Exploring Detection and Retrieval of Contiguous and Multilayer Clouds

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Earth Radiation Budget Workshop
Reading, UK, 18-21 October 2016

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: significant cloud height underestimates
  - impact the cloud top height (CTH) retrieval
    - *retrieve effective height from VIS-IR methods => TOA radiation*
    - *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>

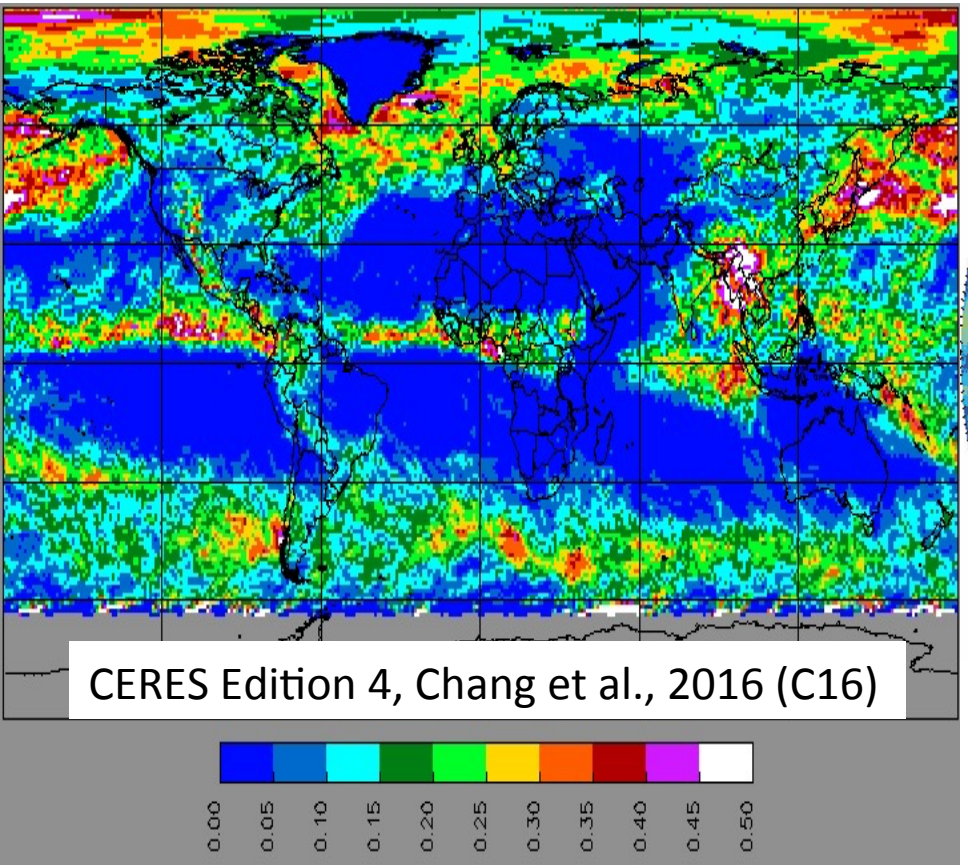
- *Pavolonis & Heidinger* (JAM, 2004) BTD(11-12) + VIS
- *Wind et al.* (JAMC, 2010) 0.94 µm +CO_2 slicing
- *Joiner et al.* (AMT,2010) UV +VIS-IR

<u>Detection & Retrieval</u>

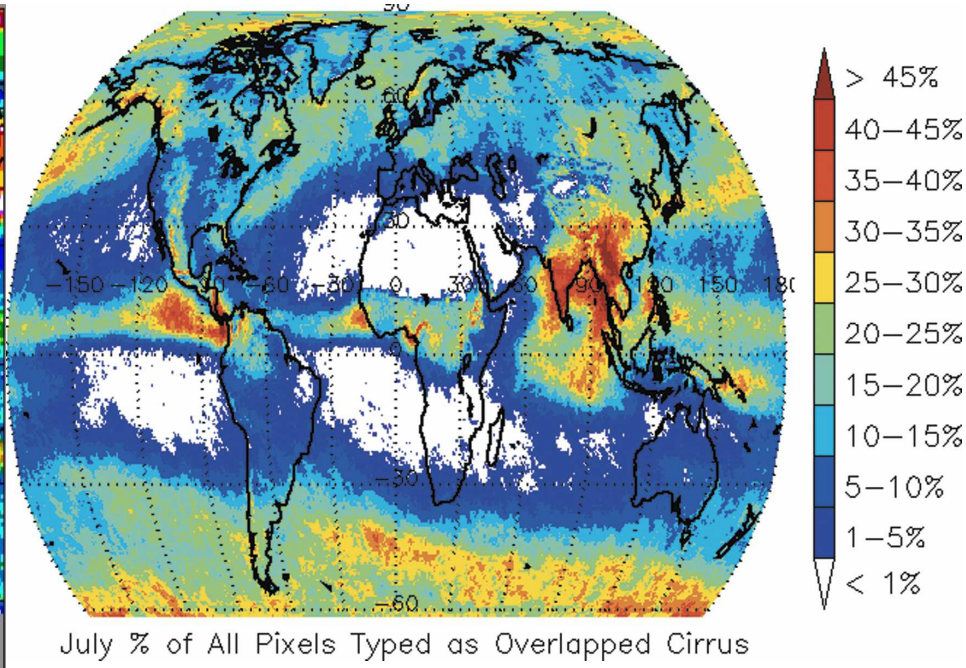
- *Lin et al.* (JGR, 1998) VIS-IR, MW
- *Chang & Li* (JGR,2005) VIS-IR, CO2-slicing (assumes low cloud from environs)
- *Minnis et al.* (2007) VIS-IR, MW ocean only
- *Watts et al.* (JGR, 2012) 9 channel VIS, IR, CO2 Optimal Estimation
- *Chang et al.* (2016, in prep) VIS-IR, CO2-slicing (retrieves low 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 92% compared to 2-layer CALIPSO-CloudSat ice-over-water, upper layer cloud optical depth $\tau > 0.3$
  - only 3.2% of all daytime cases *from A. Viúdez-Mora*

- 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 layering NN method (LANN) to detect ML conditions

Data

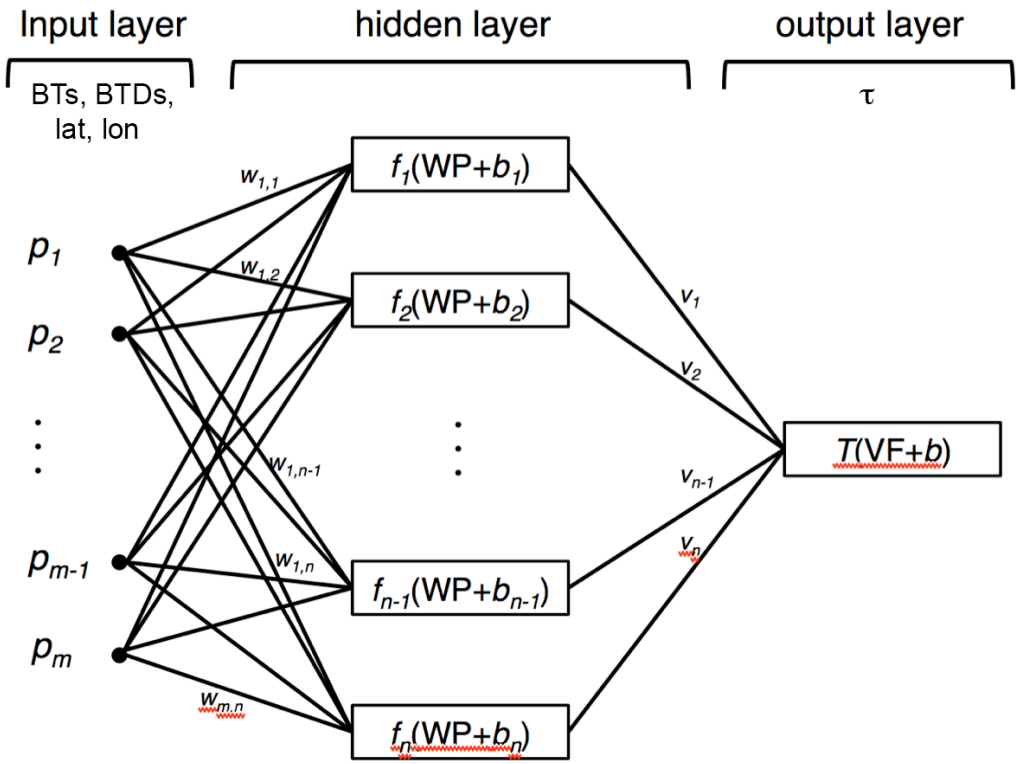
- C3M (CALIPSO, CloudSat, CERES, MODIS) *Kato et al. (JGR, 2011)*
  - CALIPSO V3.3 Vertical Feature Mask and optical depth, τ_{CL}
  - CloudSat CPR CLDCLASS vertical mask & CWC, r_e
    - $\tau_{CS} = 0.75 * \Sigma(CWC/r_e\ \rho)\ Q_e\ \Delta z$,
      - *use only layers where $T < 253$ K*
  - compute 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

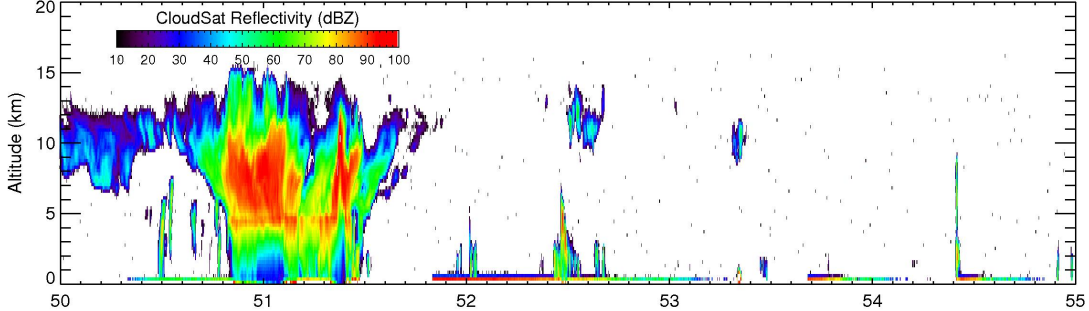
- Compute ICODIN-3a optical depth, $\tau_{NN} = f(LAT, LON, T_{11}, BTD_{1112}, BTD_{6711})$
  - only for $\tau_V > 4$, ice phase *Minnis et al. (JGR, 2016)*

Why Use a Neural Network Approach?

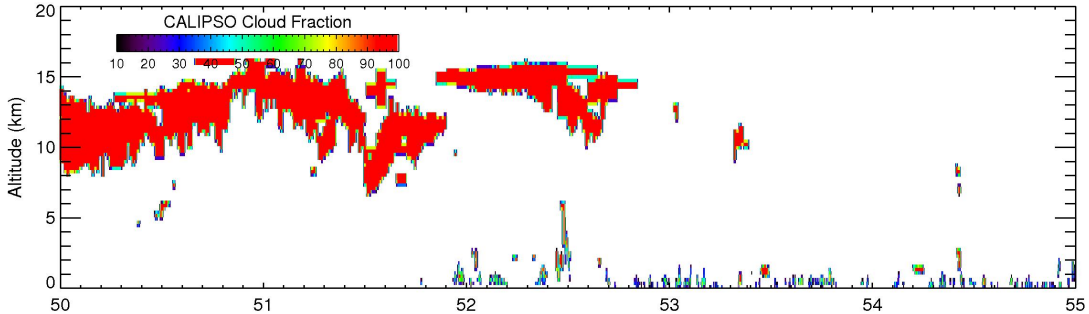
- Small ambiguous signals are found in various remote sensing radiances
- How do we extract reliable information from these small signals?
  - Example: *Kox et al. (AMT, 2014)*



- NN requires a large training database: must know the output value
- CloudSat & CALIPSO provide the first global source of a "truth dataset"
- Training can bypass many of the uncertainties in a straightforward physical retrieval
- Results can facilitate a more accurate physical retrieval

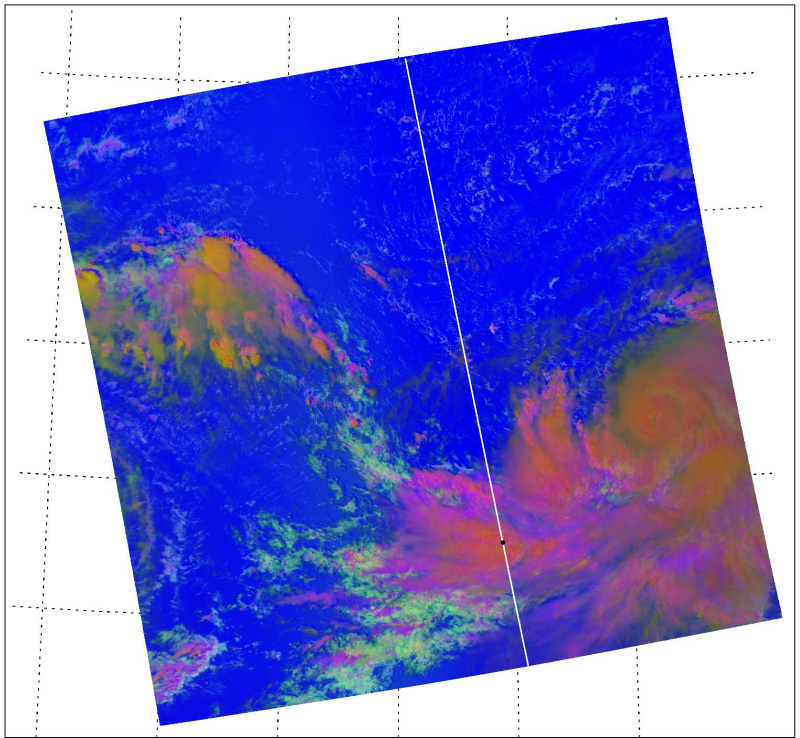


CloudSat Reflectivity



CALIPSO Cloud Fraction

OCT-01-2009 03:50-03:55



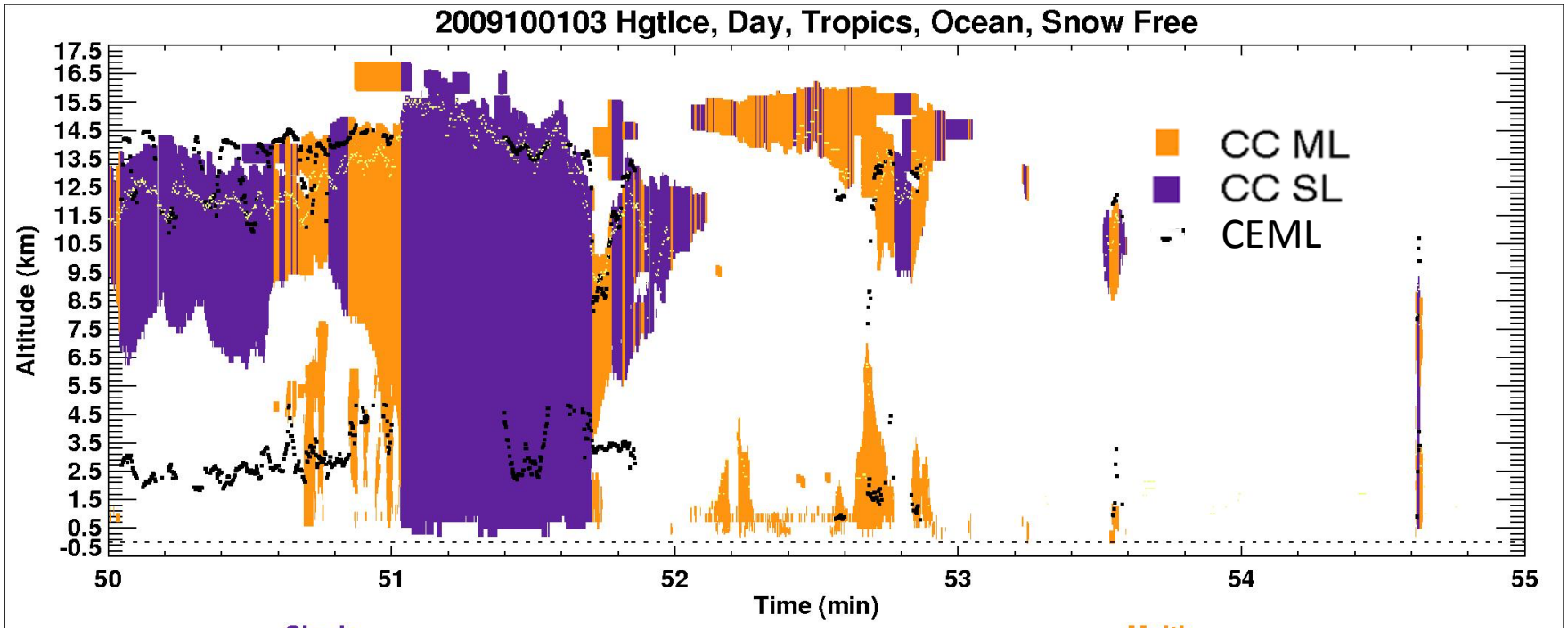
RGB MODIS Aqua
(R0.6, R2.1, flipped BTD(3.7-11))

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

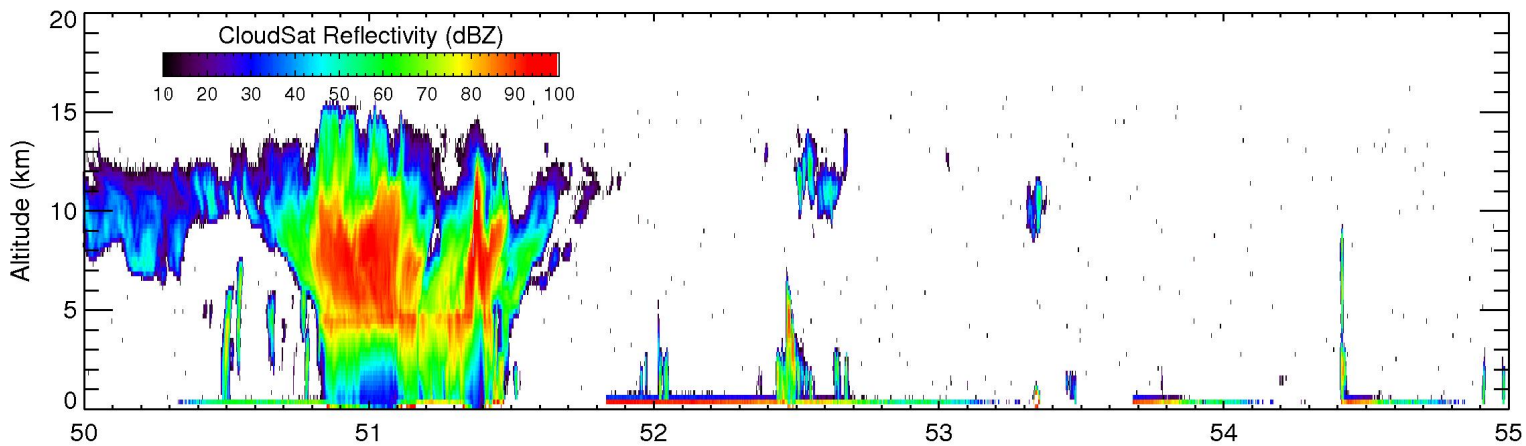
Defining a Multilayered Cloud System

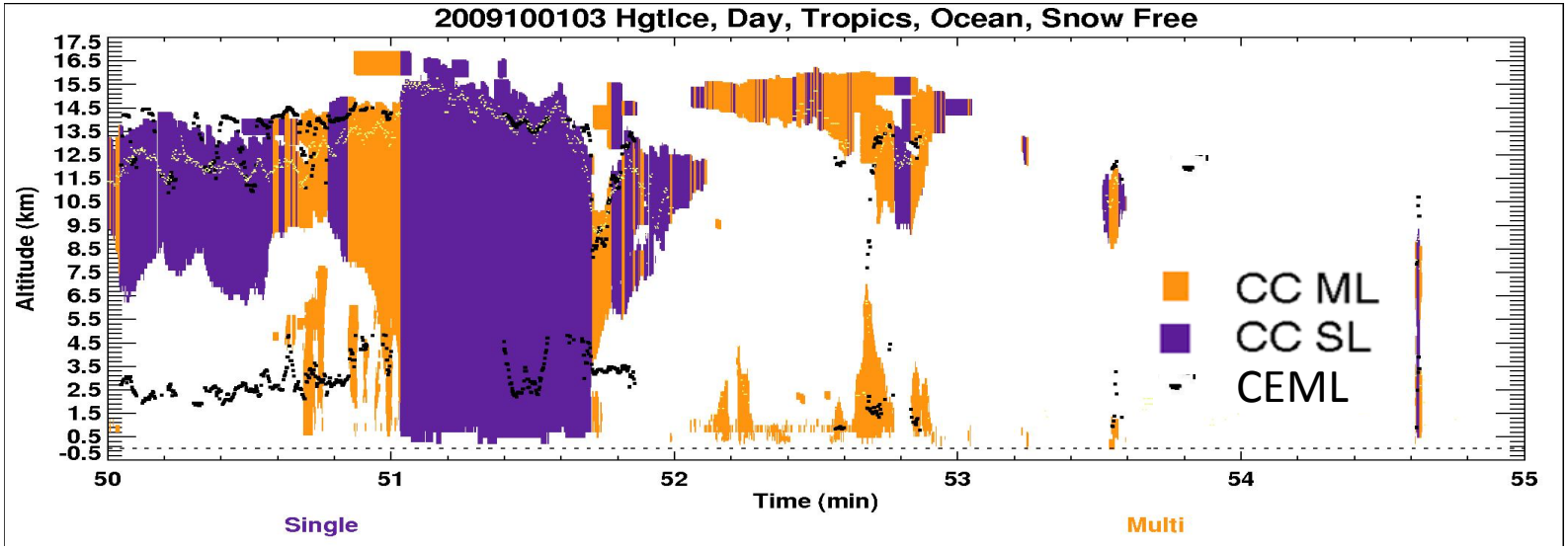
- **Ice** cloud over **water** cloud with minimum 1-km separation
  - separate ice cloud layers comprise 1 layer
  - separate water layers = 1 layer
  - ice over water with no 1-km separation = single layer (SL)
  - no ice = SL water (not counted here); no water = SL ice

- "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

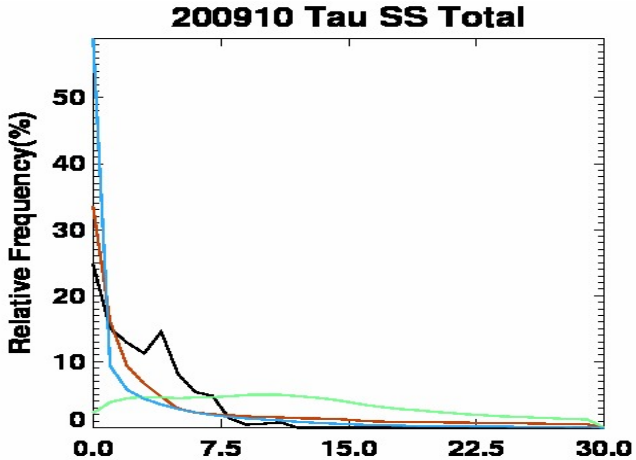
CC ML only, in % of 5.1 million with CC ice layer

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

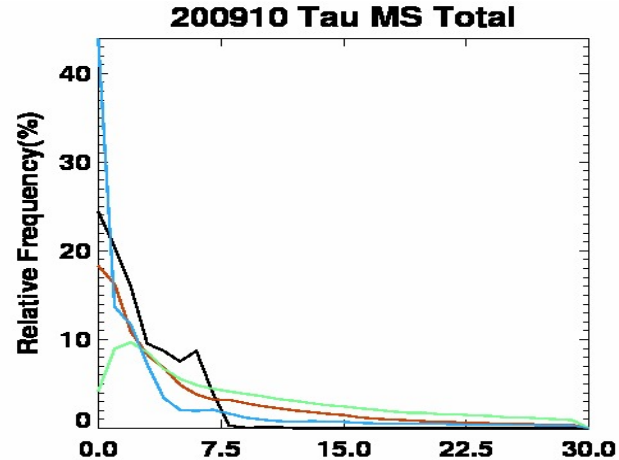
- Nearly half of missed ML clouds due to low τ of ice layer
  - do not expect CO2 to get many $\tau < 0.3$
- The other half missed due to either upper layer too thick or lower layer too thin

C3M Oct 2009 Tau Histograms

CC-Single
CEM Single



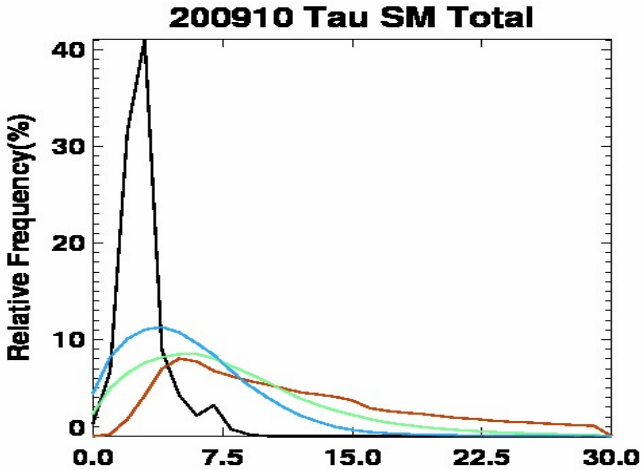
		Mean	(StdDev)
N= 1117071.	co2Tau	3.18(	2.43)
N= 736405.	visstTau	5.22(	6.97)
N= 362642.	nnTau	12.24(	7.45)
N= 2087920.	ccTau	2.66(	4.56)



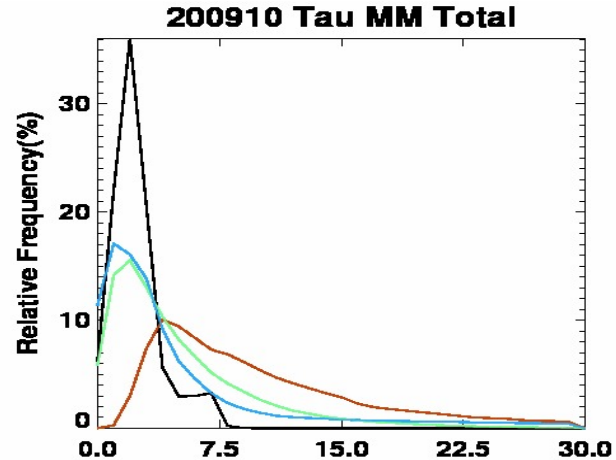
		Mean	(StdDev)
N= 782897.	co2Tau	2.89(	2.20)
N= 658897.	visstTau	6.05(	6.49)
N= 94462.	nnTau	9.60(	7.66)
N= 1630478.	ccTau	3.69(	5.84)

CC-Multi
CEM Single

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)

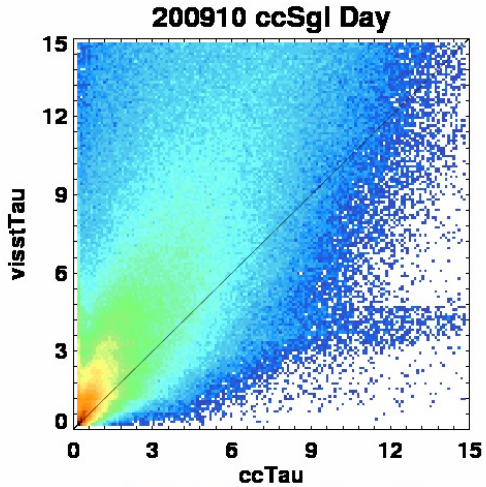


		Mean	(StdDev)
N= 590133.	co2Tau	2.86(	1.53)
N= 271646.	visstTau	10.27(	6.21)
N= 231962.	nnTau	5.47(	4.52)
N= 517999.	ccTau	5.44(	5.97)

CC-Multi
CEM Multi

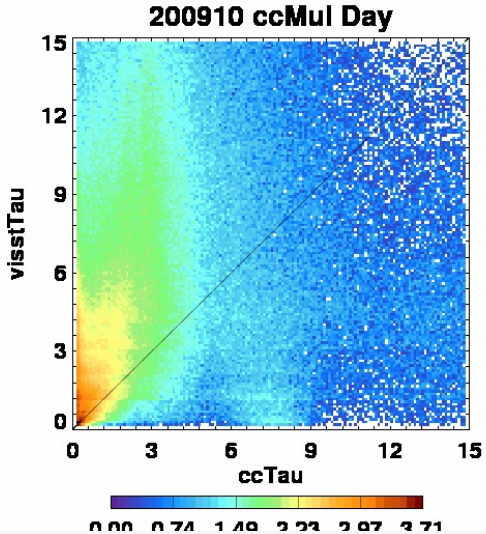
Bivariate Distributions of Passive vs CC Optical Depths, October 2009

VISST



N= 830485.

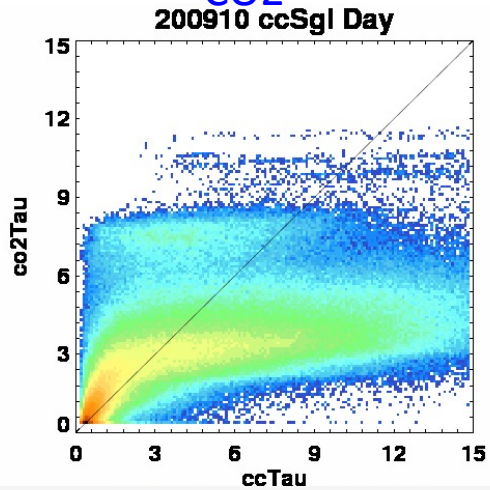
	Mean	(StdDev)
ccTau	2.44(	2.79)
visstTau	4.22(	4.17)



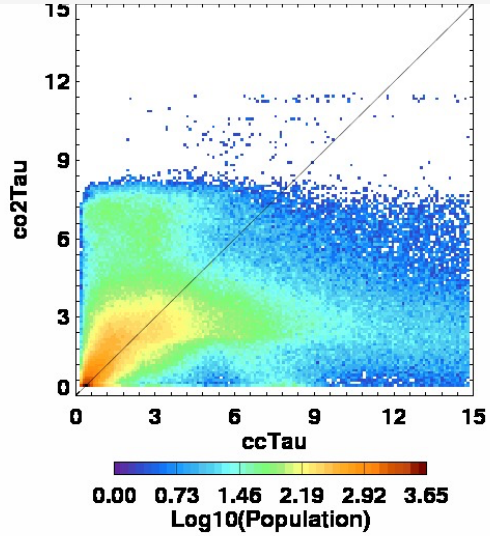
τ_V more than 2x & less correlated w/ τ_{CC} for ML clouds

Y-X 2.33(4.09)
RMS(4.70).....

CO2



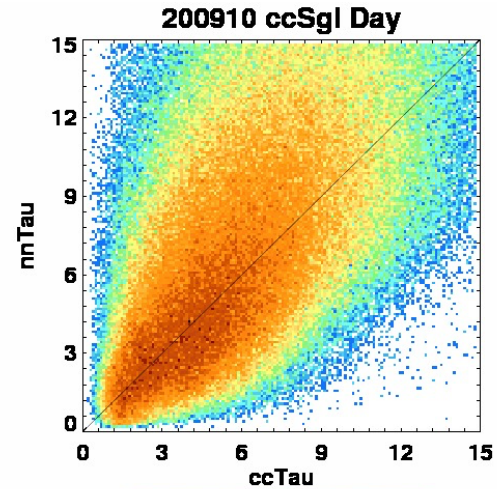
τ_{co2} has more larger values for τ_{CC} < 3 for ML clouds



N= 528709.

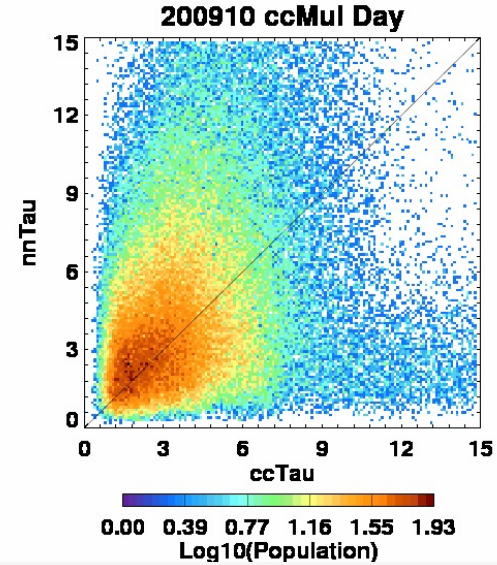
	Mean	(StdDev)
ccTau	3.27(	3.15)
co2Tau	2.69(	1.87)
Y-X	-0.585(	3.21)
RMS(	3.27).....	

ICODIN-3A



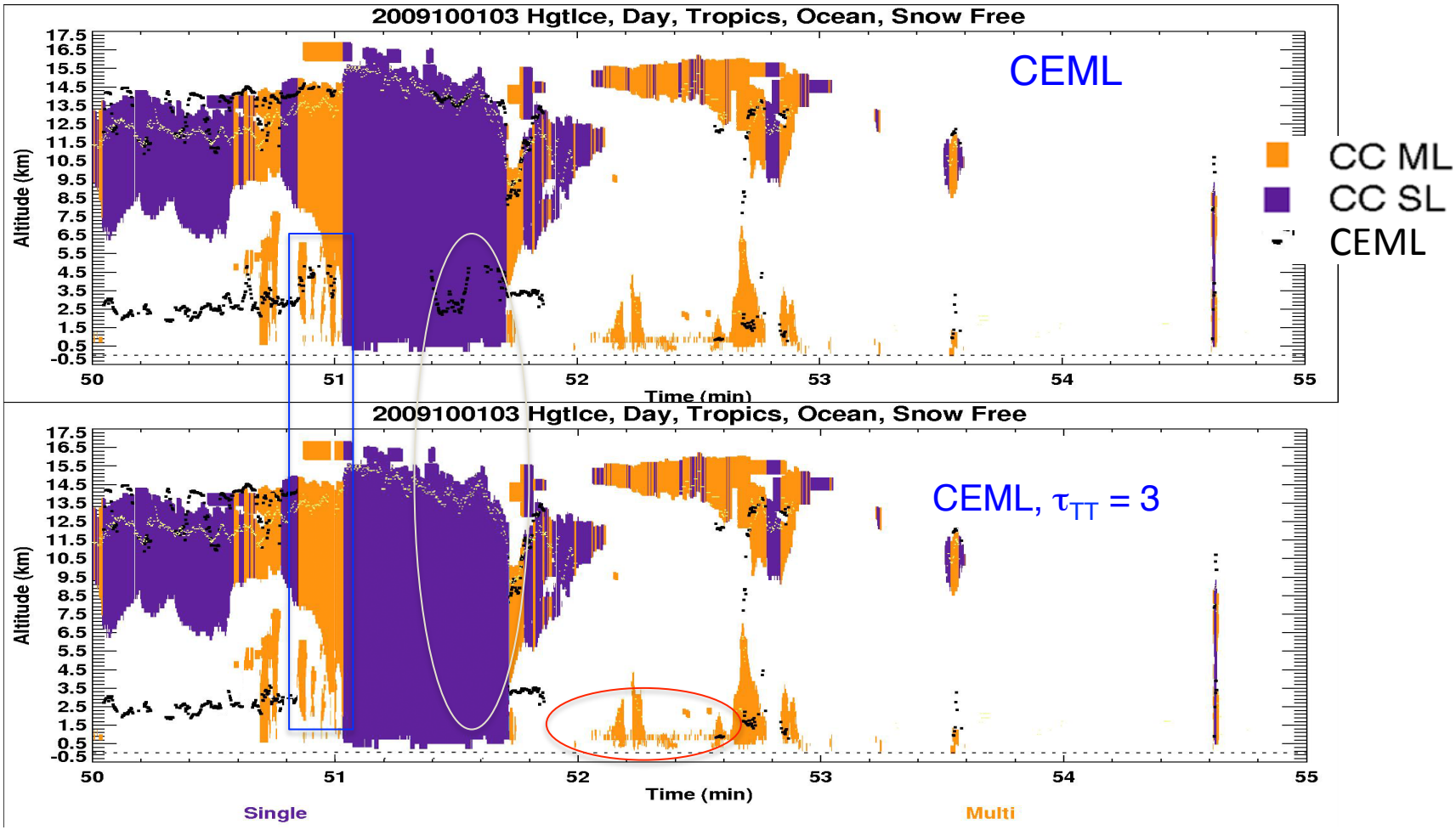
N= 349453.

	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		
$\tau_{TT} = 3$	**CERES SL**	**48.8**	**38.1**	57.4	9.4
	CERES ML	4.4	8.6		
$\tau_{TT} = 4$	**CERES SL**	**48.8**	**37.5**	58.0	9.5
	CERES ML	5.1	9.2		
$\tau_{TT} = 5$	**CERES SL**	**47.5**	**35.1**	57.2	10.8
	CERES ML	5.8	9.7		
$\tau_{TT} = 6$	**CERES SL**	**46.8**	**36.6**	56.9	12.2
	CERES ML	6.5	10.1		

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

Further Use of the Neural Network Approach

Daytime 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
- GEOS-5 surface skin temperature
- 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}

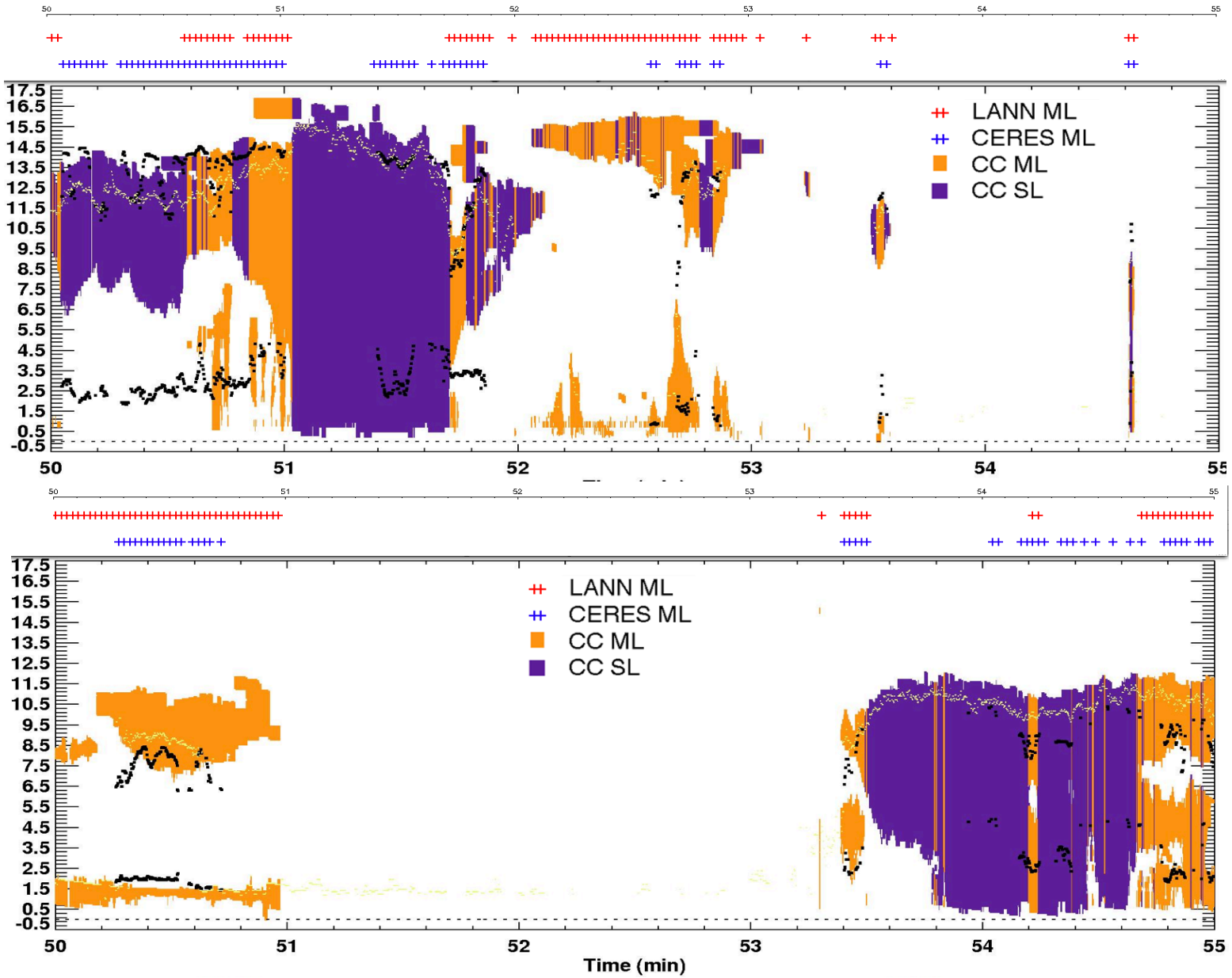
OUTPUT

- ML or SL

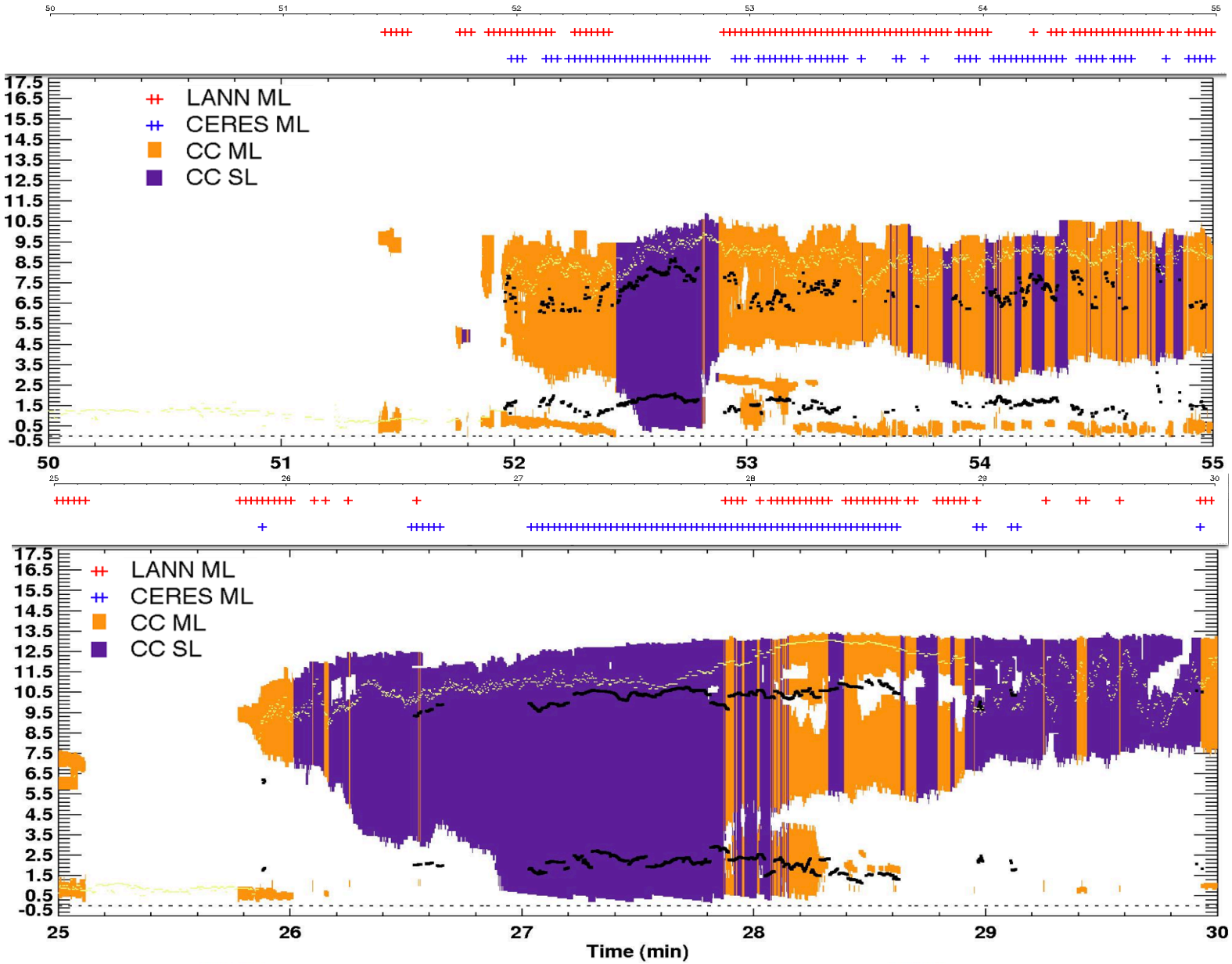
TRAINING and VALIDATION

- 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

Summary of Neural Net ML vs CALIPSO-CloudSat Layering

Daytime October 2009

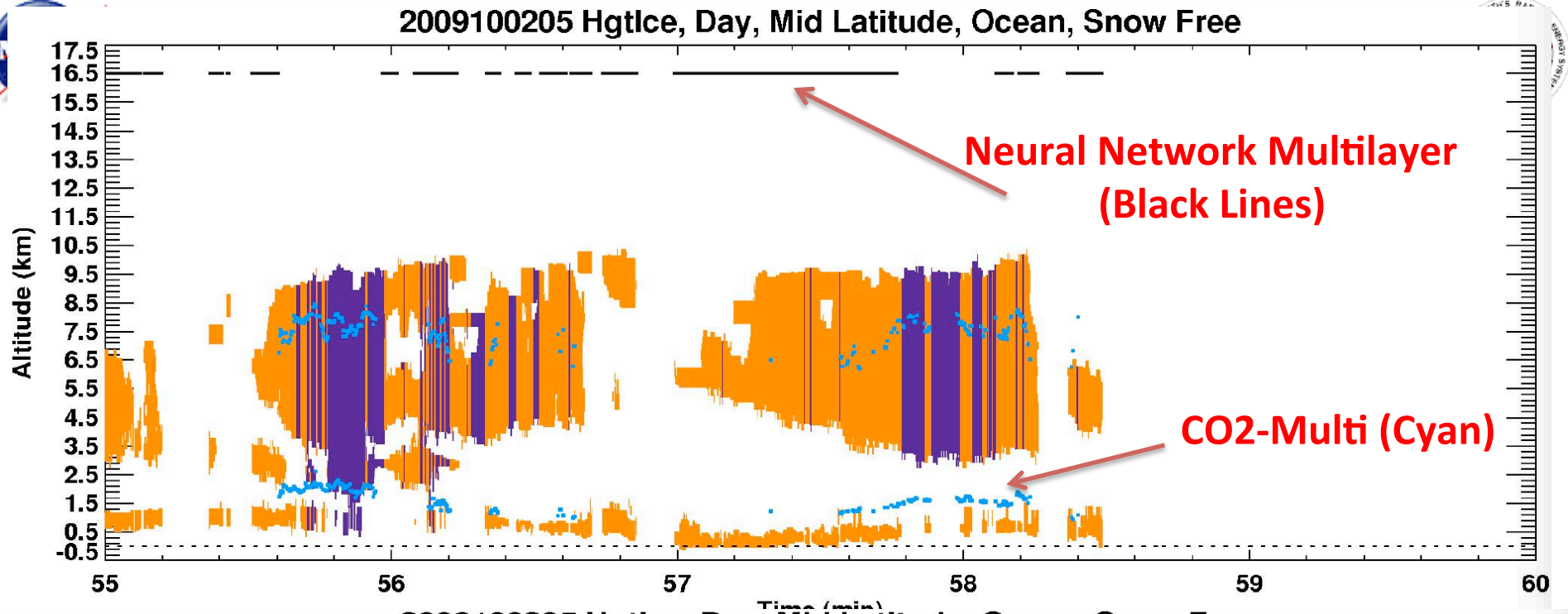
Estimating Ice Cloud Top Height with a Neural Network

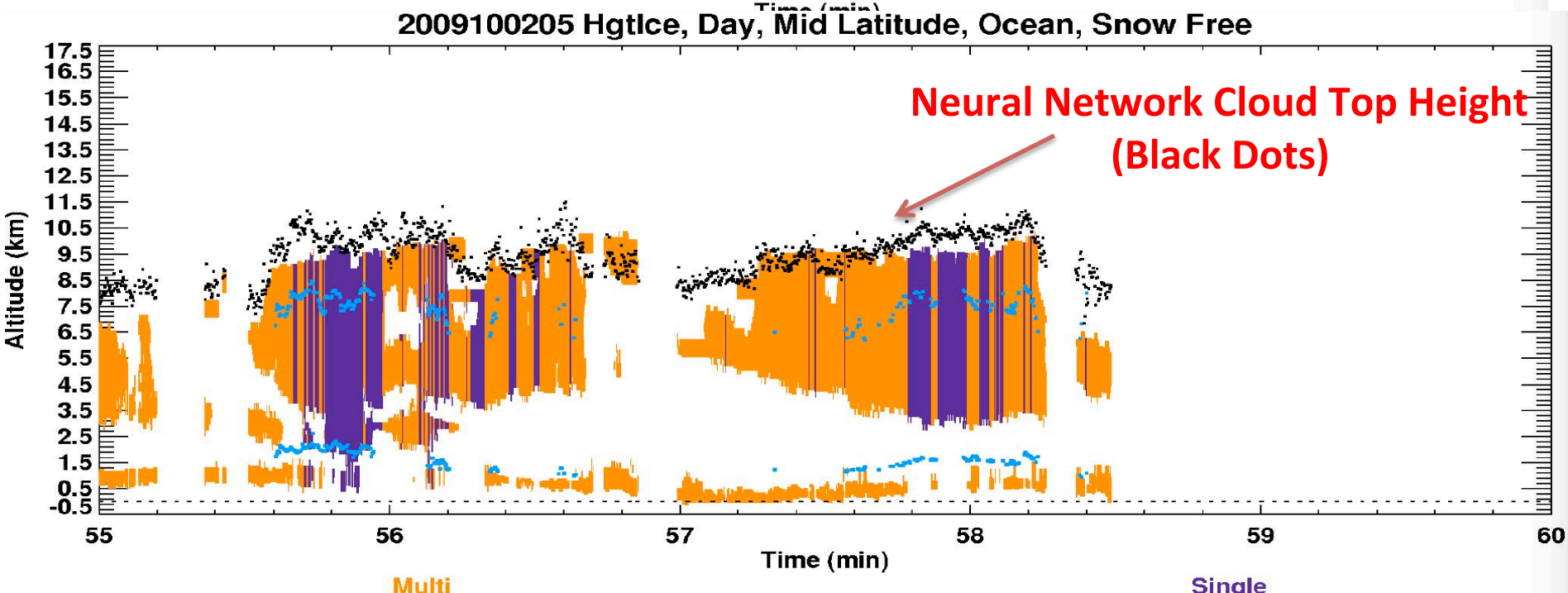
INPUT

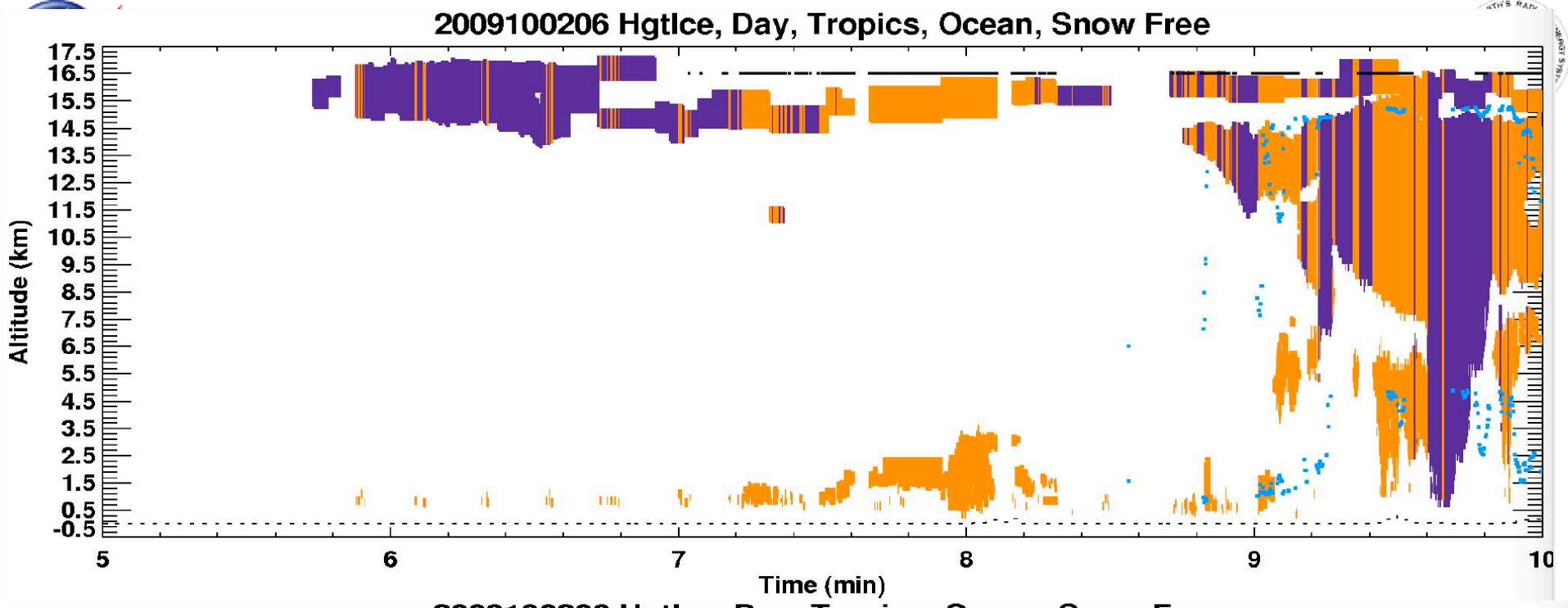
- Lat, Lon
- GEOS-5 surface skin temperature
- 3.8, 6.7, 10.8, 12.8 µm brightness temperatures
- BTD_{3811}, BTD_{3867}, BTD_{6711}, BTD_{1112}

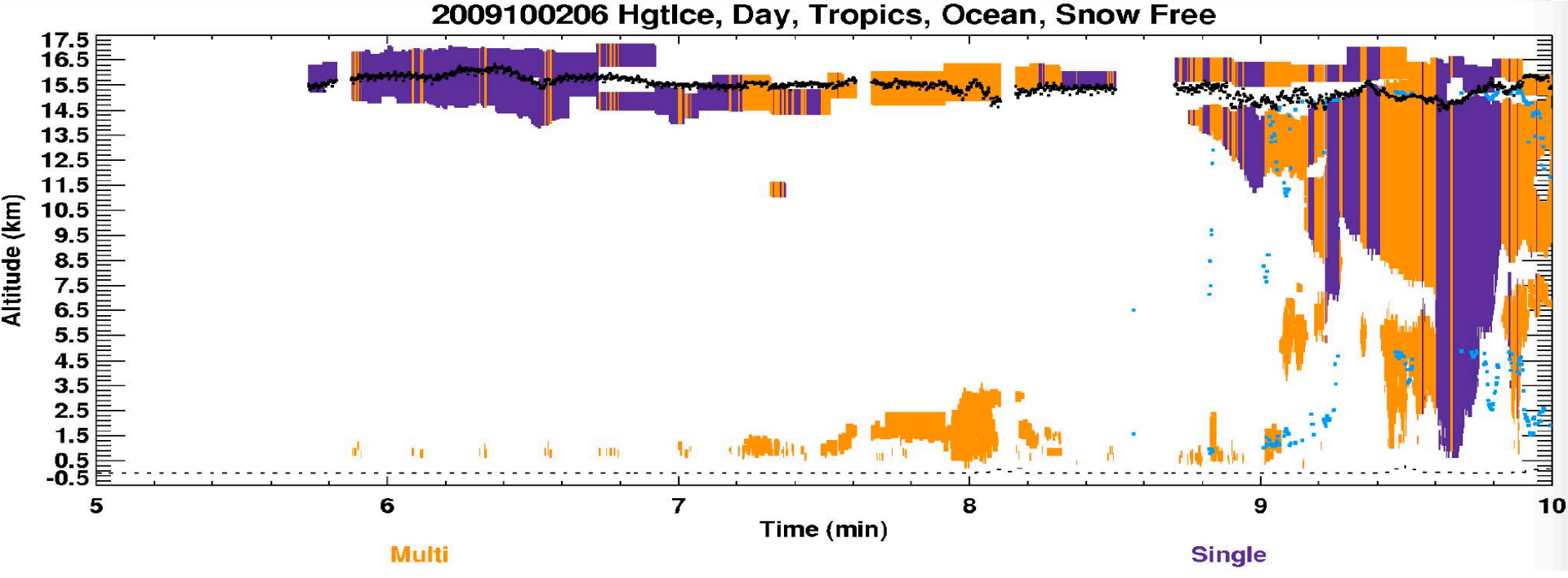
OUTPUT

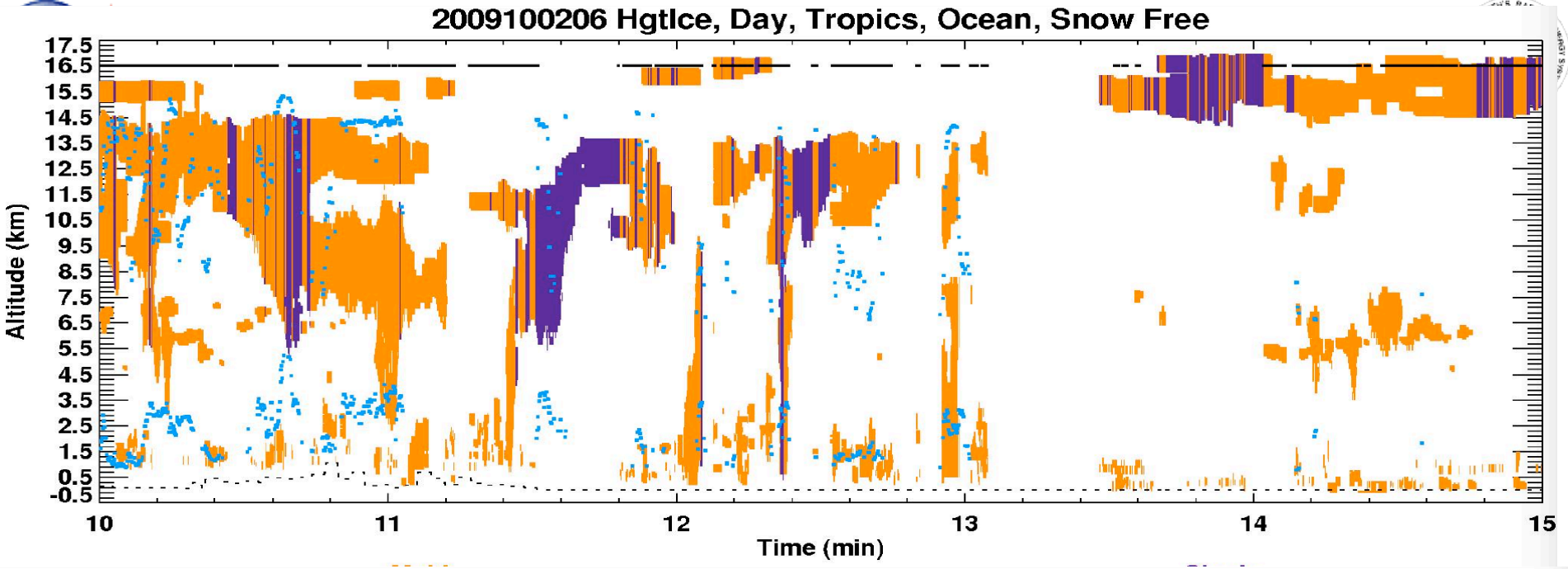
- Ztop


2009100205 HgtIce, Day, Mid Latitude, Ocean, Snow Free
Altitude (km)
Time (min)
Neural Network Multilayer
(Black Lines)
CO2-Multi (Cyan)


2009100205 HgtIce, Day, Mid Latitude, Ocean, Snow Free
Altitude (km)
Time (min)
Neural Network Cloud Top Height
(Black Dots)
Multi
Single


2009100206 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
5
6
7
8
9
10
Time (min)


2009100206 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
5
6
7
8
9
10
Time (min)
Multi
Single


2009100206 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
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12.5
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0.5
-0.5
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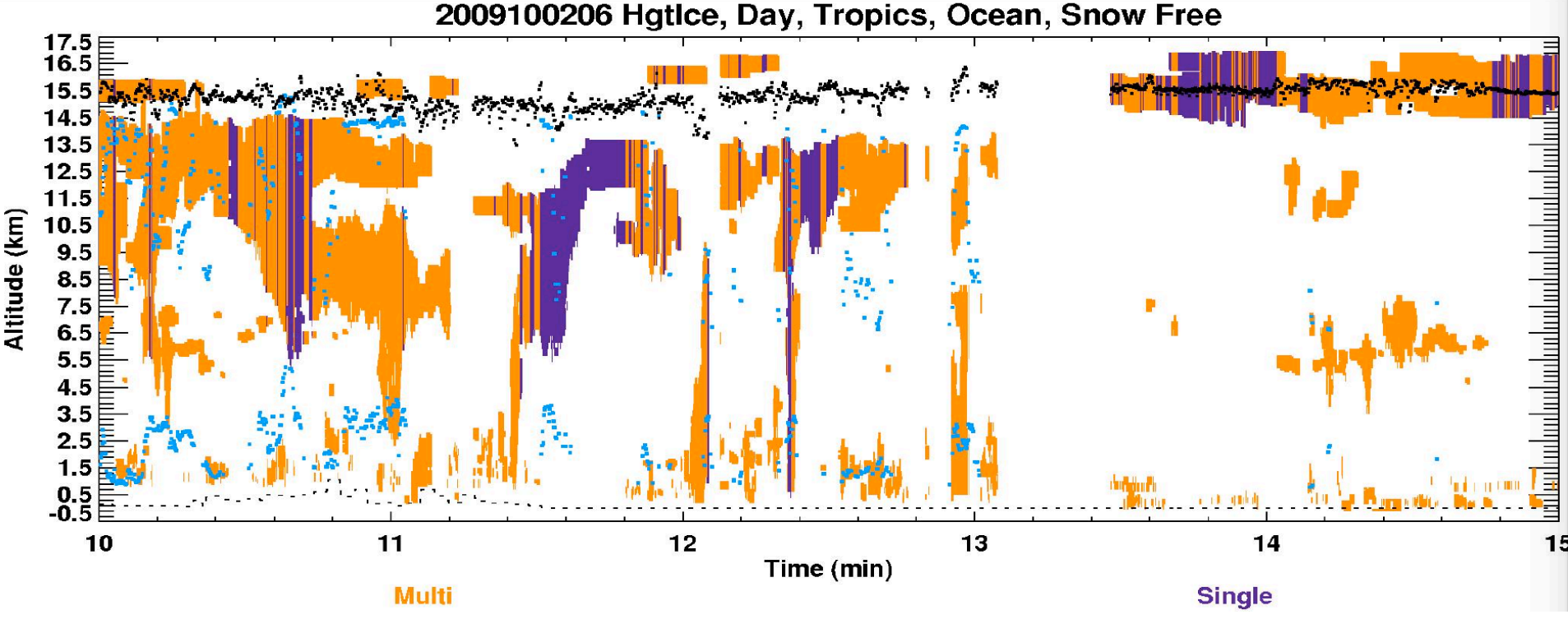
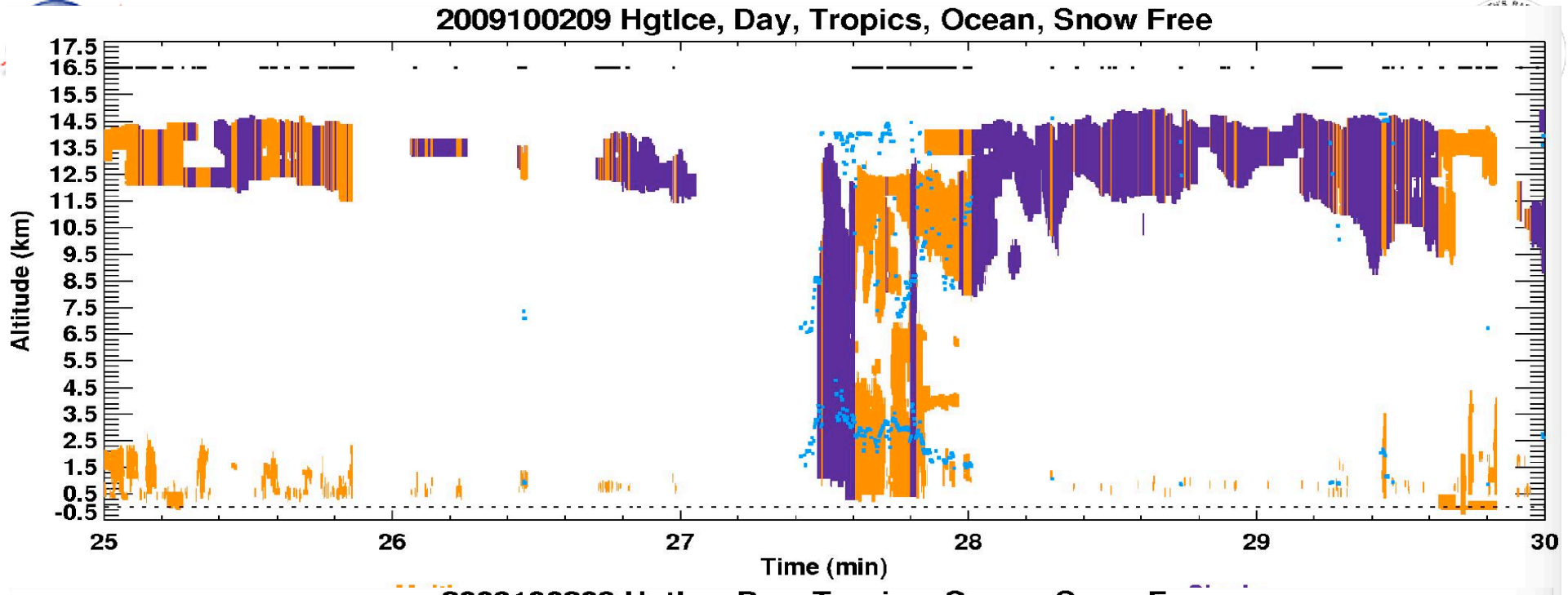
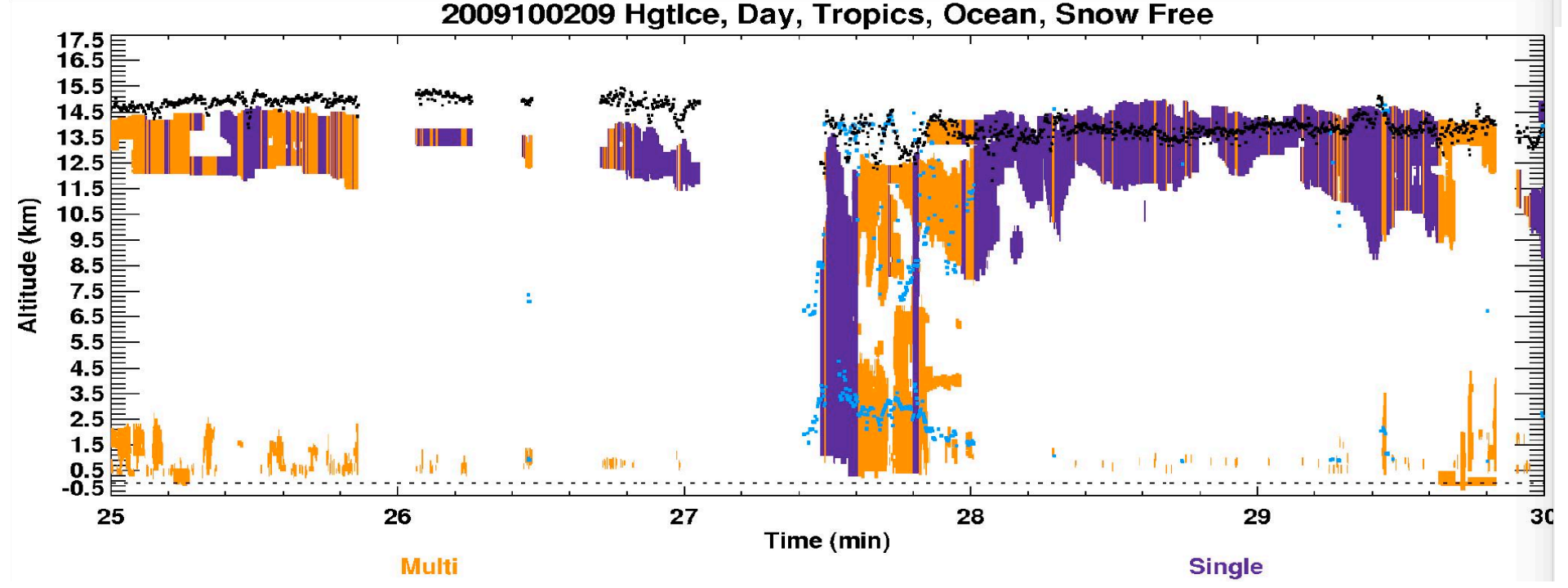
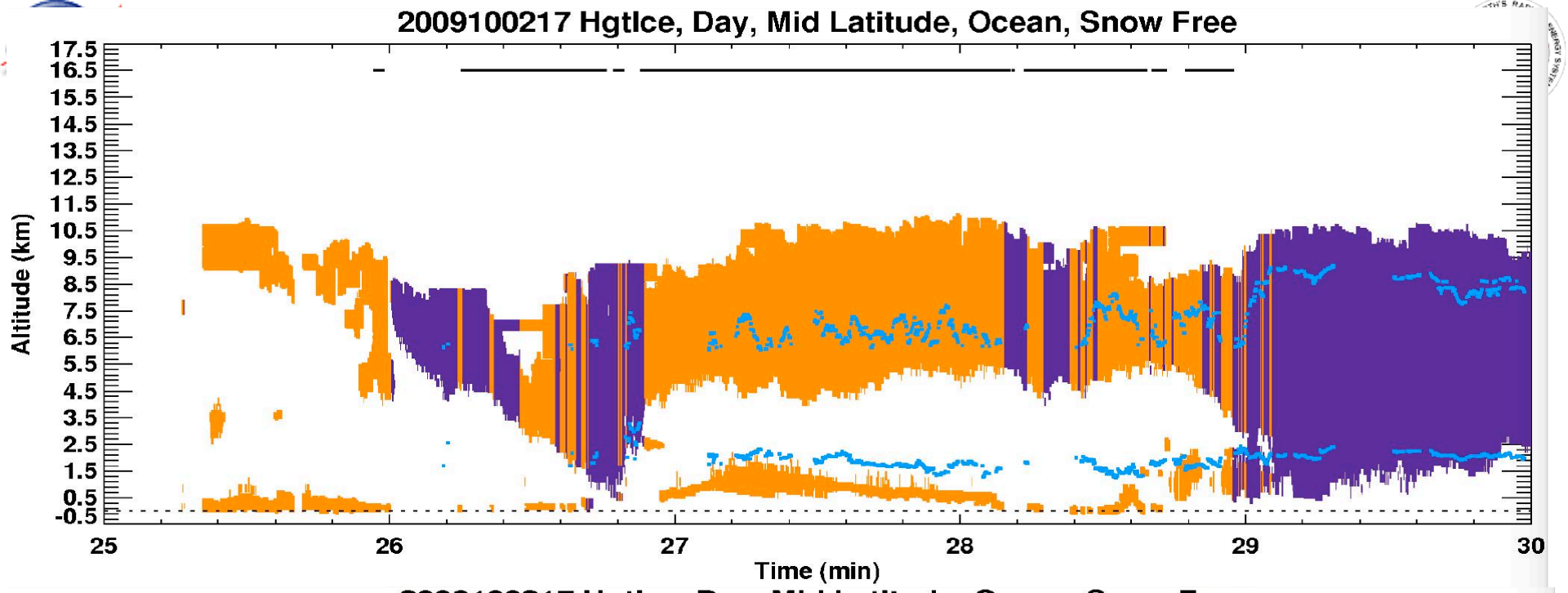
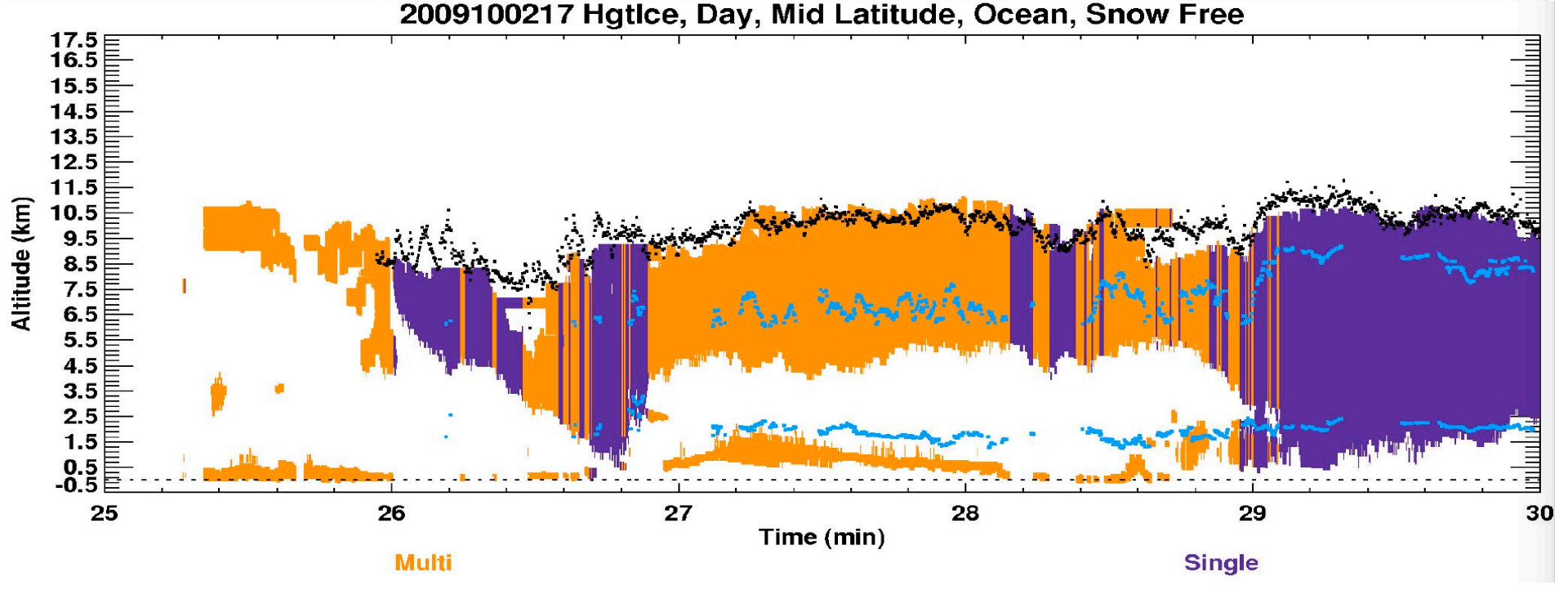
13
14
15
Time (min)

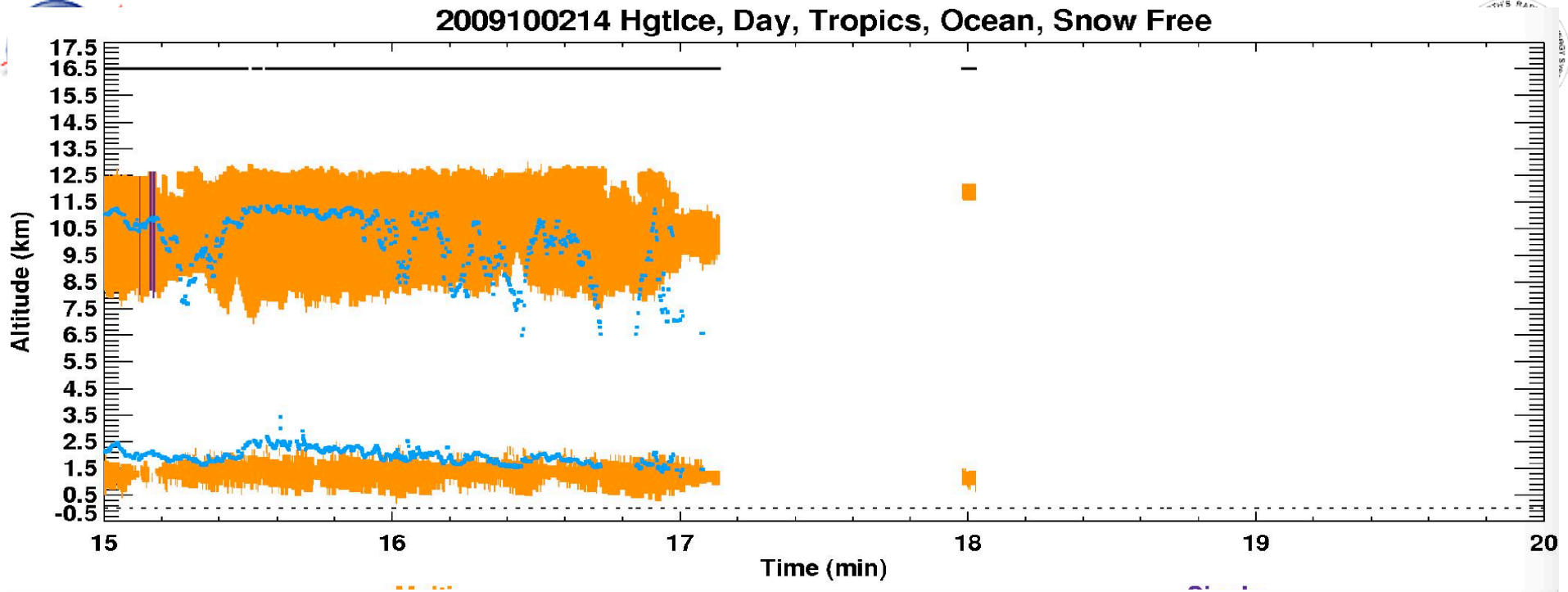

2009100206 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
10
11
12
13
14
15
Time (min)
Multi
Single

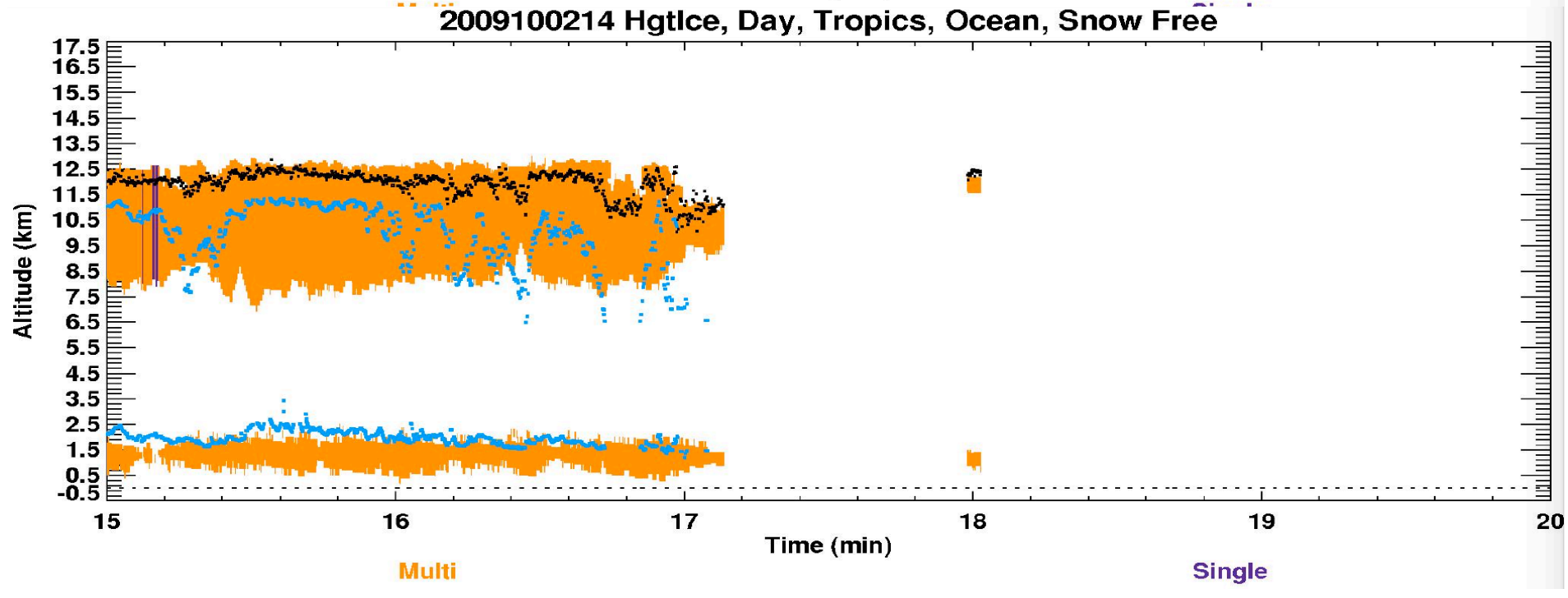

2009100209 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
25
26
27
28
29
30
Time (min)

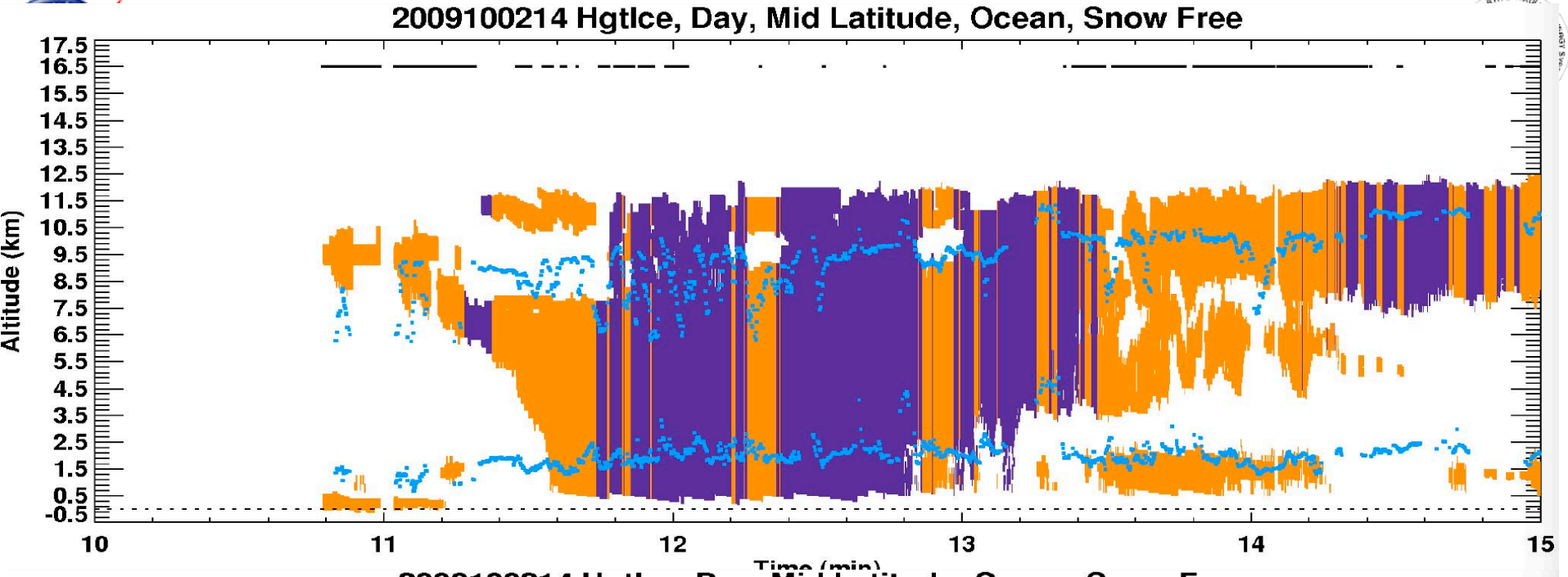

2009100209 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
25
26
27
28
29
30
Time (min)
Multi
Single


2009100217 HgtIce, Day, Mid Latitude, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
25
26
27
28
29
30
Time (min)


2009100217 HgtIce, Day, Mid Latitude, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
25
26
27
28
29
30
Time (min)
Multi
Single


2009100214 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
15
16
17
18
19
20
Time (min)


2009100214 HgtIce, Day, Tropics, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
15
16
17
18
19
20
Time (min)
Multi
Single


2009100214 HgtIce, Day, Mid Latitude, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
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8.5
7.5
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3.5
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1.5
0.5
-0.5
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14
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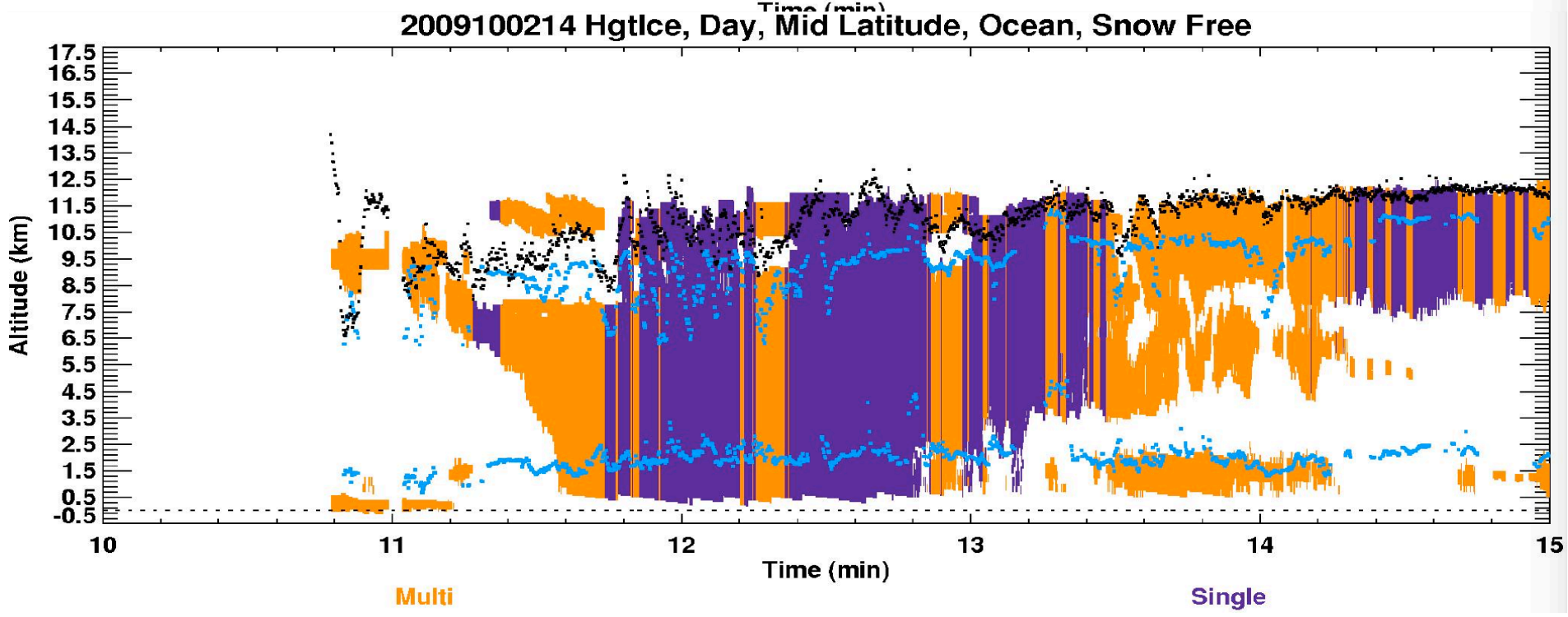
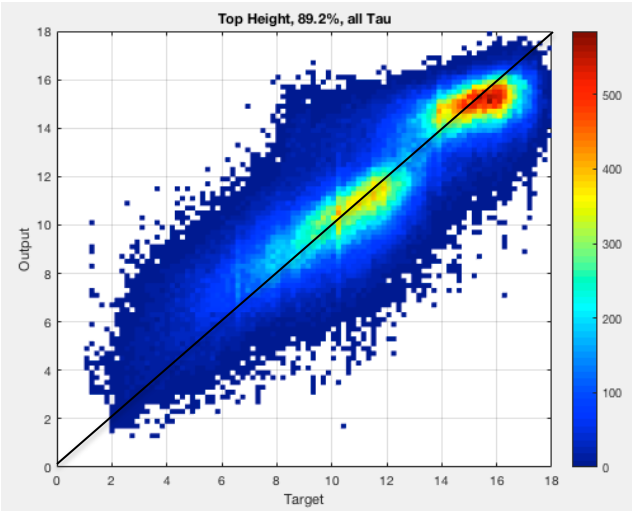
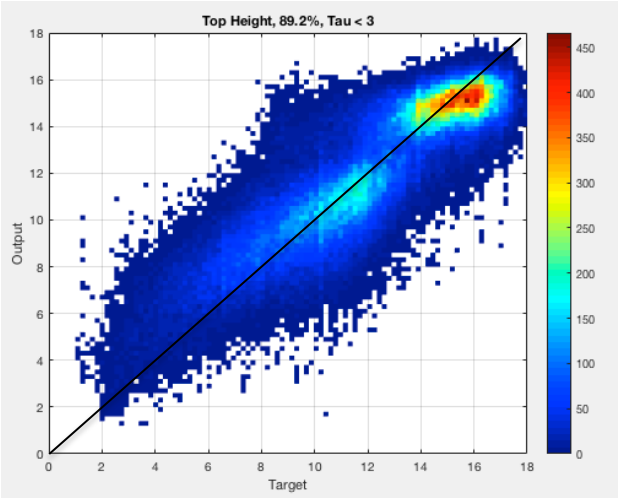

2009100214 HgtIce, Day, Mid Latitude, Ocean, Snow Free
Altitude (km)
17.5
16.5
15.5
14.5
13.5
12.5
11.5
10.5
9.5
8.5
7.5
6.5
5.5
4.5
3.5
2.5
1.5
0.5
-0.5
10
11
12
13
14
15
Time (min)
Multi
Single

NN Cloud Top Height Training Stats with the net trained for all Tau

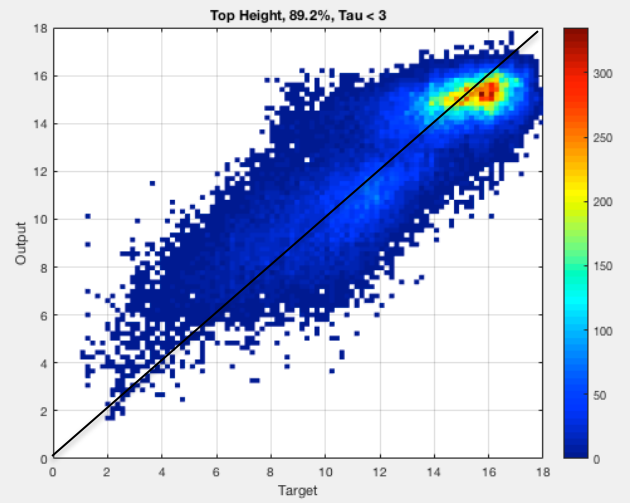
All Tau



Tau < 3.0



Tau < 0.3



Bias = Simulated with the trained net - ccTopHeight

	Bias (km)	Std Dev of Difference (km)
All Tau	0.004	1.484
Tau < 3	0.041	1.552
Tau < 0.3	-0.051	1.522

- Compare to Ed4 all ice clouds: -3.01 ± 4.01 km
  SL ice clouds: -1.07 ± 2.77 km

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% for $\tau > 0.3$*
  - has not been optimized, misidentified clouds not yet classified (e.g., τ ranges)
- Initial test of ice cloud height also promising
  - Ztop accurate to ± 1.5 km for all ice cloud conditions

FUTURE

- Optimize LANN detection & Ztop estimation
  - assess sensitivity to vertical separation assumption
  - perform analyses at other viewing angles (matched GEOsat, VIIRS)
  - include 1.38 µm reflectance, NWP analysis data as input
- Develop tests to objectively apply the LANN and Ztop NN
- Test capability of NN method to estimate Z_{eff}, τ_{icer}, etc.
  - if only one parameter can be determined, other approaches (e.g., MCOAT) will be able to retrieve the remaining ML parameters

Assume We Start Getting ML correctly?

- How does one handle the 2-D ISSCP-like histogram?

- We currently slam ML clouds into some lower layer?
  - with ML retrieval: tau for high and low: but only one albedo

??