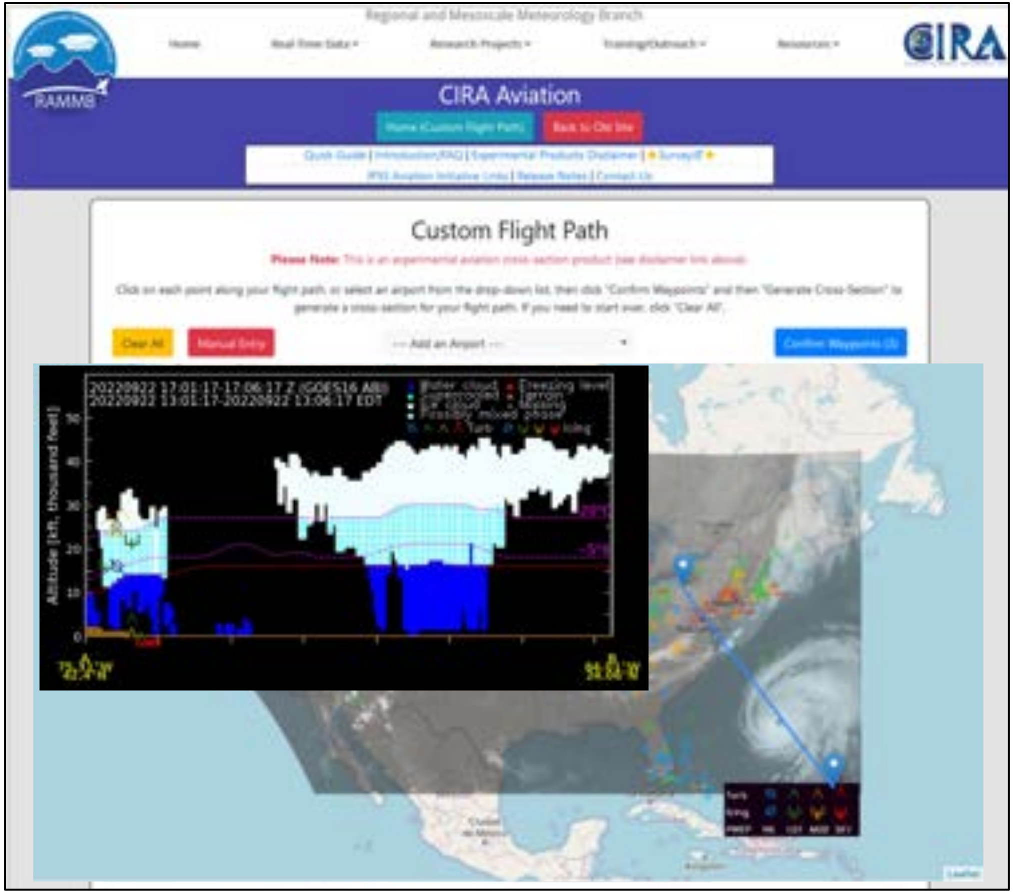
Leigh Cheatwood-Harris
Mattie Niznik

Aviation Cross Sections: CONUS

- Building on the success of our Alaska (VIIRS) product, and supporting user requests from West Coast WFOs, we are now testing a CONUS, ABI-based cross section product

Aviation Cross Sections

Hurricane Fiona (*)



(*) Not a flight path we would recommend…

User Engagement

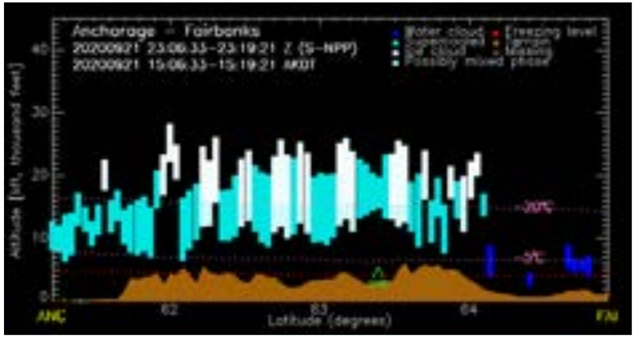
- We have regular interactions with pilots (JPSS Aviation Initiative), many opportunities for feedback

Feedback for This Image

- Partner with Aviation Weather Center for product evaluation and forecaster interaction

- Featured in Aircraft Owners & Pilots Association *ePilot* newsletter and weekly program, as well as the annual survey, receiving generally favorable marks

"I took off from FAI at 2300Z Sept 21 and landed at MRI (Merrill Field Anchorage) at 0100Z Sept 22 (3 pm to 5 pm AKDT). I observed no ceiling from FAI to the Alaska Range foothills, which is basically in agreement with the cross sections. By the time I was over Totatlanika River strip (9AK) I was under scattered to broken clouds with bases around 5,500 ft MSL. Basically, I flew under a broken to overcast ceiling that was at about 5,500 to 6,000 ft nearly all the way from McKinley Park (PAIN) to about Willow (PAOU). These bases were considerably lower than shown on the cross sections for most of the route…" (*AK local pilot*)



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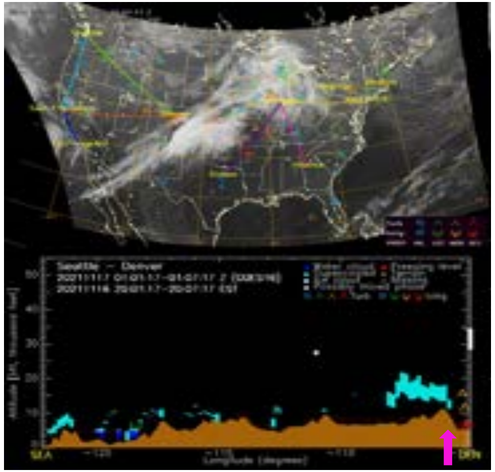
- We have provided data for multiple NTSB investigations

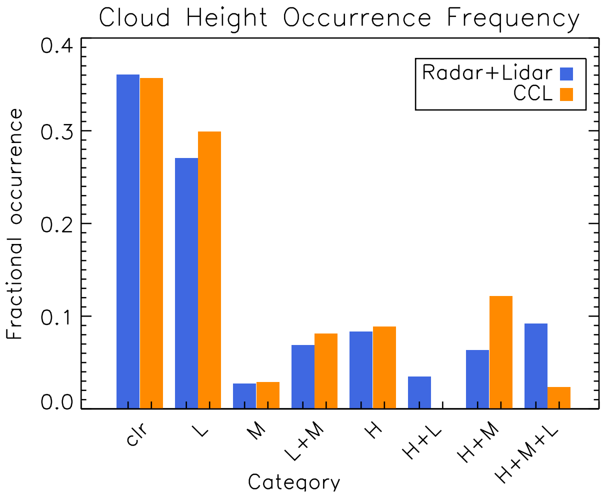


Small plane crash in Front Range Colorado mountains

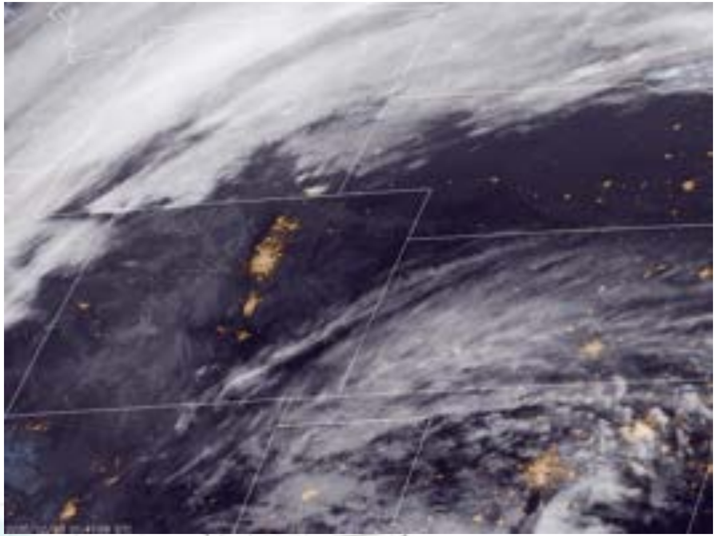
III. Machine Learning for Difficult to Retrieve Clouds

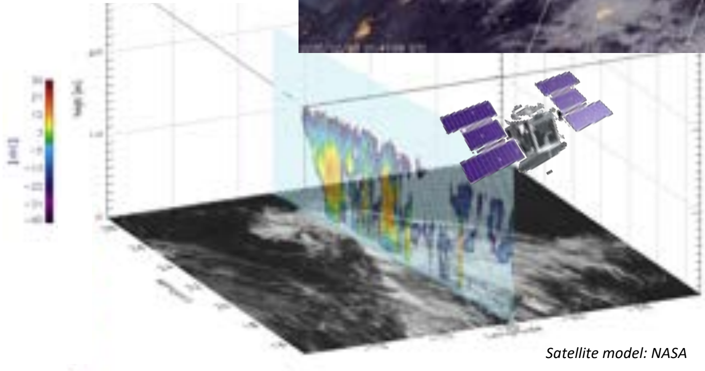
Multilayer clouds

- Multi-layer clouds are a problem for our current scheme, which is expected to perform best for single-layer clouds
- We are addressing this with machine learning, using CloudSat/CALIPSO (matched to GOES-16 ABI) as “truth”



Multilayer cloud example (CIRA GeoColor)





Satellite model: NASA

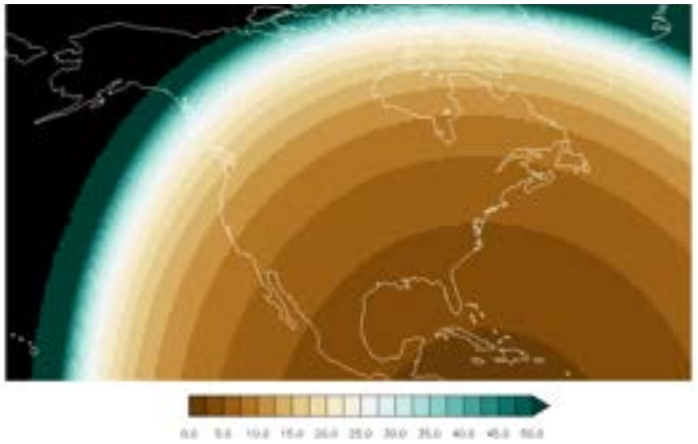
CloudSat and GOES-16 ABI

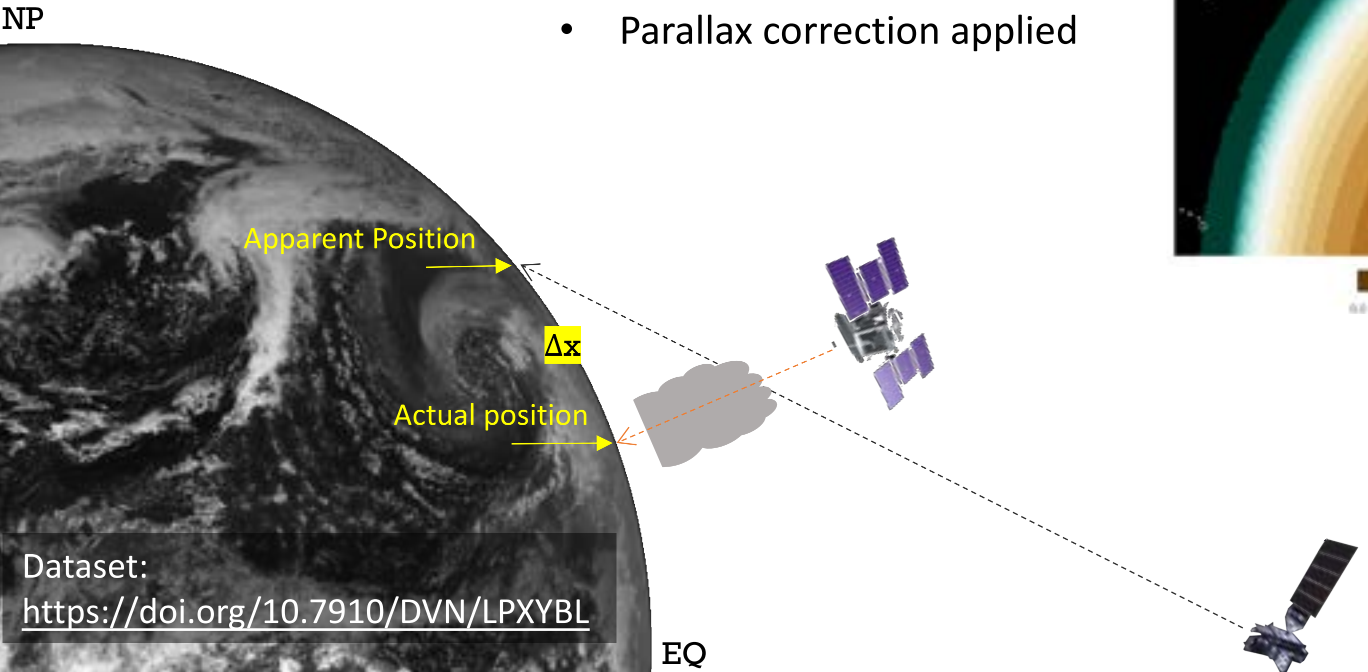
Start with a matchup dataset between GOES 16 ABI and CloudSat/CALIPSO

Matchup characteristics:

- Oct 2018 – Jun 2019
- Parallax correction applied

Parallax Error Δx (km) for 5 km High Cloud





Dataset:
https://doi.org/10.7910/DVN/LPXYBL

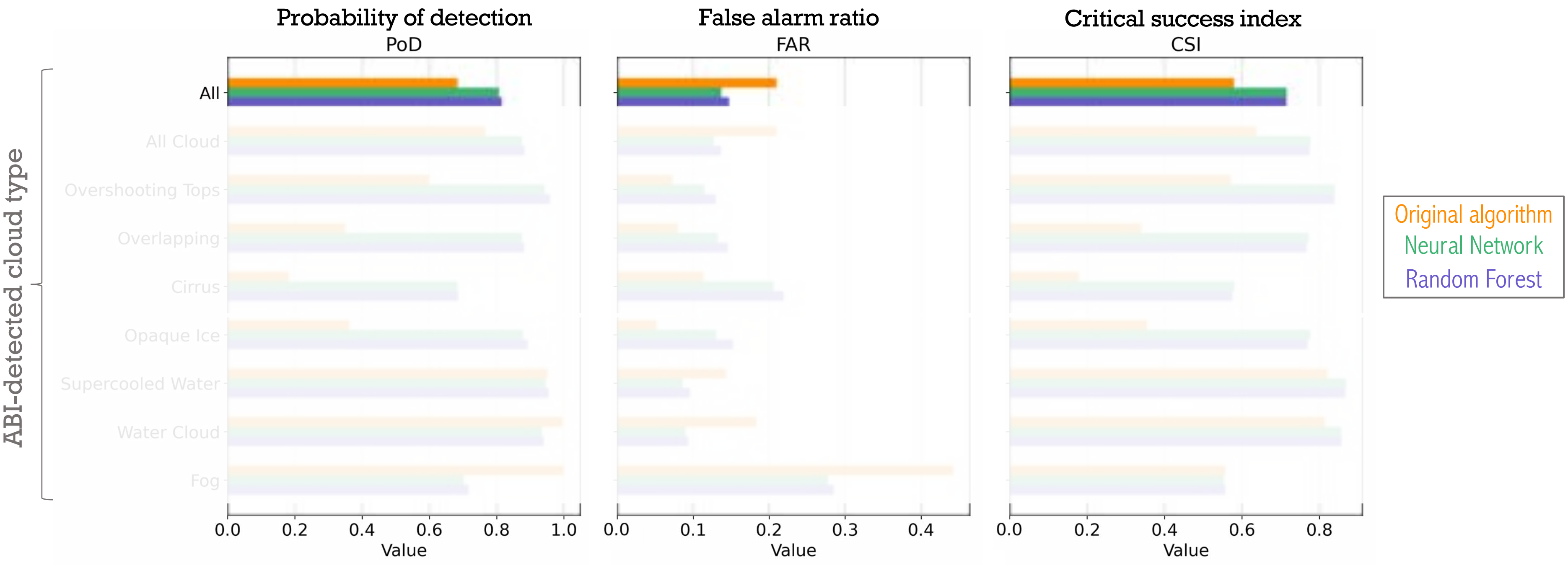
Algorithm Details

- Dataset:
  - ~ 22 million radar profiles matched to parallax-corrected GOES-16 ABI Refl / T_b
- Inputs:
  - ABI channels (all channels; common ratios and channel differences also tested)
  - Low-level relative humidity (serves as a low cloud proxy) from NWP model
  - Surface information
- "Truth":
  - Was a low cloud present ($p > 631$ hPa) present? 0 or 1 … classification problem
- Models (All pixel-based)
  - Random forest
    - 125 trees, max depth of 30
  - Artificial neural network
    - 3 fully connected layers
    - 37 / 77 / 71 hidden units per layer

Variable	Description and units	Notes
REFL01 through REFL06	ABI Channel 01 through 06 visible reflectances	Normalized by cos(solar zenith angle)
TB07 through TB16	ABI Channel 07 through 16 brightness temperature (K)	
RH_{max}	Maximum RH between 650 and 1000 hPa (%)	
RH_{150}	RH at 150 hPa (%)	
Lat	Latitude in (degrees north)	
$Flag_{sfc}$	0 indicates land or mix, 1=water surface	Set to 1 where CLAVR-x *land_class* is 0,5,6,7
$Flag_{snow/ice}$	0 indicates snow/ice free land surface, 1=snow/ice present	Set to 1 if either GFS snow depth or ice fraction are > 0

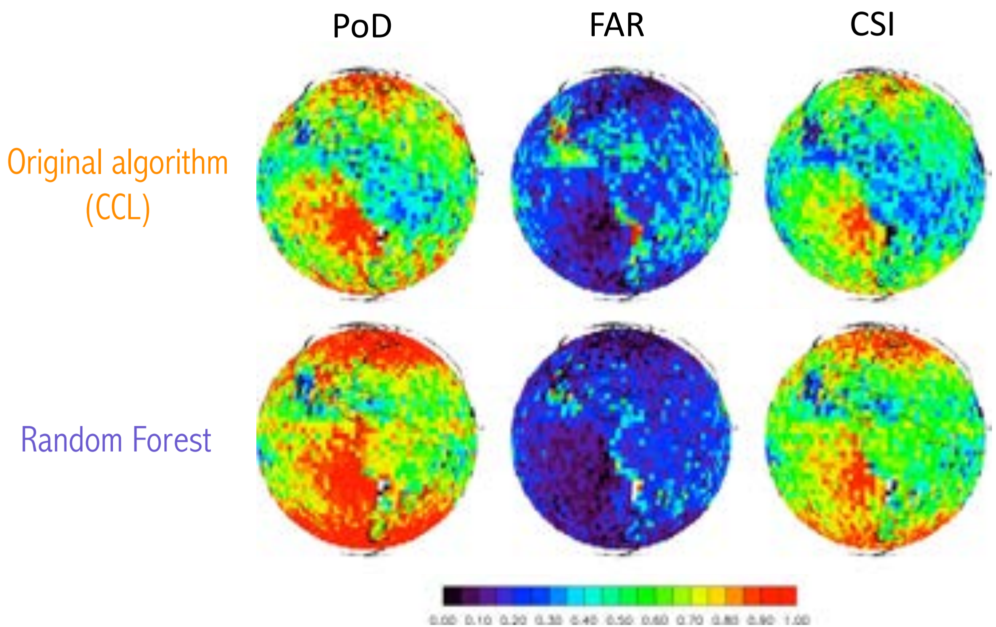
See Haynes et al. (2022), JTECH

Statistics for **low cloud** detection on ABI testing dataset



- Machine learning models outperform original algorithm, especially for mixed “Cirrus”/”Overlapping”
- ANN and RF are remarkably similar in performance!

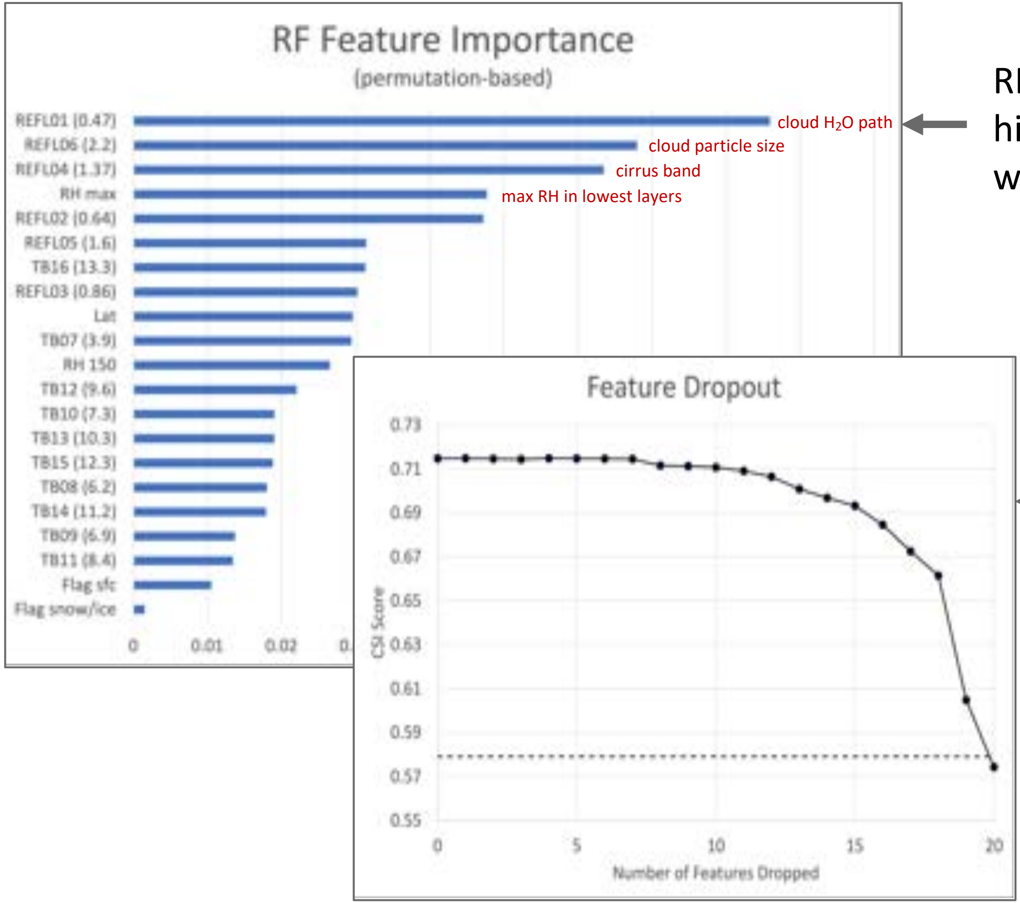
Machine Learning: Low Cloud Detection



	Low Cloud Detection Algorithm	Prob of Detection	False Alarm Ratio
All cases	Original statistical (CCL) Random Forest / ANN	0.685 0.815 / 0.807	0.210 0.147 / 0.137
ABI Cirrus	Original statistical (CCL) Random Forest / ANN	0.183 0.686 / 0.684	0.114 0.219 / 0.206

- Machine learning produces greatest performance enhancements relative to original algorithm…
    - … in higher latitudes
    - … in cases where Enterprise/ABI identifies "Cirrus" (hidden low cloud / multilayer)

Feature Importance



RF permutation-based feature importance highlights importance of visible channels and RH, which is used as a cloud proxy

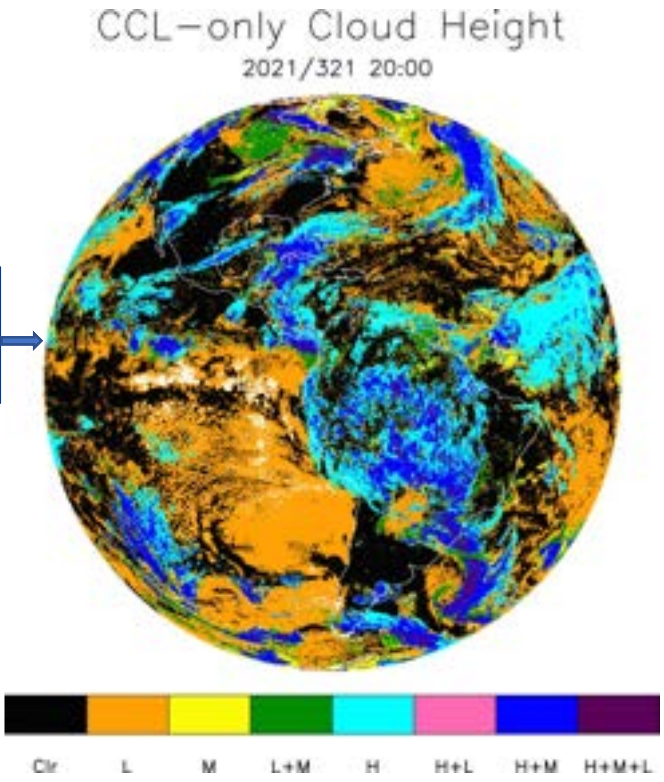
- The top 3 channels (0.47, 2.2, 1.37 μm) contain information that is useful for differentiating cirrus with and without underlying low cloud

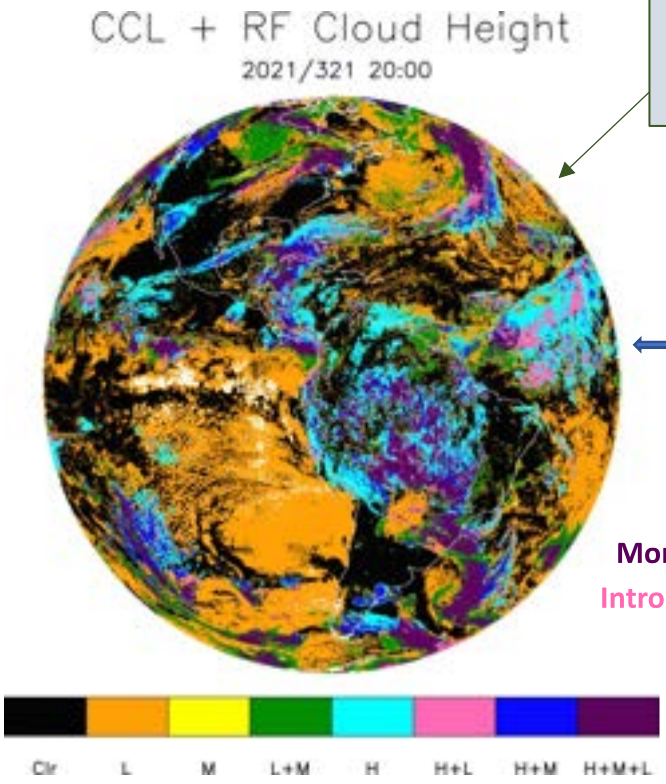
The "Feature Dropout" plot demonstrates how the CSI score changes as features are cumulatively dropped as predictors, from least to most important.

- The curve is flat for up to ~10 features dropped!
- Very little influence by surface-type flags
- Demonstrates correlation between ABI channels.
- Also suggests a simplified model will have similar performance!

CCL supplemented by RF on full disk

Before **machine learning**





Includes a “nighttime version” 🌙 that excludes channels 1 through 7 (vis) from training

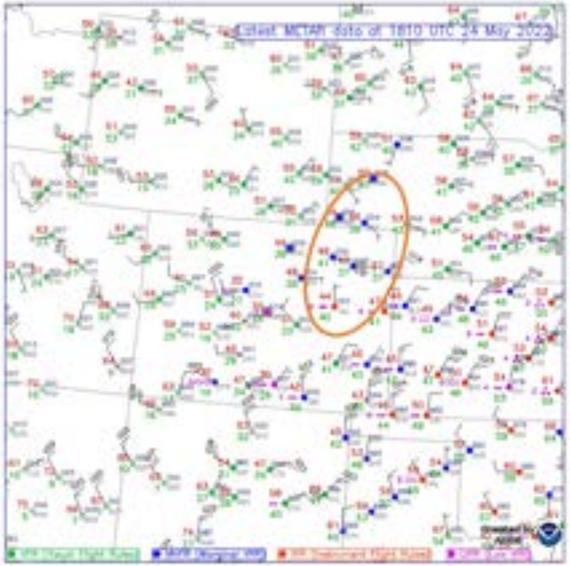
***After* machine learning**

More deep clouds (purples)

Introduction of high-over-low (pinks)

Cast Study: Machine Learning Impact

Case studies suggest the machine learning augmentation to CCL produces a much more accurate representation of low cloud presence



Example case study: upper-level low exits Rockies

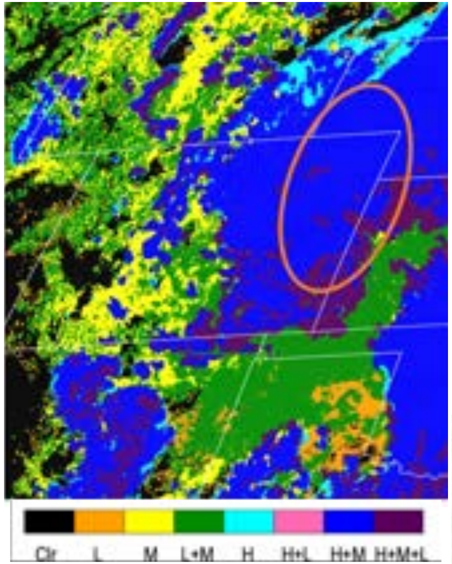
Marginal VFR conditions with 1-3kft ceilings in northeast Colorado and Neb. Panhandle

These ceilings are better represented with machine learning addition

KOGA 241755Z AUTO 11003KT 10SM SCT027 SCT032 OVC038 12/06 A3006 RMK AO2 T01170061 10120 20070

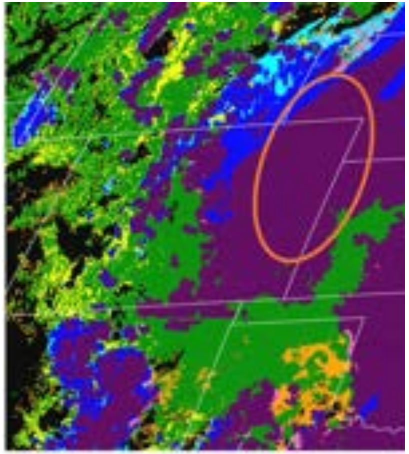
KSTK 241735Z AUTO 04004KT 10SM OVC021 09/05 A3004 RMK AO2

CCL supplemented by RF



***Before* machine learning**

***After* machine learning**



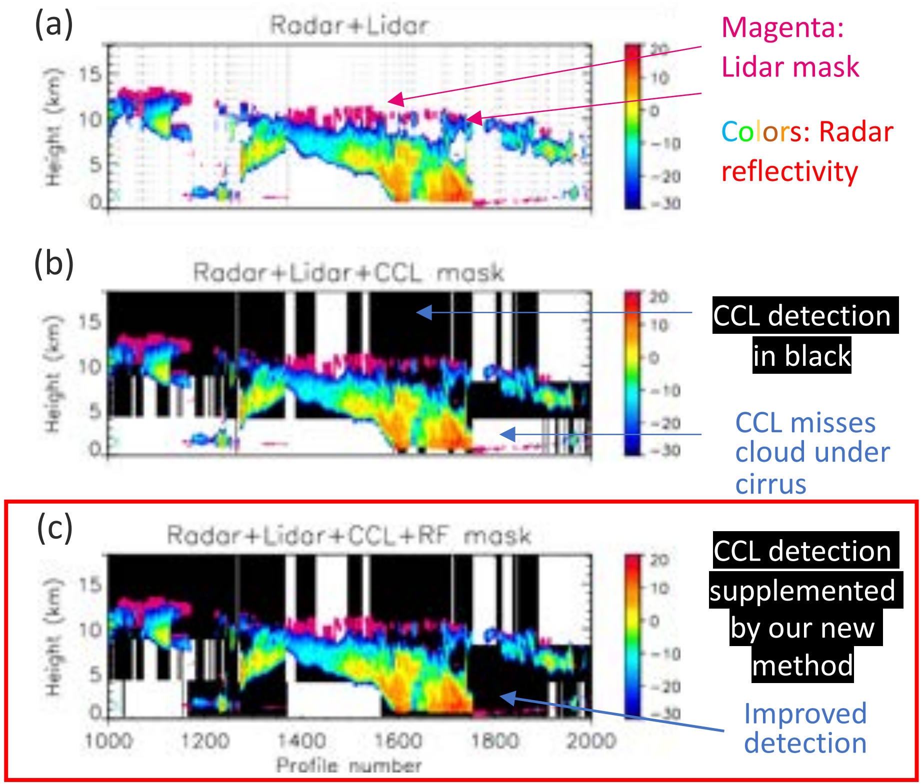
More deep clouds (purples)

NEW high-over-low (pinks)

Case: 2022/05/24 18:10 UTC

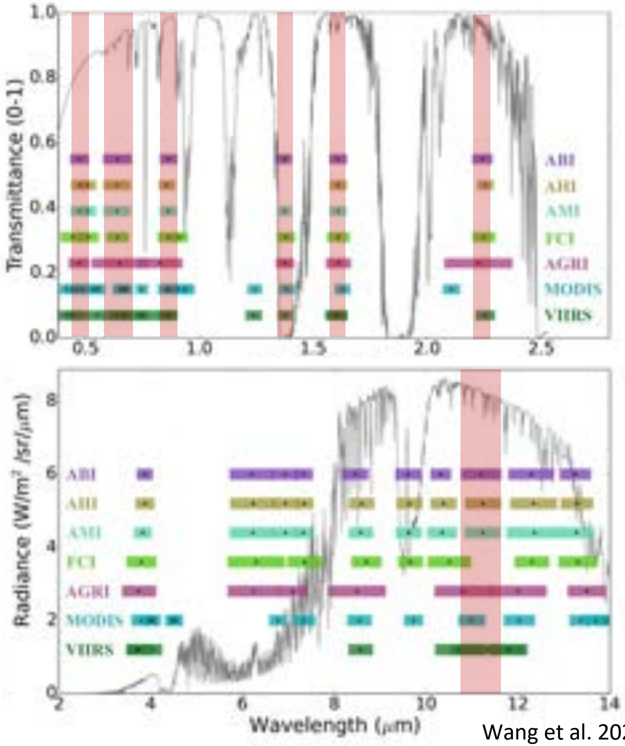
CCL with Machine Learning

Example cross sections through ABI "Cirrus"

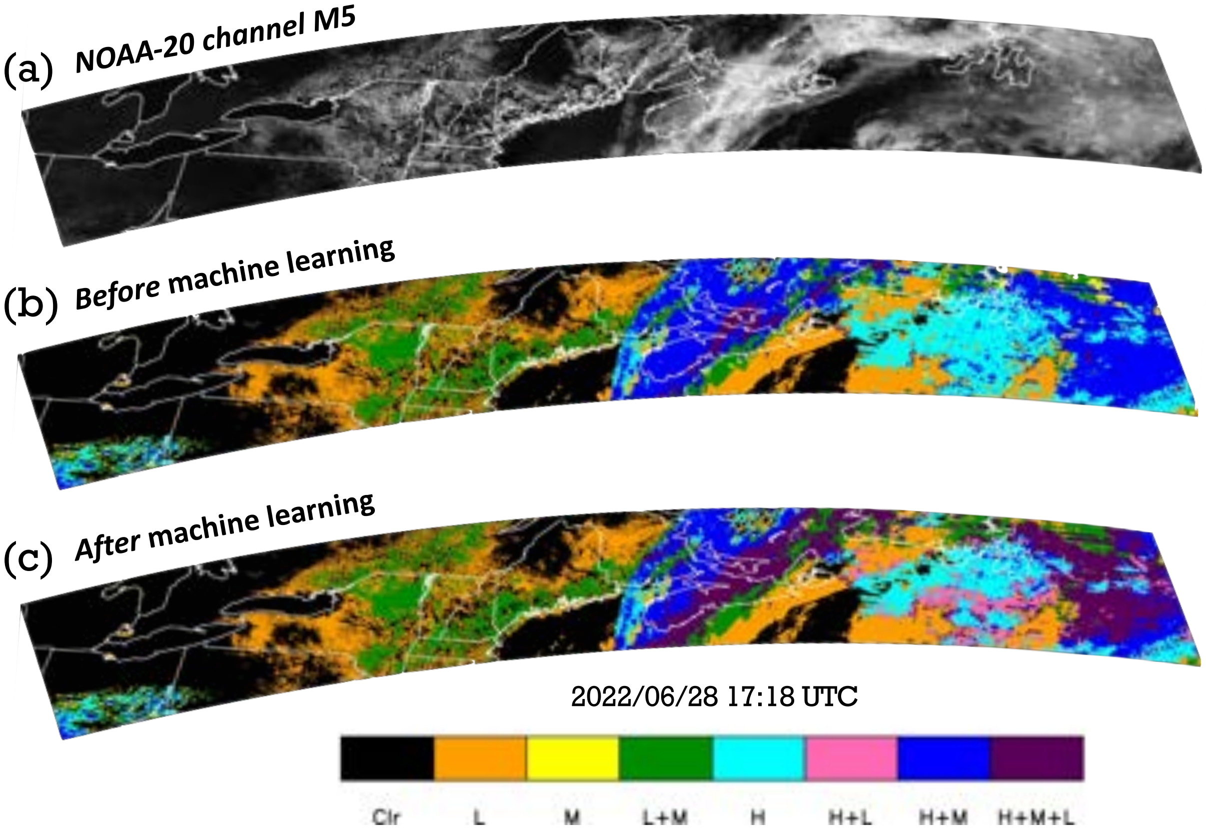


Translation for VIIRS

- Simplified “7 channel model” for VIIRS



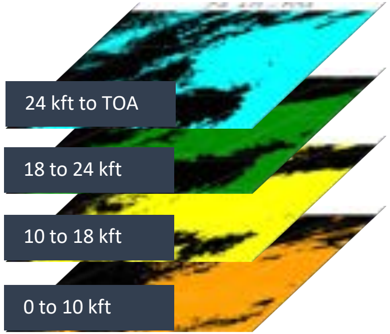
Wang et al. 2020, Remote Sens.



Preliminary example - uncalibrated

ML Model: Multilevel prediction

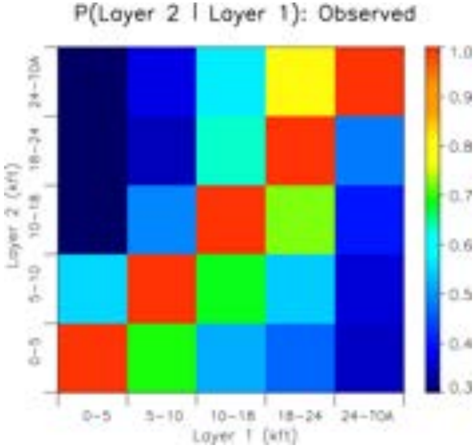
- Using multi-output prediction, we can use the same inputs to predict not only low cloud, but cloud in any layer of our choosing.
- This should ideally (and to a large extend does) preserve the observed correlation between cloud layers.



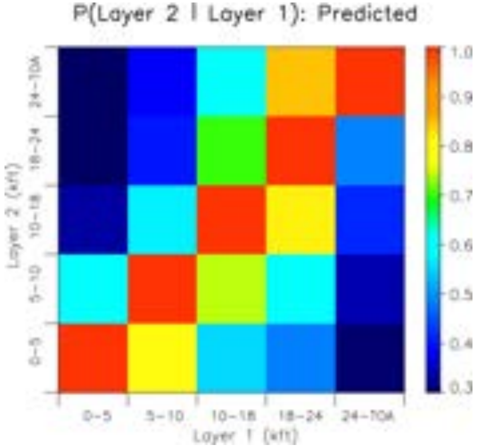
Global Evaluation of multilayer cloud mask

	PoD	Success ratio	Accuracy
Topmost layer	0.86	0.89	0.93
(… intermediate layers not shown …)			
Bottommost layer	0.72	0.80	0.84

Observed correlation between cloud layers



Predicted correlation between cloud layers



IV. Towards the Future

NASA / NOAA

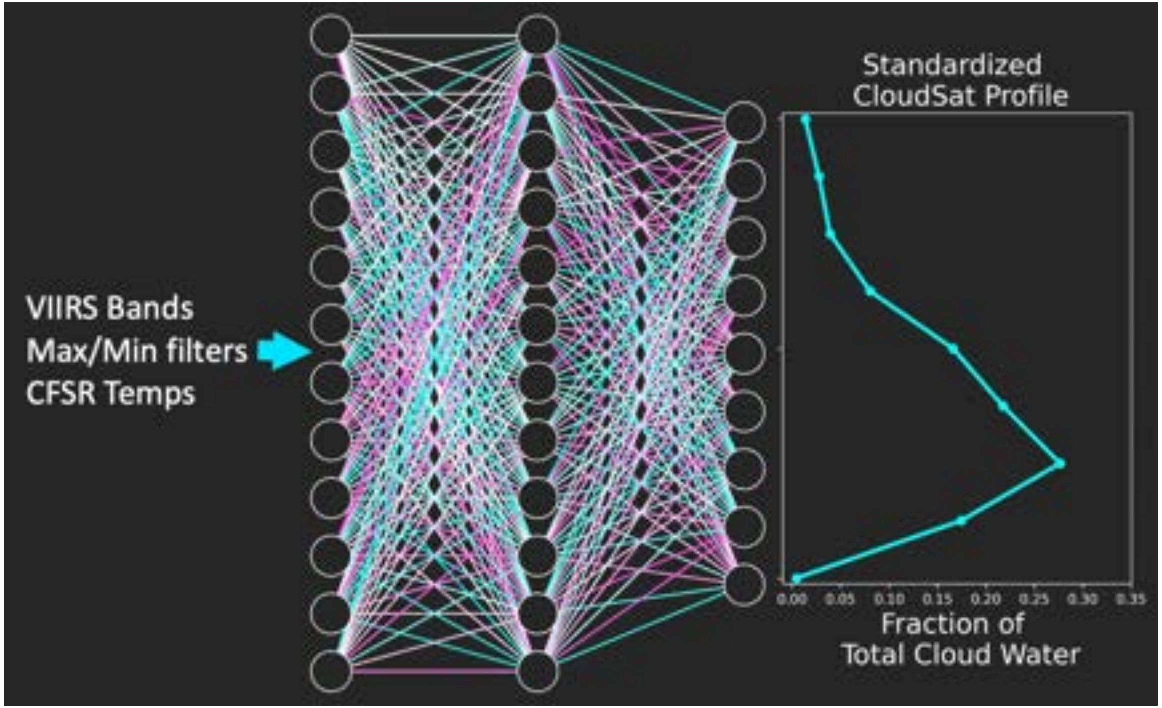
CWC Profiles

Credit: Chuck White et al.

In progress: Can we predict vertical profiles of cloud water content from passive sensors?

Again, we appeal to active sensors!

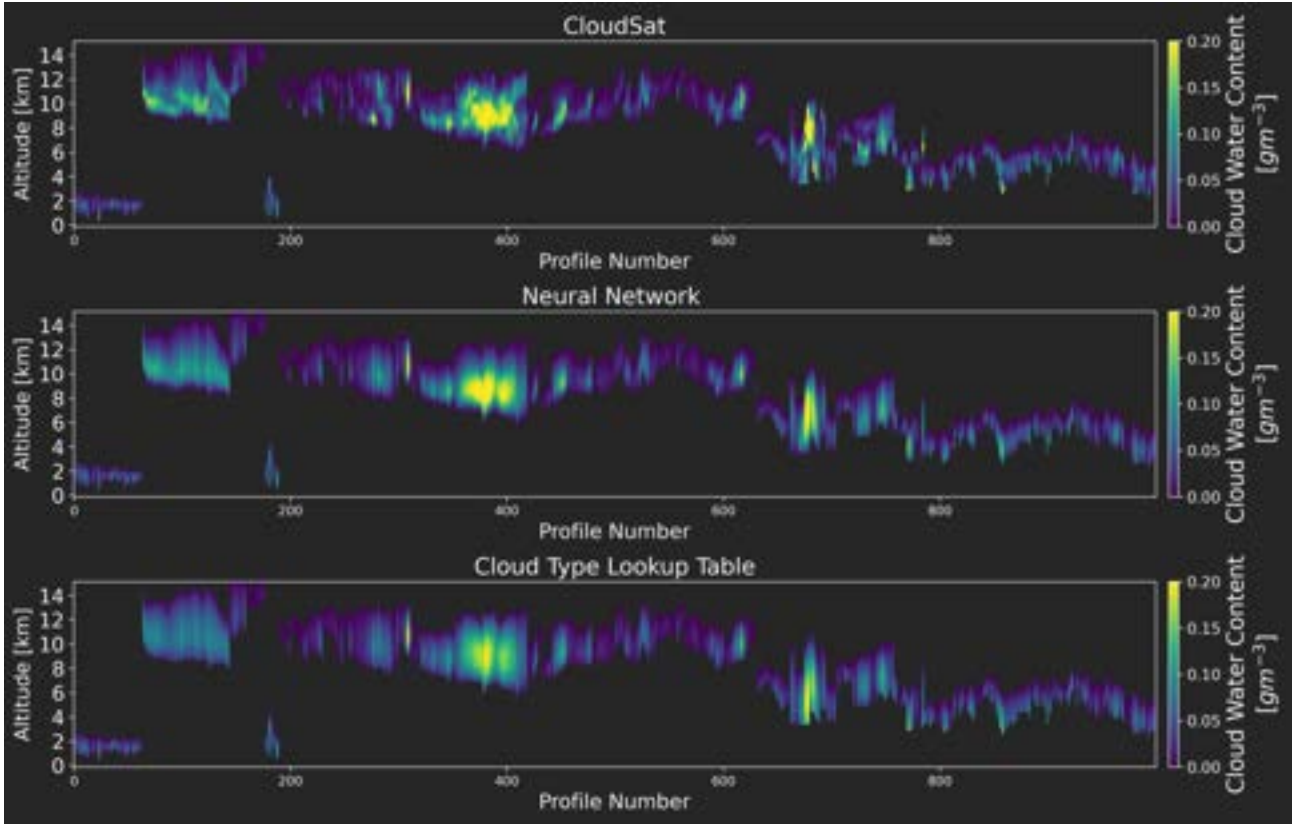
- Multi-layer perceptron
  - 4 fully-connected layers with 64 units each
  - Leaky ReLU
- Output
  - 9-valued standardized profile
  - Softmax



CWC Profiles

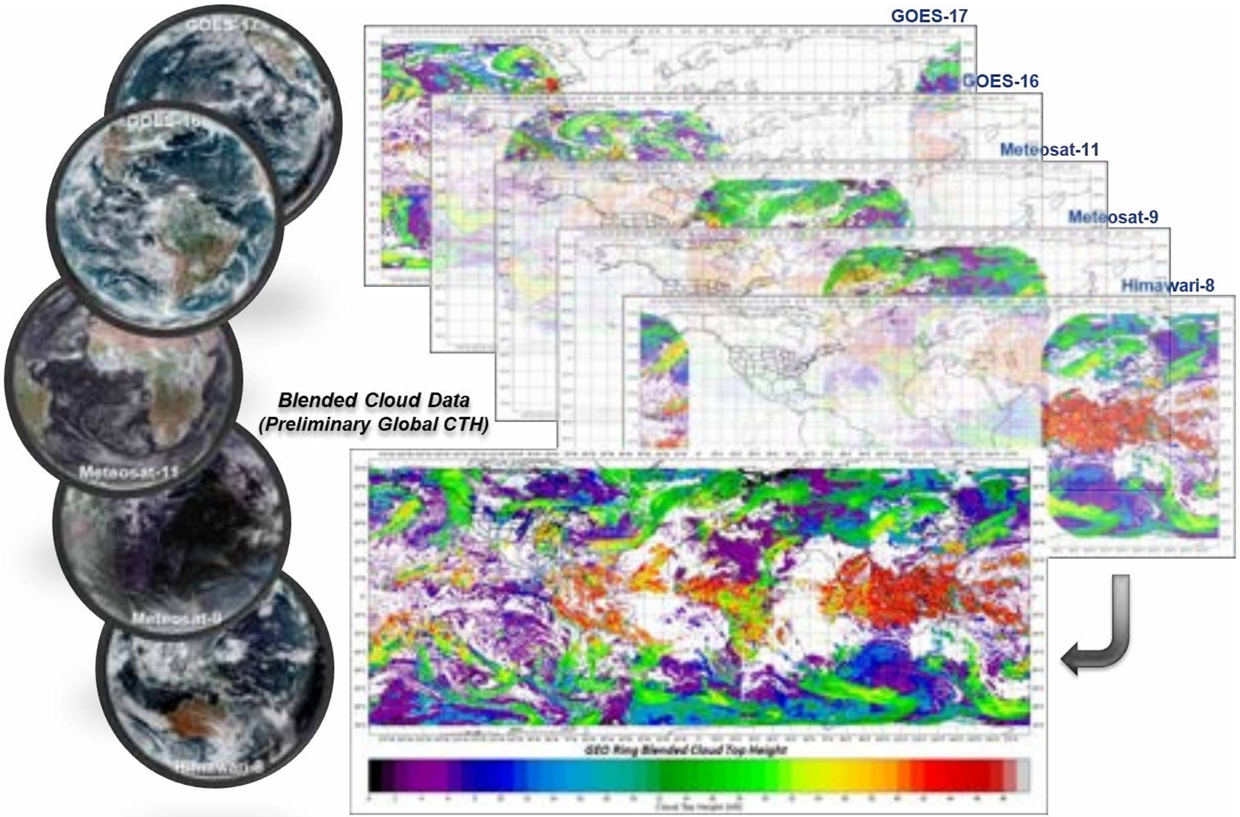
Credit: Chuck White et al.

- Example preliminary result
- For demonstration purposes, we assume we know the actual cloud thickness for these single-layer cases
- Demonstrates a future capability that may be useful for aircraft icing



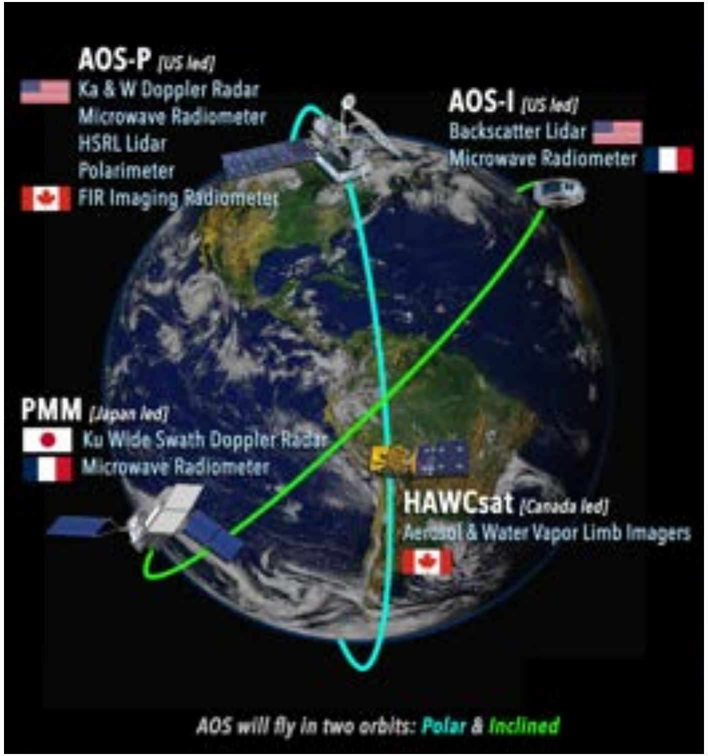
Work in progress

- Working towards creation of a global, 3D gridded real-time cloud product
- Combine GEO and LEO sensors
- Compliments ISCCP-NG



More Measurements

- We need more measurements to do more science!
- Machine learning is data-hungry. So is validation.
- CloudSat and CALIPSO have made this work possible. AOS, EarthCARE, INCUS, and other missions of this type are needed to continue it.

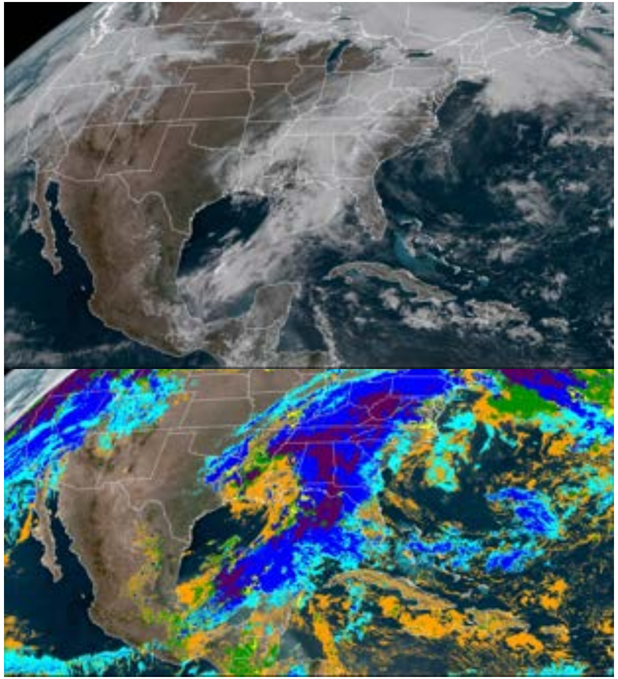


NASA

Conclusions

- Active sensors have been instrumental in our work to derive 3D cloud profiles from passive sensors

- 3D cloud products are now being produced in near real-time to benefit NOAA operational users, particularly in aviation
  - Cloud cross-sections available from: https://aviation.cira.colostate.edu for Alaska and CONUS
  - Machine-learning is used to augment our statistical based cloud cover layer product (CONUS), accessible via https://rammb-slider.cira.colostate.edu
  - Testing with operational users at the Aviation Weather Center



Conclusions

- CIRA is now working toward production of a global, real-time gridded 3D cloud product combining geostationary and polar orbiter sensors

- We're interested in more than just cloud masks…
  currently working on vertical cloud water content profiles as well.

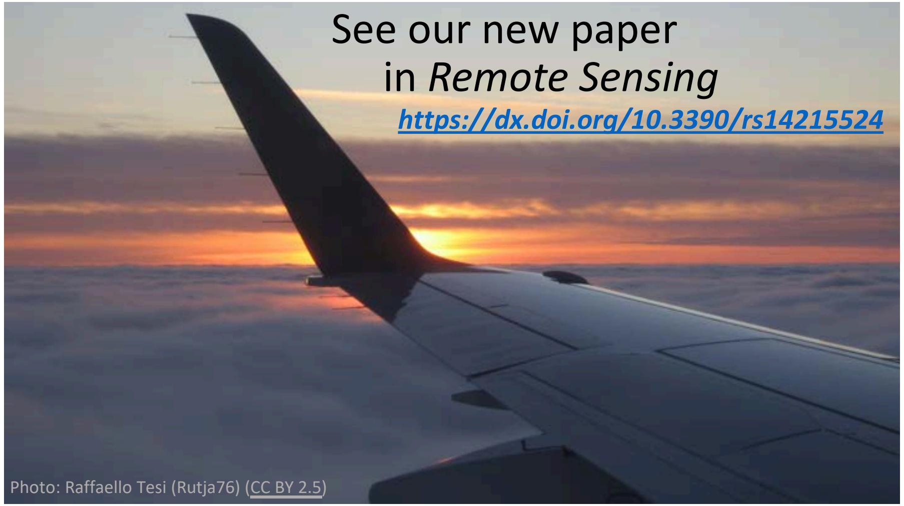
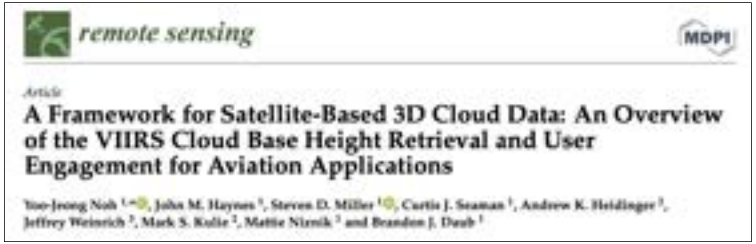


Photo: Raffaello Tesi (Rutja76) (CC BY 2.5)


remote sensing

MDPI

Article

A Framework for Satellite-Based 3D Cloud Data: An Overview of the VIIRS Cloud Base Height Retrieval and User Engagement for Aviation Applications

Yoo-Jeong Noh [1,*], John M. Haynes [1], Steven D. Miller [1], Curtis J. Seaman [1], Andrew K. Heidinger [2], Jeffrey Weinrich [3], Mark S. Kulie [2], Mattie Niznik [3] and Brandon J. Daub [1]

Thank you!

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Haynes, J. M., Y.-J. Noh, S. D. Miller, K. D. Haynes, I. Ebert-Uphoff, and A. Heidinger, 2022: Low cloud detection in multilayer scenes using satellite imagery with machine learning methods. *J. Atmos. Ocean. Technol.*, **39**, https://doi.org/10.1175/JTECH-D-21-0084.1.

Noh, Y.-J., and Coauthors, 2017: Cloud-base height estimation from VIIRS. Part II: A statistical algorithm based on A-Train satellite data. *J. Atmos. Oceanic Technol.*, **34**, 585–598, https://doi.org/10.1175/JTECH-D-16-0110.1.

Noh, Y.-J., and Coauthors, 2022: A framework for satellite-based 3D cloud data: an overview of the VIIRS cloud base height retrieval and user engagement for aviation applications. *Remote Sensing*, **14**, 5524, https://doi.org/10.3390/rs14215524.

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