Exploring Detection of Multilayer Clouds and Retrieval of Their Properties Using Multispectral Satellite Data in an Artificial Neural Network Approach

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Background

- Multi-layered (ML) cloud systems are common feature around the globe
  - ML systems are sloppy, rarely meet our idealizations

- ML systems affect the satellite retrieval of cloud properties using a single-layer (SL) cloud assumption
  - impact the cloud top height (CTH) retrieval
    - *retrieve effective height from VIS-IR methods*
    - *retrieve top of highest cloud layer in IR methods*
  - distort cloud distribution and the atmosphere-surface radiation budget
  - makes direct model comparisons and assimilations more uncertain

- Variety of methods developed to passively detect and retrieve ML clouds

  <u>Detection</u>

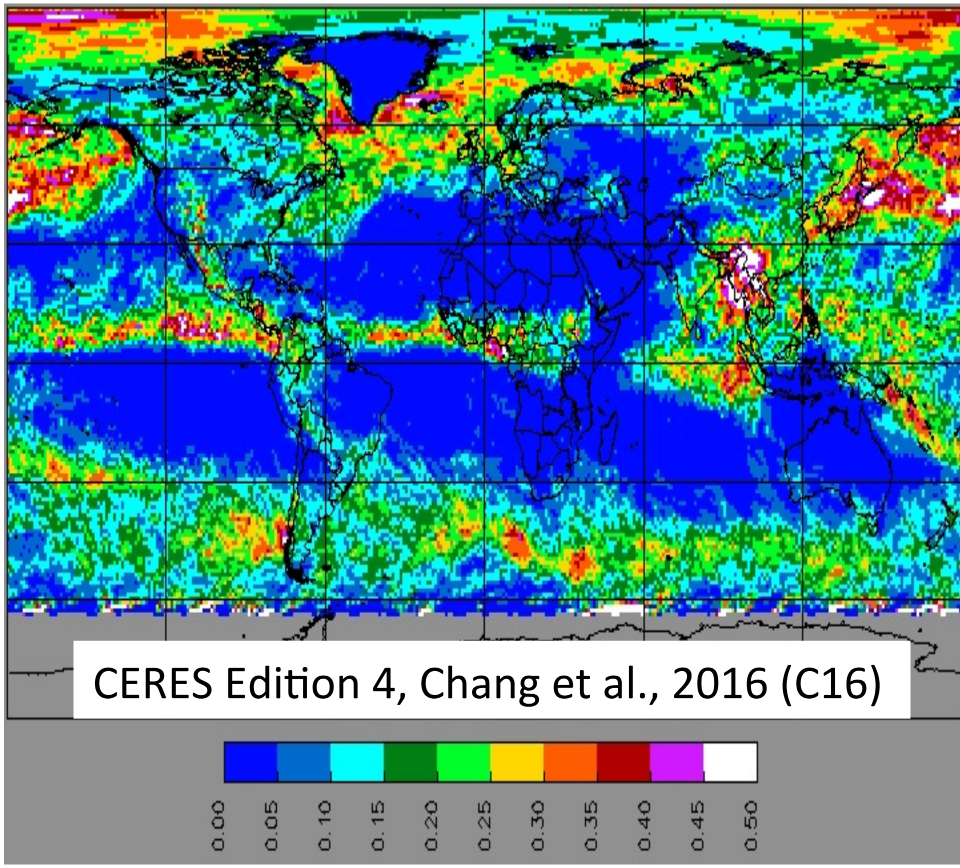
  - *Pavolonis & Heidinger* (JAM, 2004) BTD(11-12) + VIS
  - *Wind et al.* (JAMC, 2010) 0.94 µm +CO_2 slicing
  - *Joiner et al.* (AMT,2010) UV +VIS-IR

  <u>Detection & Retrieval</u>

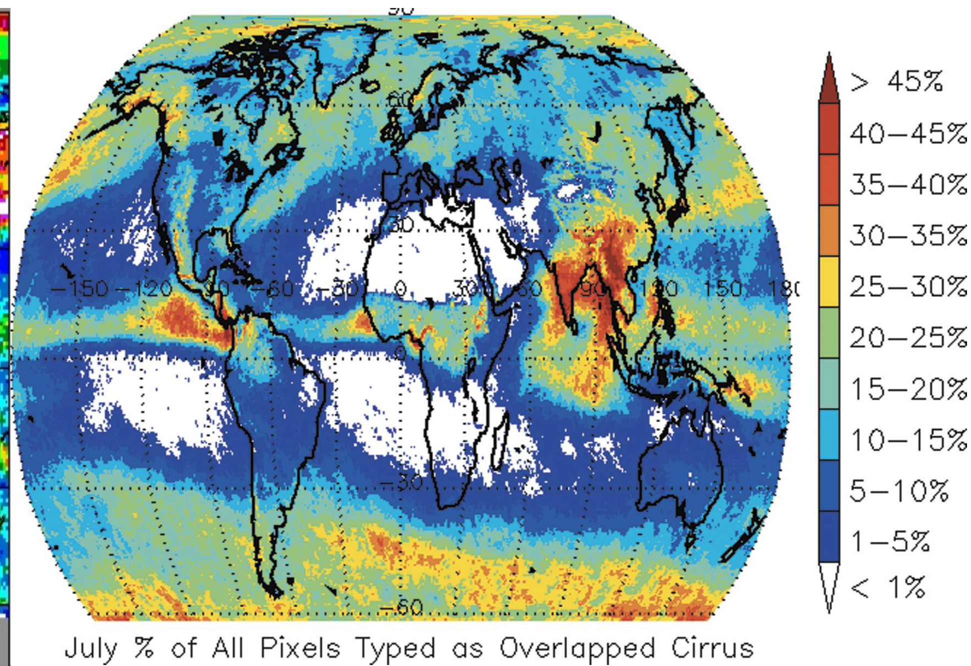
  - *Lin et al.* (JGR, 1998) VIS-IR, MW
  - *Chang & Li* (JGR,2005) VIS-IR, CO2-slicing (assumes low cloud from environs)
  - *Minnis et al.* (2007) VIS-IR, MW ocean only
  - *Watts et al.* (JGR, 2012) 9 channel VIS, IR, CO2 Optimal Estimation
  - *Chang et al.* (2016, in prep) VIS-IR, CO2-slicing (retrieves low cloud directly)

Global Distributions of Multilayer Cloud Occurrence

Aqua MODIS, July 2002



AVHRR, July 1982, 86, 91, & 98



Heidinger & Pavolonis (JAM, 2005)

- Patterns and magnitudes similar between the methods, and are reasonable
  - H&P compared to several other datasets: reasonable

- Some regional differences due to method and years used

PROBLEM?

- CERES ML identifies ML clouds at 83% compared to 2-layer CALIPSO-CloudSat ice-over-water, upper layer cloud optical depth $\tau > 0.3$
  - only 3.2% of all daytime cases *Viúdez-Mora et al. (CERES STM, 2016)*

- Despite very reasonable monthly averages, CERESML has many false positives when compared 1:1 with CALIPSO-CloudSat profiles mainly due to ice clouds being thicker than the CO2-slicing COD retrieval
  - 53% overestimate

- Need to reduce the overestimation by identifying thick ice clouds that are either contiguous or overlapped lower water clouds & improve missed ML pixels

APPROACH

- Identify thick ice clouds with 3-channel daytime Ice Cloud Optical Depth from Infrared using a Neural network (ICODIN-3a) *Minnis et al.* (JGR, 2016)

- Screen out contiguous clouds using ICODIN-3a results

- Explore use of direct NN method (LANN) to detect ML conditions

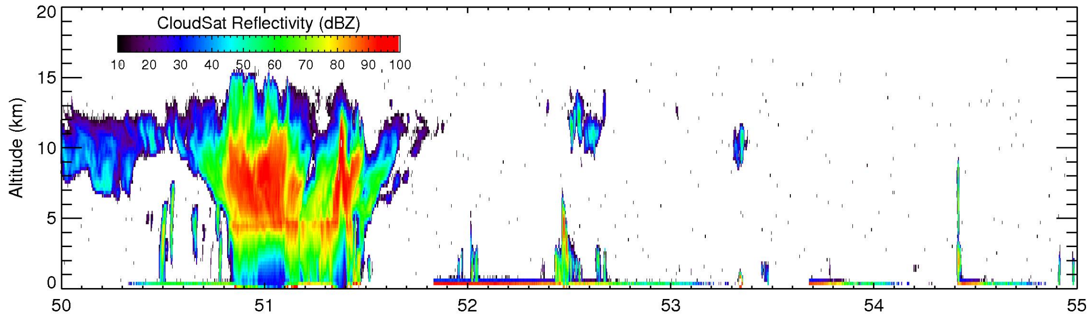
Data

- C3M (CALIPSO, CloudSat, CERES, MODIS) *Kato et al. (JGR, 2011)*

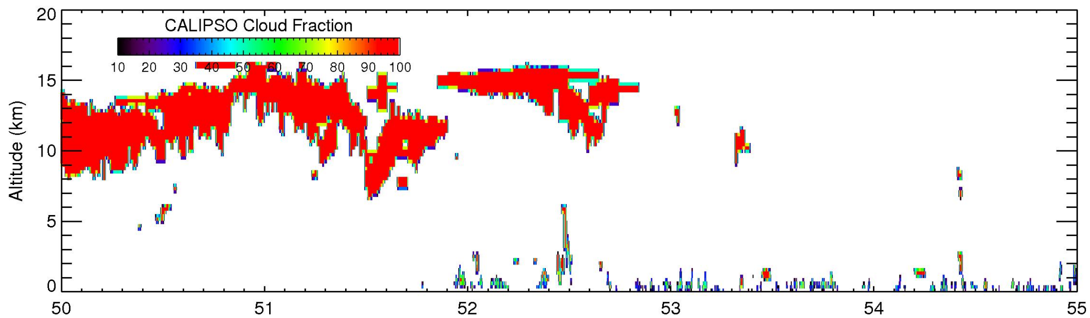
  - CALIPSO V3.3 Vertical Feature Mask and optical depth, τ_{CL}
  - CloudSat CPR CLDCLASS vertical mask & CWC, r_e
    - $\tau_{CS} = 0.75 * \Sigma(CWC/r_e\ \rho)\ Q_e\ \Delta z$,
      - *use only layers where $T < 253$ K*
  - compute merged CloudSat-CALIPSO ice optical depth, τ_{CC}
  - CERES Edition 4 Cloud Retrievals (revised VISST applied to MODIS)
    - includes multilayered clouds, CERES MCOAT Multilayer Cloud Detection (CEML) *Chang et al. (2016)*
      - *CO2 slicing to estimate cloud emissivity ε & CTP above 600 hPa*
        - $\tau_{CO2} = 2 * \ln(1-\varepsilon)$ at nadir
      - *optical depth & phase from VISST, τ_V*

- Use only daytime, 60°N – 60°S, October 2009

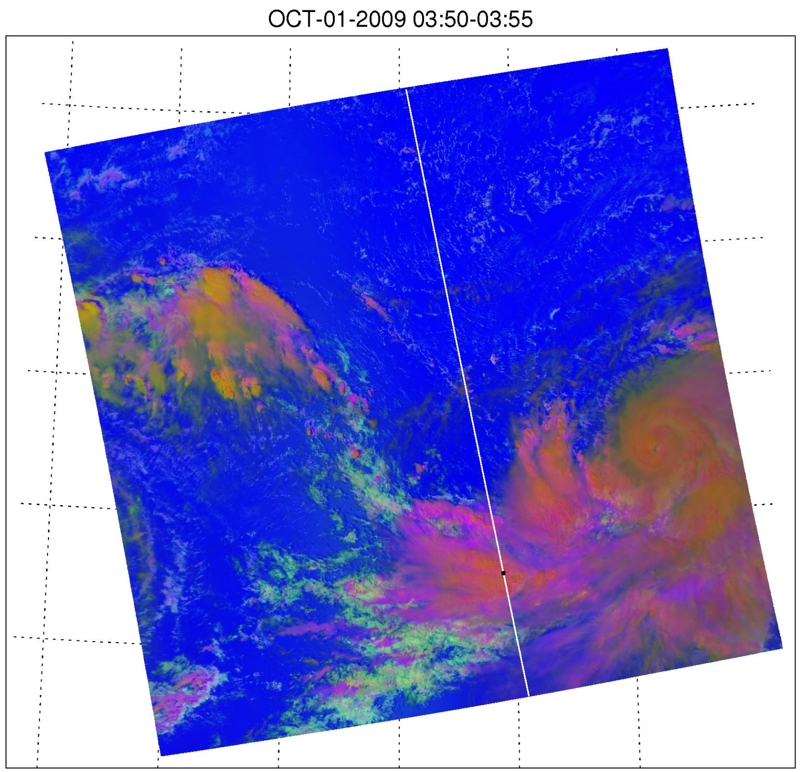
- Compute ICODIN-3a optical depth, $\tau_{NN} = f(LAT, LON, T_{11}, BTD_{1112}, BTD_{6711})$
  - only for $\tau_V > 4$, ice phase *Minnis et al. (JGR, 2016)*



CloudSat Reflectivity



CALIPSO Cloud Fraction



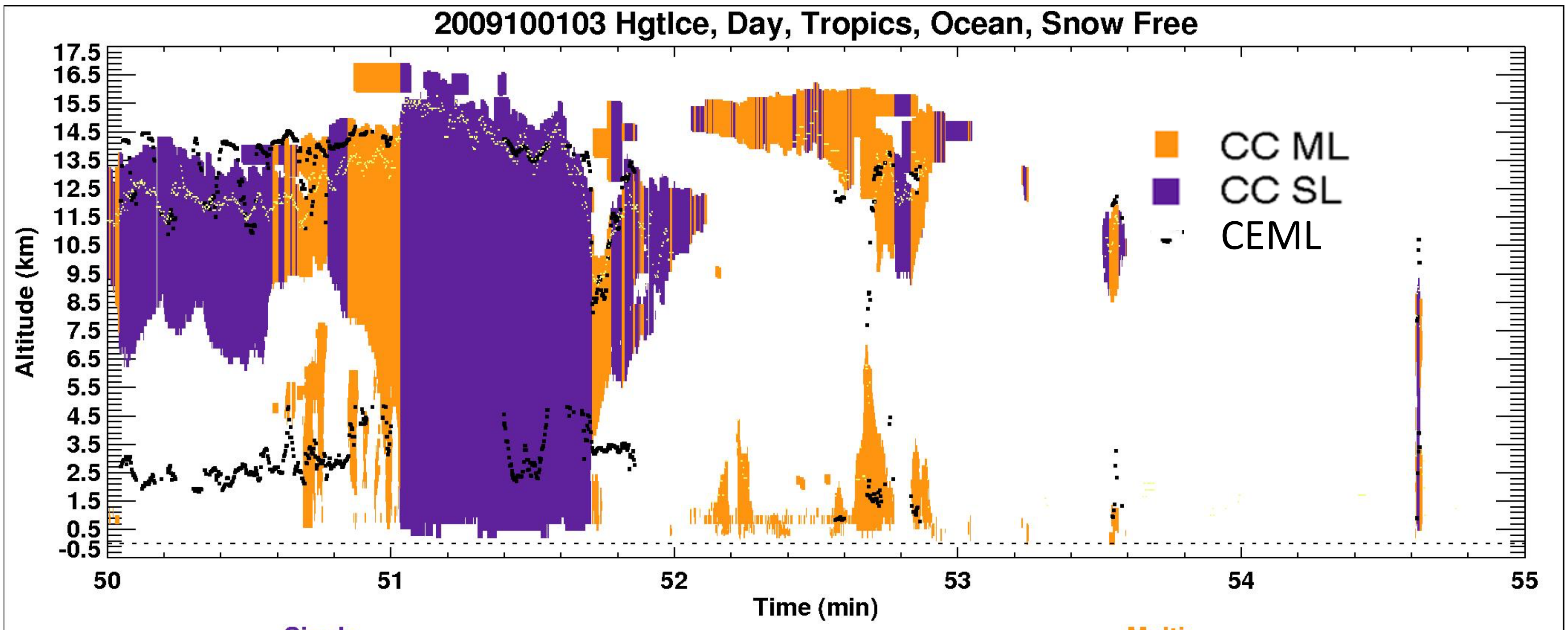
RGB MODIS Aqua
(R0.6, R2.1, flipped BTD(3.7-11))

White line from 03:50-03:55
Black dot in the white line at 03:51

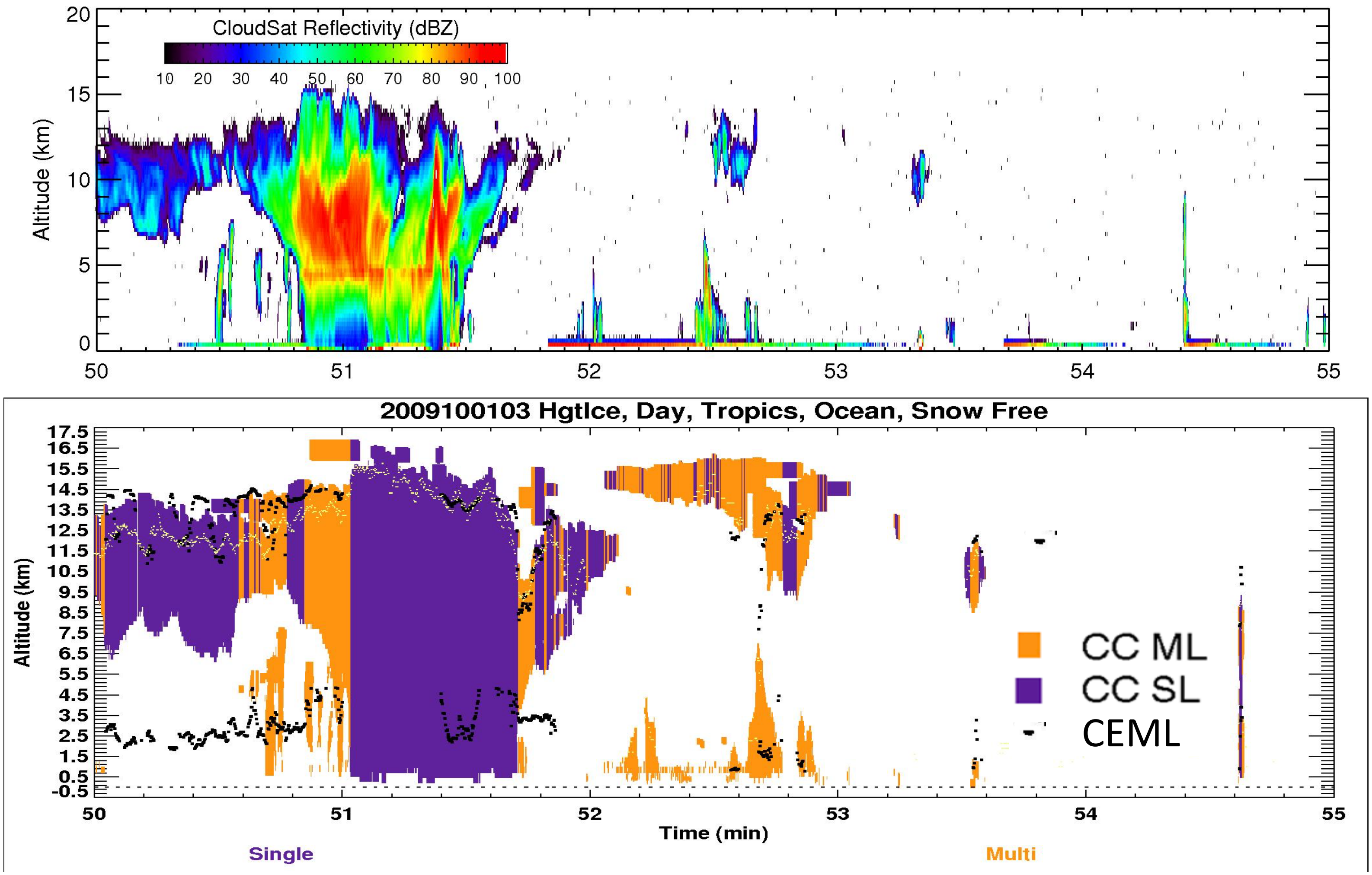
Defining a Multilayered Cloud System

- **Ice** cloud over **water** cloud with minimum 1-km separation
    - separate ice cloud layers comprise 1 layer
    - separate water layers = 1 layer
    - ice over water with no 1-km separation = single layer (SL)
    - no ice = SL water (not counted here); no water = SL ice

- "Truth" is CALIPSO-CloudSat profile from C3M product



Multilayer Detection from CALIPSO-CloudSat Not Perfect



- Lowest clouds difficult for CloudSat to identify
  - some errors likely in truth set

Summary of CERES-ML vs CALIPSO-CloudSat Layering

Daytime October 2009

Overall Results, in %, N = 5.1 million with CC ice layer

Classification	CC SL	CC ML
CERES SL	41.5	35.1
CERES ML	11.8	11.6

- Percent correct: 53.1; Percent wrong: 46.9; FAR = 22%
- CERES ML coverage is only half of CC coverage, only ¼ of true coverage

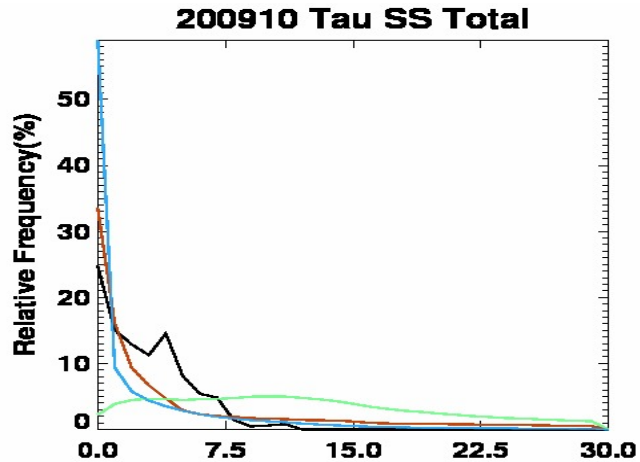
CC ML only, in % of 5.1 million with CC ice layer

Classification	$\tau(CC) < 0.3$	$\tau(CC) \geq 0.3$
CERES SL	16.2	18.9
CERES ML	0.6	11.0

- Nearly half of missed ML clouds due to low τ of ice layer
  - do not expect CO2 to get many $\tau < 0.3$
- The other half missed due to either upper layer too thick or lower layer too thin

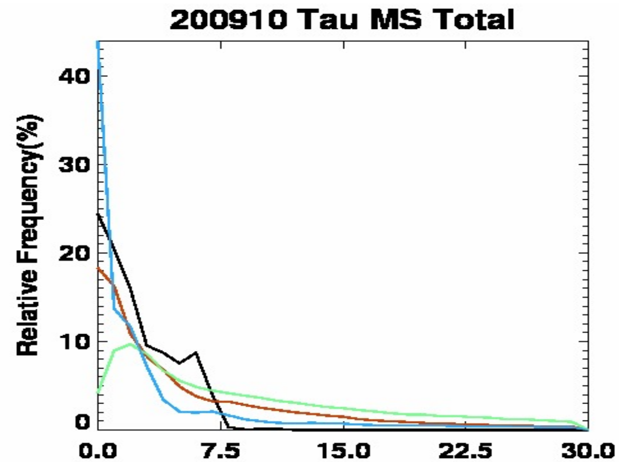
C3M Oct 2009 Tau Histograms

CC-Single CEM Single



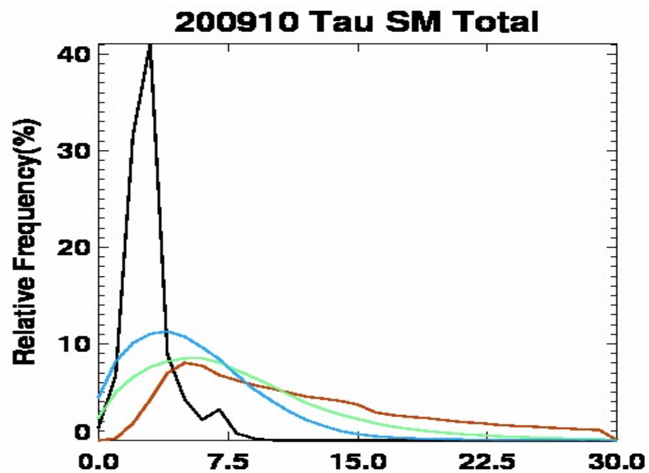
			Mean	(StdDev)
N=	1117071.	co2Tau	3.18(	2.43)
N=	736405.	visstTau	5.22(	6.97)
N=	362642.	nnTau	12.24(	7.45)
N=	2087920.	ccTau	2.66(	4.56)

CC-Multi CEM Single



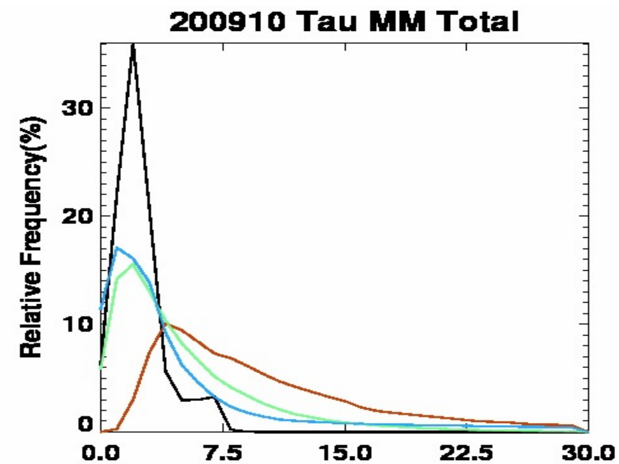
			Mean	(StdDev)
N=	782897.	co2Tau	2.89(	2.20)
N=	658897.	visstTau	6.05(	6.49)
N=	94462.	nnTau	9.60(	7.66)
N=	1630478.	ccTau	3.69(	5.84)

CC-Single CEM Multi



			Mean	(StdDev)
N=	600820.	co2Tau	3.42(	1.36)
N=	262256.	visstTau	12.02(	6.79)
N=	430713.	nnTau	8.38(	5.30)
N=	594913.	ccTau	6.06(	3.85)

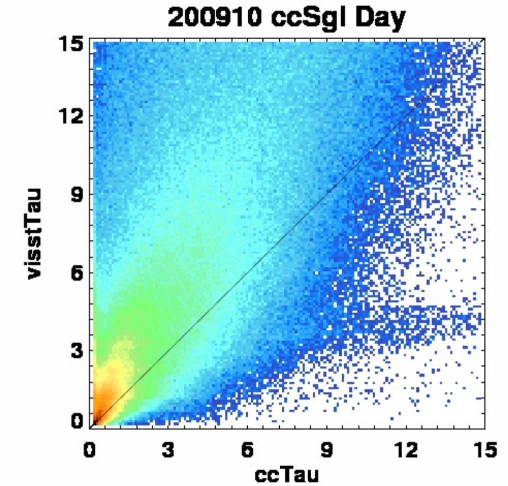
CC-Multi CEM Multi



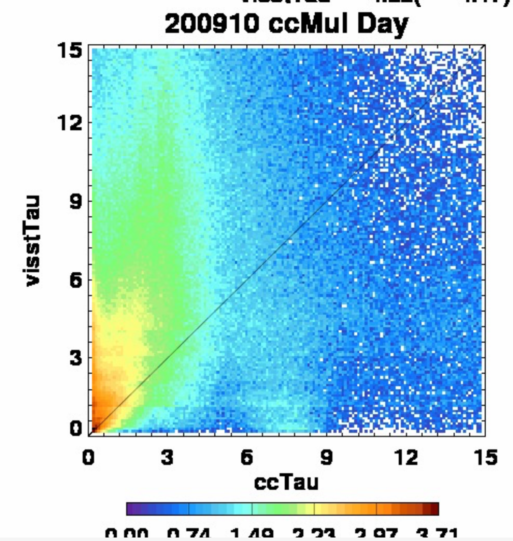
			Mean	(StdDev)
N=	590133.	co2Tau	2.86(	1.53)
N=	271646.	visstTau	10.27(	6.21)
N=	231962.	nnTau	5.47(	4.52)
N=	517999.	ccTau	5.44(	5.97)

Bivariate Distributions of Passive vs CC Optical Depths, October 2009

VISST



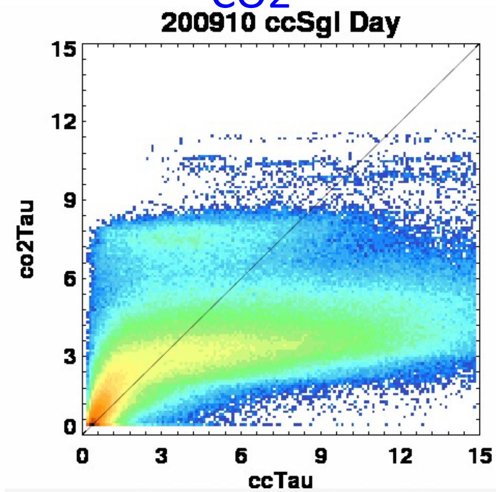
N= 830485. Mean (StdDev)
ccTau 2.44(2.79)
visstTau 4.22(4.17)



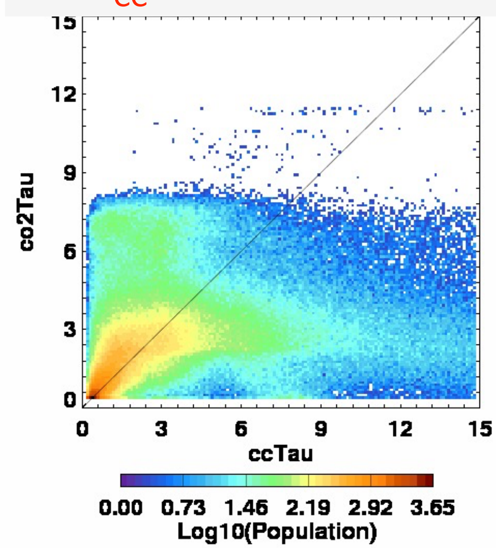
τ_V more than 2x & less correlated w/ τ_{CC} for ML clouds

RMS(4.70)...............

CO2

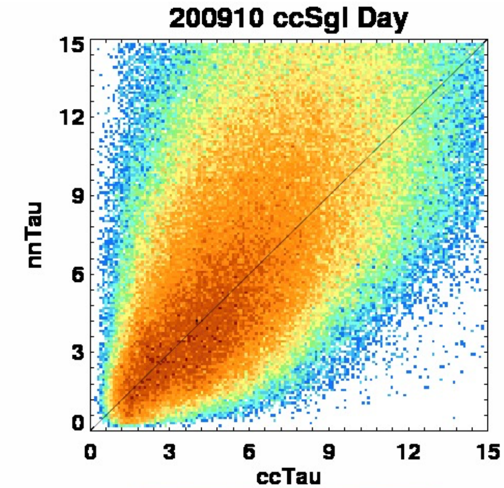


τ_{co2} has more larger values for τ_{CC} < 3 for ML clouds

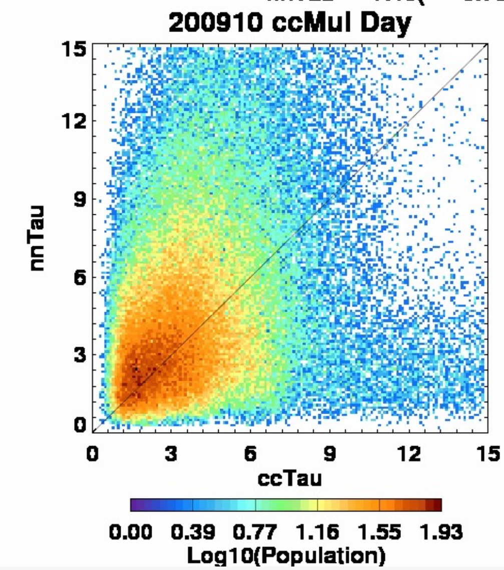


N= 528709. Mean (StdDev)
ccTau 3.27(3.15)
co2Tau 2.69(1.87)
Y-X -0.585(3.21)
RMS(3.27)...............

ICODIN-3A

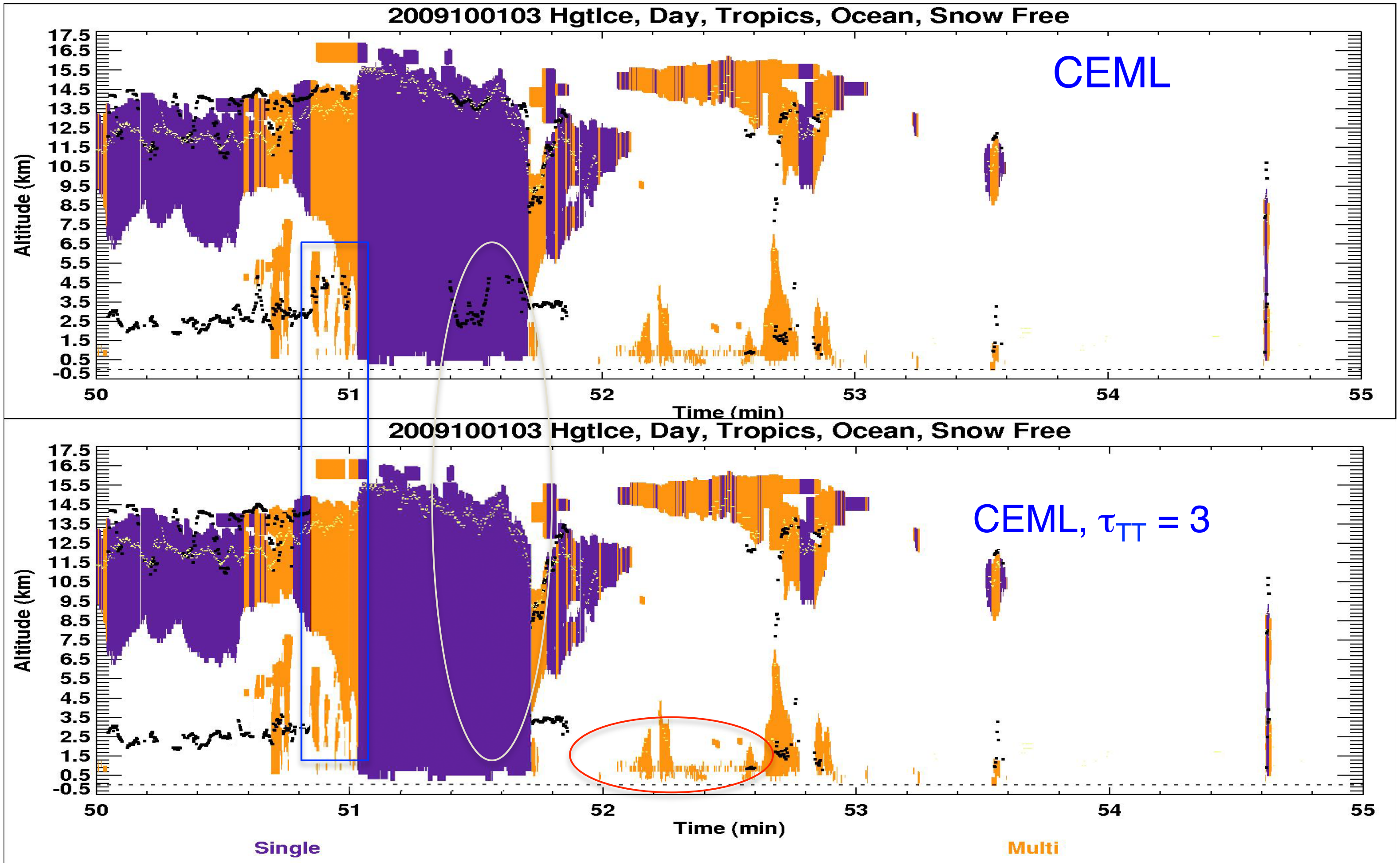


N= 349453. Mean (StdDev)
ccTau 6.04(3.12)
nnTau 7.13(3.79)



τ_{NN} less correlated w/ τ_{CC} for ML clouds, tends to be greater

Screening with ICODIN-3a



- Since CEML assumes it cannot detect ML clouds if upper layer is too thick,
  - reclassify all CEML ML results as SL if, $\tau_{NN} > \tau_{TT}$,
  - τ_{TT} is thick threshold (TT) optical depth

Summary of CERES-ML vs CALIPSO-CloudSat Layering

Daytime October 2009

	Classification	CC SL	CC ML	FC %	FAR %
No τ_{TT}	CERES SL	41.5	35.1	53.1	22.0
	CERES ML	11.8	11.6		
τ_{TT} = 3	**CERES SL**	**48.8**	**38.1**	57.4	9.4
	CERES ML	4.4	8.6		
τ_{TT} = 4	**CERES SL**	**48.8**	**37.5**	58.0	9.5
	CERES ML	5.1	9.2		
τ_{TT} = 5	**CERES SL**	**47.5**	**35.1**	57.2	10.8
	CERES ML	5.8	9.7		
τ_{TT} = 6	**CERES SL**	**46.8**	**36.6**	56.9	12.2
	CERES ML	6.5	10.1		

- Optimum threshold is τ_{TT} = 4
- Still not satisfactory detection rate
- Need to address missed ML cases

Further Use of the Neural Network Approach
Layering Neural Network (LANN)

- ICODIN-3a threshold increased fraction correct and reduced false ML detection
  - still no help for the larger error: missed ML clouds

- No obvious signal for missed ML clouds vs. SL clouds
  - try applying neural network directly

INPUT

- Lat, Lon, SZA
- 0.65 & 2.13 µm reflectance
- 3.8, 6.7, 8.5, 10.8, 12.8 µm brightness temperatures
- BTD_{3811}, BTD_{3867}, BTD_{6711}, BTD_{8511}, BTD_{1112}

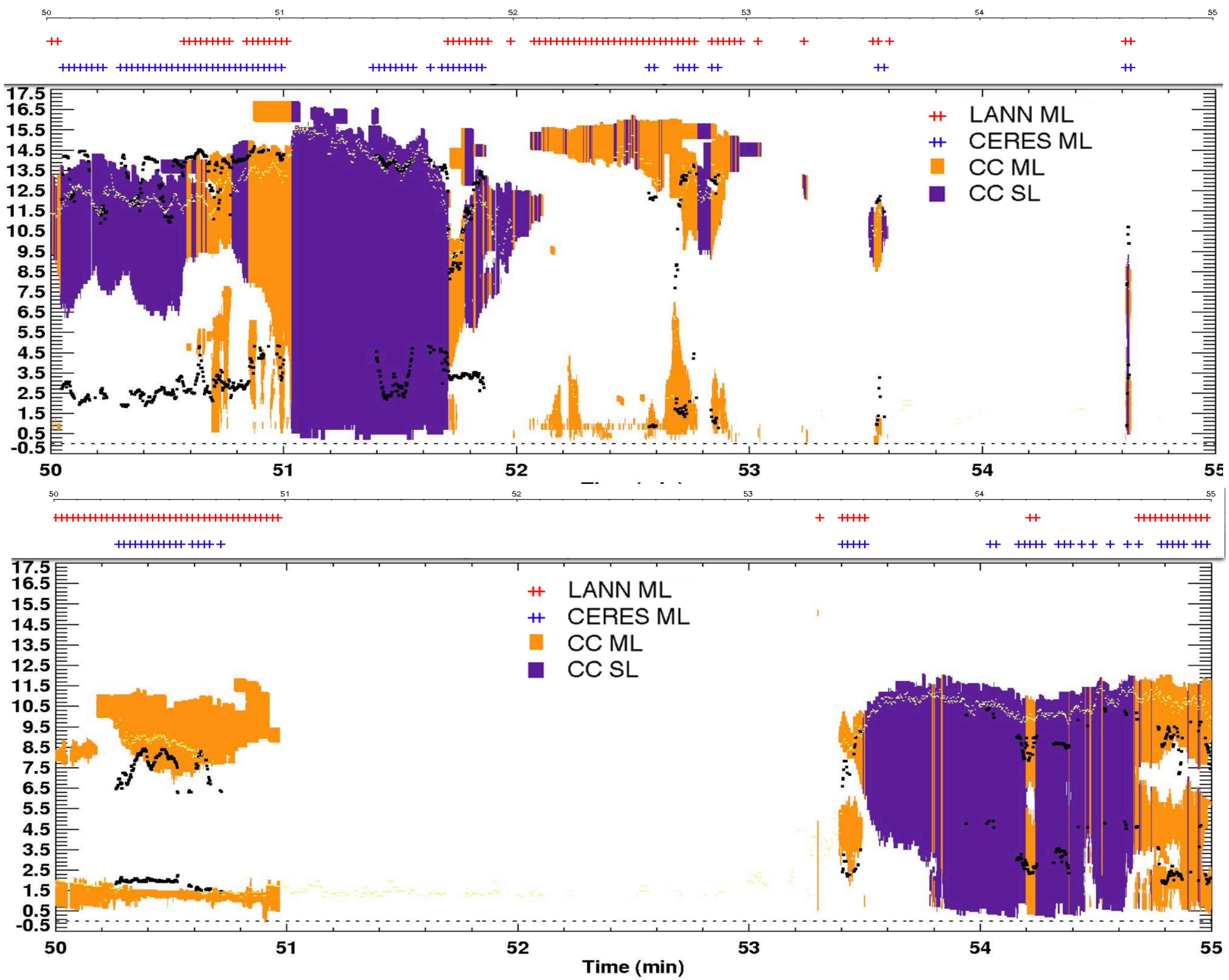
OUTPUT

- ML or SL

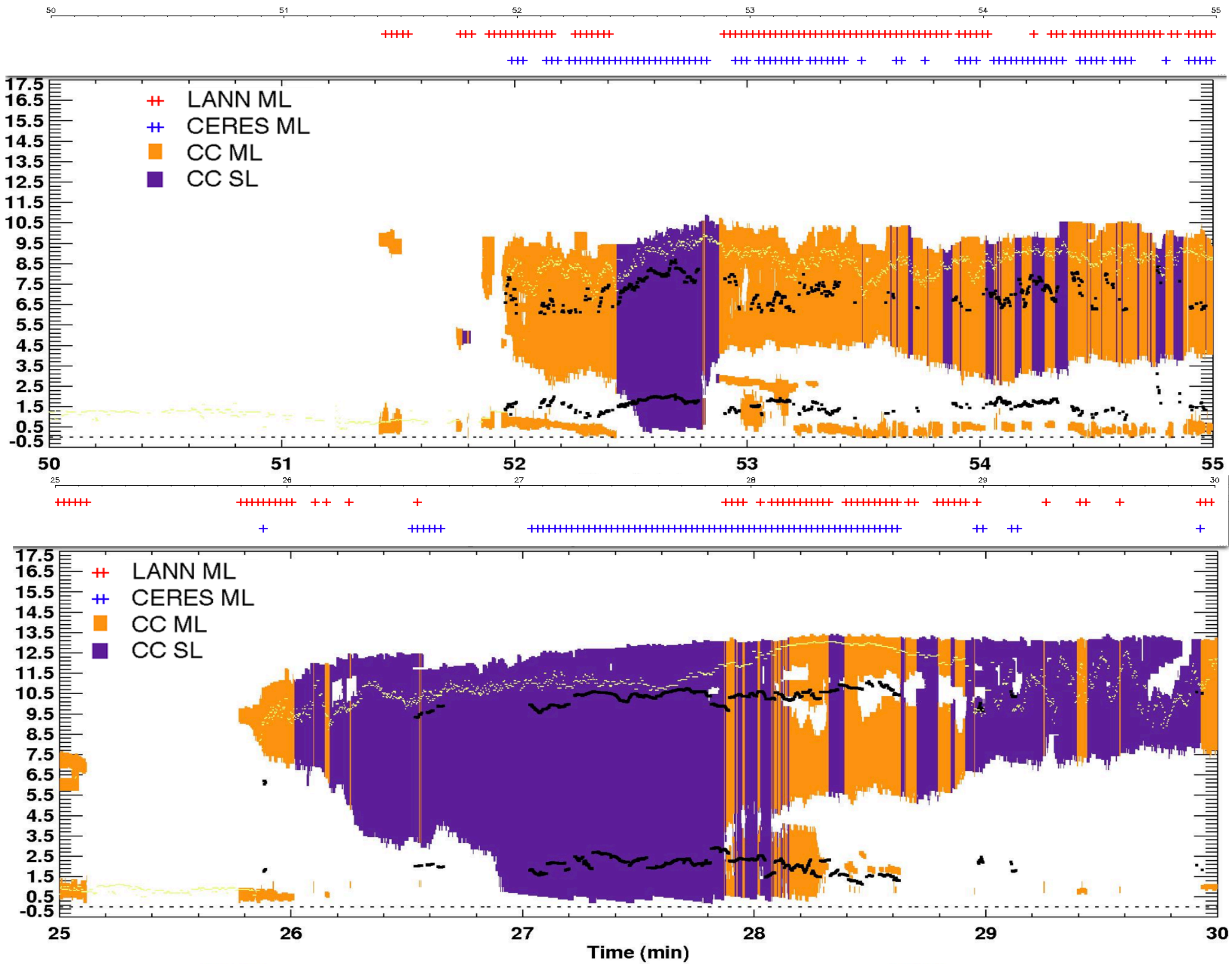
TRAINING and VALIDATION

- 1/5 of data for training, 1/5 for validation

Examples of Applying Layering Neural Network (LANN)



Examples of Applying Layering Neural Network (LANN)



Summary of Neural Net ML vs CALIPSO-CloudSat Layering

Daytime October 2009

Overall Results, in % with all CC ice layers

Classification	CC SL	CC ML
CERES SL	49.0	14.0
CERES ML	8.5	28.5

- Percent correct: 77.5; Percent wrong: 22.5; FAR = 17%
- NN ML coverage is 87% CC coverage,
  but only 2/3 of true coverage

Results in % CC ice layer, for $\tau_{CC} > 0.3$ only

Classification	CC SL	CC ML
CERES SL	45.0	12.0
CERES ML	8.5	34.5

- Percent correct: 79.5; Percent wrong: 20.5; FAR = 15%
  - slightly better than for all ice clouds
- NN ML coverage is 92% of CC coverage,
  only 2/3 of true coverage

CONCLUSIONS

- Thick ice cloud neural net (ICODIN-3a) increases CERES ML layer FC by 4-5%
  - decreases FAR and total fraction of ML clouds
- Initial test of layering neural network (LANN) very promising
  - increases fraction correct by 25% and even detects ML when $\tau < 0.3$
    - *FC up to 80%*
  - has not been optimized
  - misidentified clouds not yet classified (e.g., τ ranges)

FUTURE

- Optimize LANN detection
  - assess sensitivity to vertical separation assumption
  - determine which channels are truly needed
  - perform analyses at other viewing angles (matched GEOsat, VIIRS)
  - include 1.38 µm reflectance, NWP analysis data as input
- Test capability of NN method to estimate Z_{upper}, τ_{upper}, etc.
  - if only one parameter can be determined, other approaches (e.g., MCOAT) will be able to retrieve the remaining parameters