A Neural Network Approach to Infer Optical Depth of Thick Ice Clouds at Night

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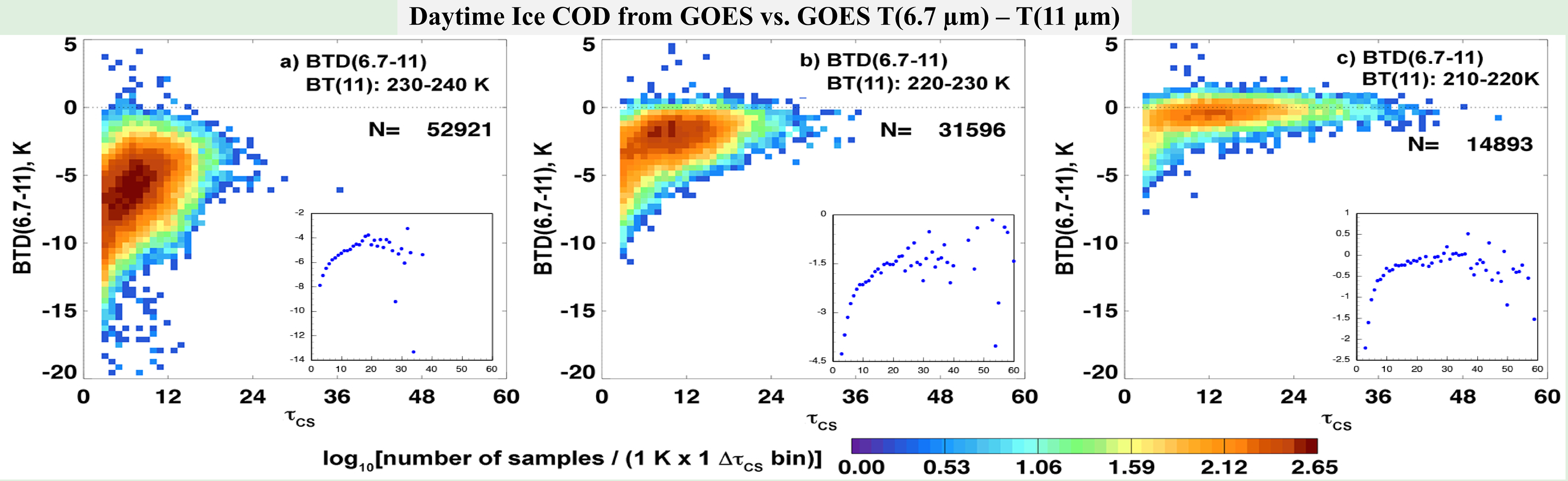
Introduction

During daytime, cloud properties such as cloud optical depth (COD or τ), effective particle size Re, and water path (WP) can be derived for a wide range of cloud thicknesses because the reflectance at visible wavelengths is sensitive to changes in optical depth from $\tau < 1$ to $\tau > 100$. At night, information from solar channels is unavailable, so retrievals of the cloud properties are typically limited to clouds having COD < 6, because the cloud is essentially a blackbody at greater optical depths, at least for the window channel wavelengths (10- 12 µm) typically used for retrievals from satellite imagers. This limitation constrains the monitoring of cloud properties over the full diurnal cycle and leaves a gap in the ability to characterize clouds both at meteorological and climate scales. This paper examines the potential of using a neural network method with channels available on many current imagers to extend the range of ice cloud optical depths that can be determined from radiances measured at night. Wavelengths, 3.9, 6.7, 10.8, and 12-µm, are considered here.

Correlation of IR data and COD

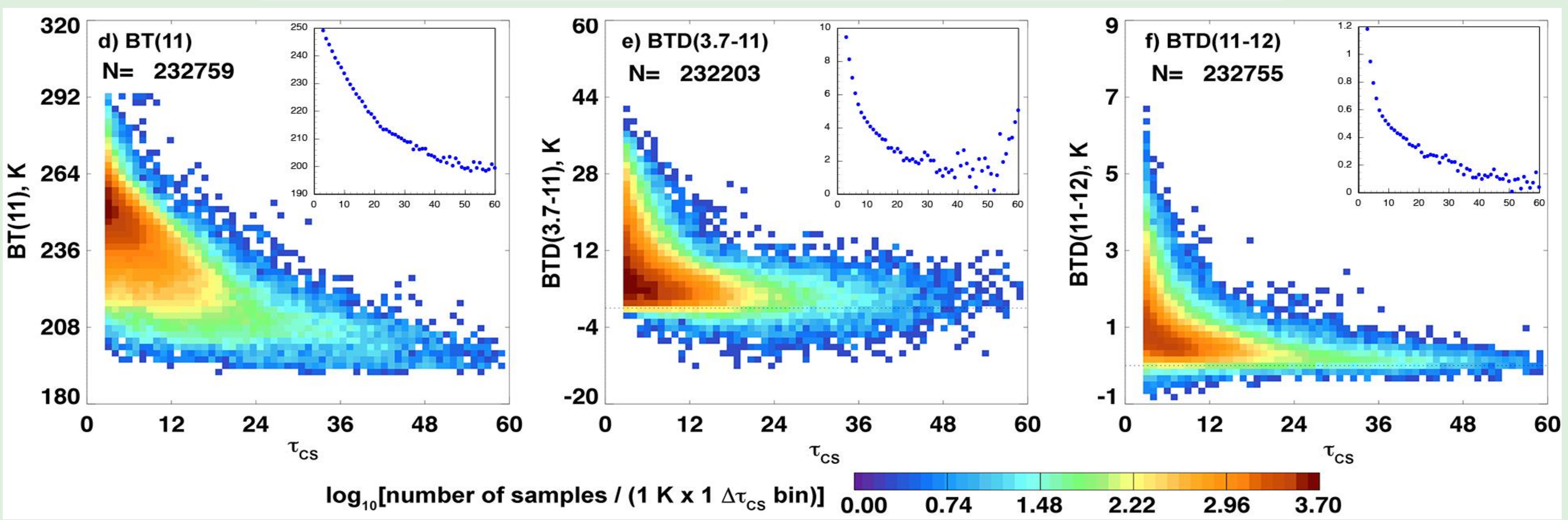
Matched BTD and COD data from several months of GOES-12 data were amassed and plotted as a function of COD. The apparent correlation tends to increase as Tcld increases, with possible usable information up OD = 20 or so. Yet, even for low Tcld values, there may be some independent information. Note that GOES data were not screened for ML clouds that cause some of the spread or decorrelation. These observations indicate potential for using the IR data.

Daytime Ice COD from GOES vs. GOES T(6.7 µm) – T(11 µm)



Several thermal channels have sensitivity to ice COD up values > 50 because of the vertical non-uniformity of the thicker ice cloud tops. This sensitivity can be seen in several other channel sets below where ice COD is estimated from the CloudSat 2B-CWC-RO product and compared with matched Aqua MODIS data from the C3M dataset (Kato et al. 2010).

Nighttime Ice COD from CloudSat vs. Aqua MODIS Infrared Parameters, October 2010



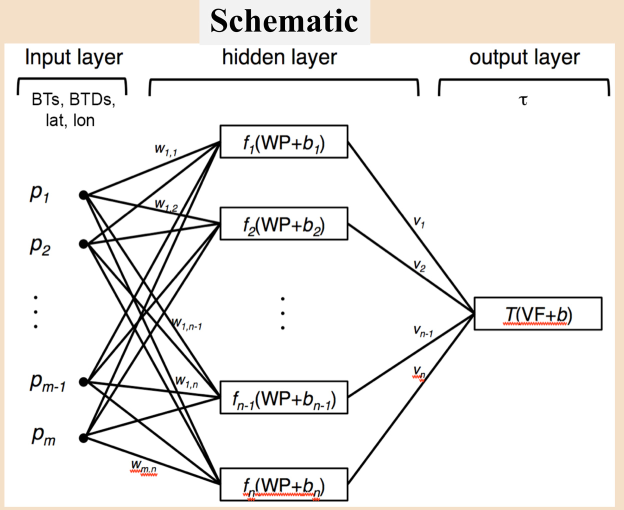
Because the values of each parameter asymptote to some value as τ increases past 16 and are a bit noisy for a given COD, a neural network was selected as the approach to obtain better estimates of ice COD from these various parameters.

DATA

- **Training Set:** Matched March and October 2007 CloudSat Ver. 4 2B-CWC-RO and Aqua MODIS Infrared Brightness Temperatures
  1. **BCH:** Select only opaque ice clouds based on *Baum et al. (2000), Choi et al. (2007), & Hong et al. (2010), only use T11 < 260 K (**BCH** method)*
  2. **Ideal:** Use only pixels selected by BCH that have $\tau_{CS} \geq 8$. No thin clouds included.
     - Use up to 10 input parameters, e.g., T11, BTD(11-12), BTD(3.7-11), BTD(6.7-11), BTD is brightness temperature difference & wavelengths are in parentheses
     - Compute ice COD by integrating CloudSat CWC and Re profiles for T < 0° C (for T > -20° C, use linearly weighted fraction of COD between -20° C and 0° C
- **Validation Set:** Matched March and October 2008 CloudSat COD and Aqua MODIS Infrared Brightness Temperatures
  - Test with both **BCH** and with Shortwave-infrared Infrared Split-window Technique (***SIST***, Minnis et al. 2011) selections of opaque ice cloud pixels
- **Sample Images**: to illustrate results

APPROACH: Ice Cloud Optical Depth using a Neural Network (ICODIN)

Schematic



Weighting vector in hidden layer

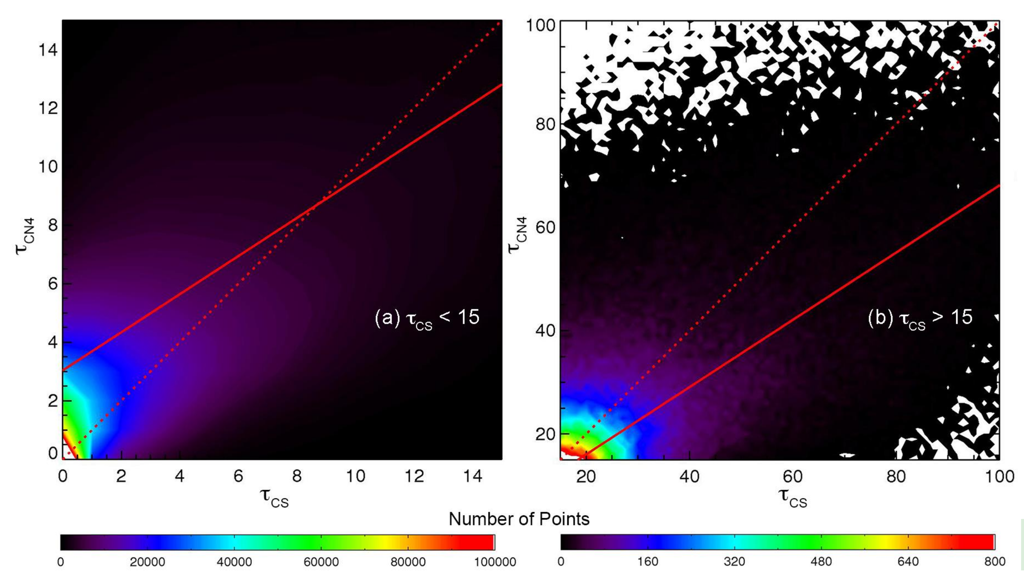
$$\begin{pmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,n-1} & w_{1,n} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,n-1} & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{m-1,1} & w_{m-1,2} & \cdots & w_{m-1,n-1} & w_{m-1,n} \\ w_{m,1} & w_{m,2} & \cdots & w_{m,n-1} & w_{m,n} \end{pmatrix}$$

- neurons of input layer: vector $\boldsymbol{P}(p_1, p_2, \ldots p_{m-1}, p_m)$, where m is number of input neurons or parameters.
- m=10 neurons of $\boldsymbol{P}$
  - T(3.7), T(6.7), T(11), and T(12), BTD(3.7-6.7), BTD(3.7-11), BTD(6.7-11), BTD(11-12), LAT, LON
- n=50 neurons are used in the hidden layer for training, 1 neuron (COD) in output layer
- output layer weighting vector, $\boldsymbol{V}(v_1, v_2, \ldots, v_{n-1}, v_n)$: weights between hidden and output neurons
- vector, $\boldsymbol{B}(b_1, b_2, \ldots, b_{n-1}, b_n)$: bias in the hidden layer and b is bias in the output layer
- network training function of Bayesian regulation backpropagation is used for three-layer neural network
  - training function updates the weight and bias values according to Levenberg-Marquardt optimization
  - minimizes squared errors & weights, then finds the correct combination to produce a network that generalizes well
  - log-sigmoid transfer function $s(x)$ to propagate to the hidden layer
  - hyperbolic tangent sigmoid transfer function $t(x)$ to propagate to the output layer
- 60% of 2007 data used for training, 20% for updating, and 20% for testing
- 4 channel combinations were used
  - **ICODIN4**: all ten parameters
  - **ICODIN3a**: no 3.7 µm
  - **ICODIN3b**: no 6.7 µm
  - **ICODIN3c**: no 12 µm

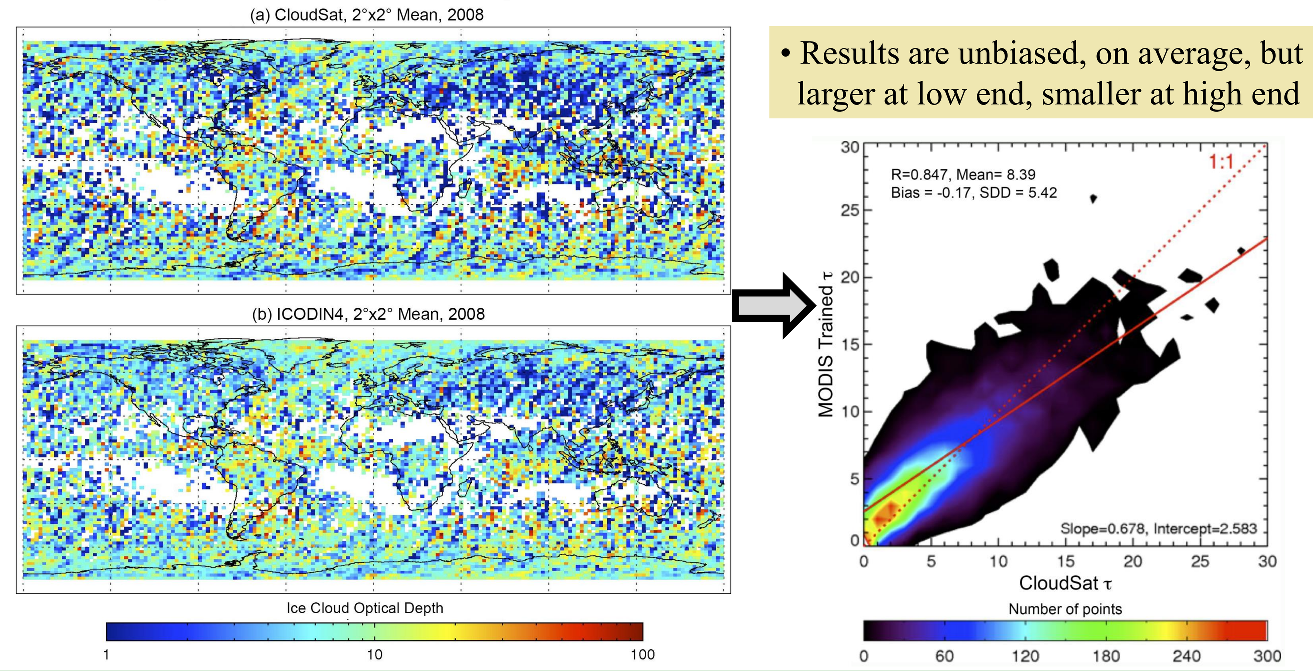
RESULTS: Opaque from BCH

- Opaque defined by MODIS data (BCH method)

BCH Training Results

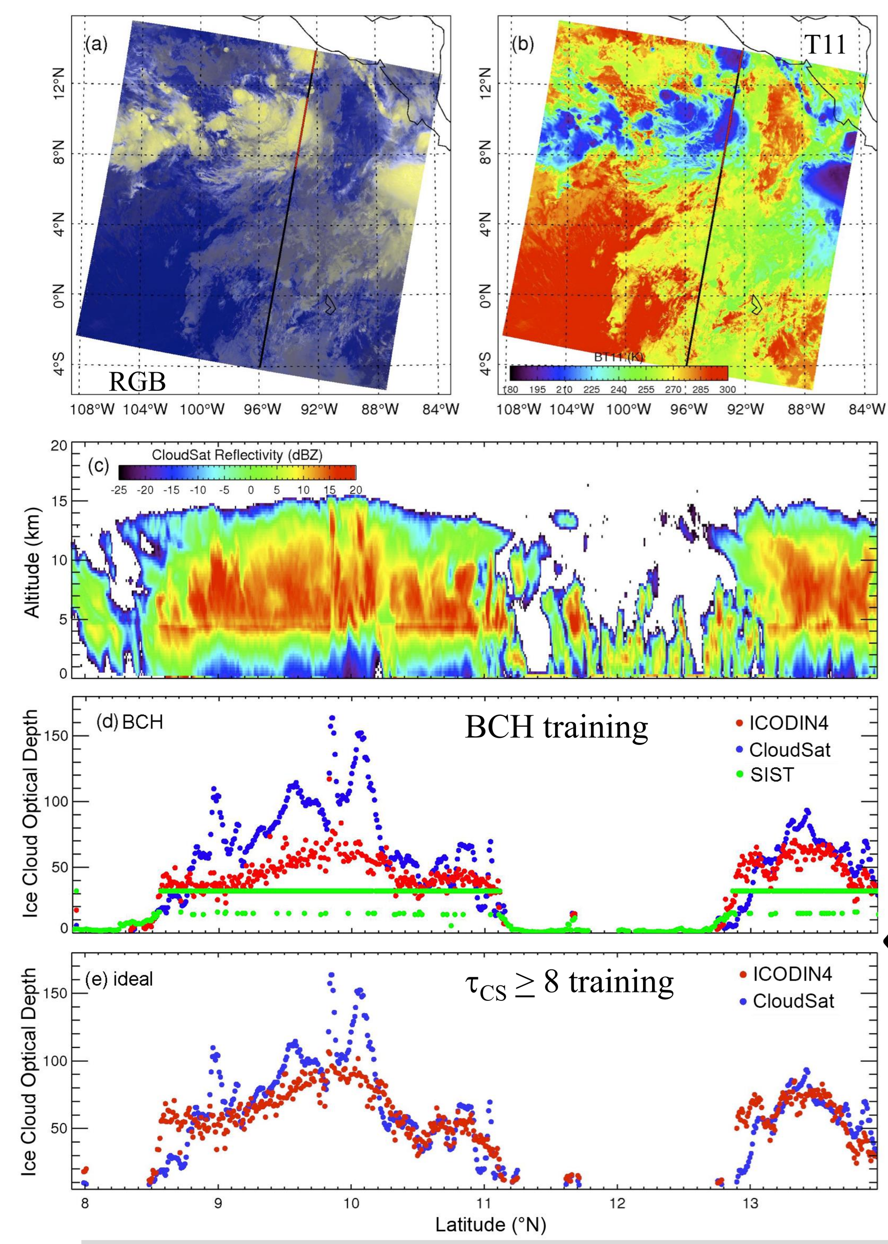


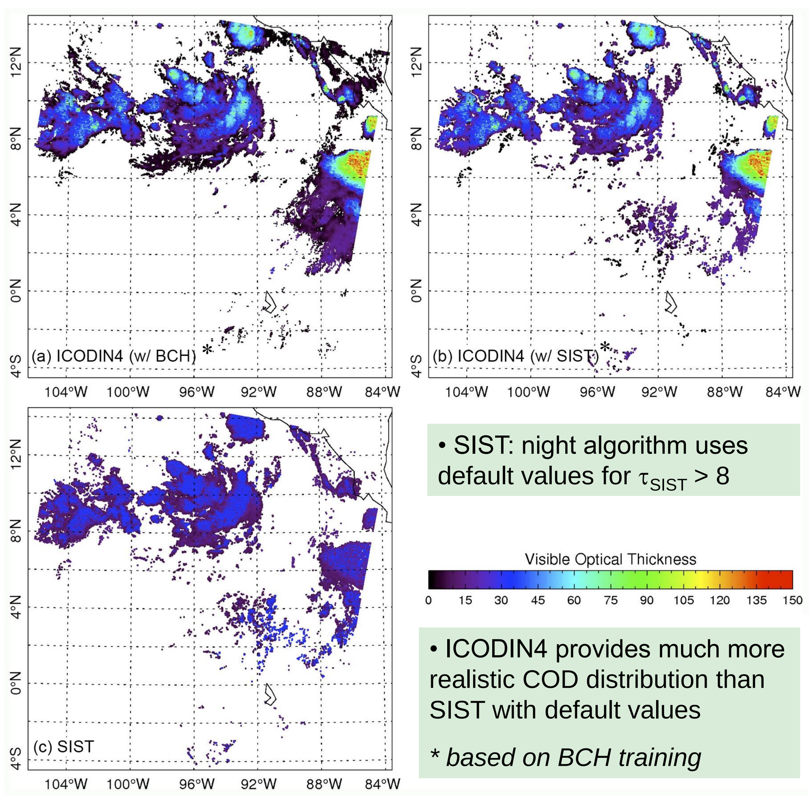
Regional COD comparisons with validation dataset



- Results are unbiased, on average, but larger at low end, smaller at high end
- BCH training reveals shortcomings in opaque cloud detection; gives large uncertainties

Aqua MODIS/CloudSat data and retrievals (108°W-84°W, 4°S-15°N), 0800 UTC, 6 June 2008



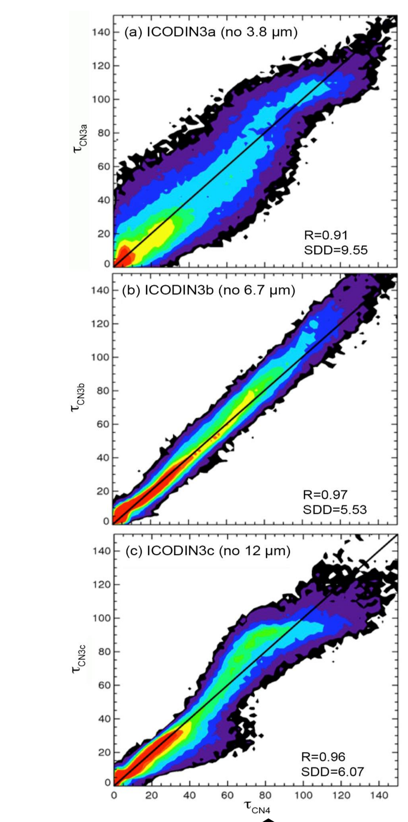


- SIST: night algorithm uses default values for $\tau_{SIST} > 8$
- ICODIN4 provides much more realistic COD distribution than SIST with default values

** based on BCH training*

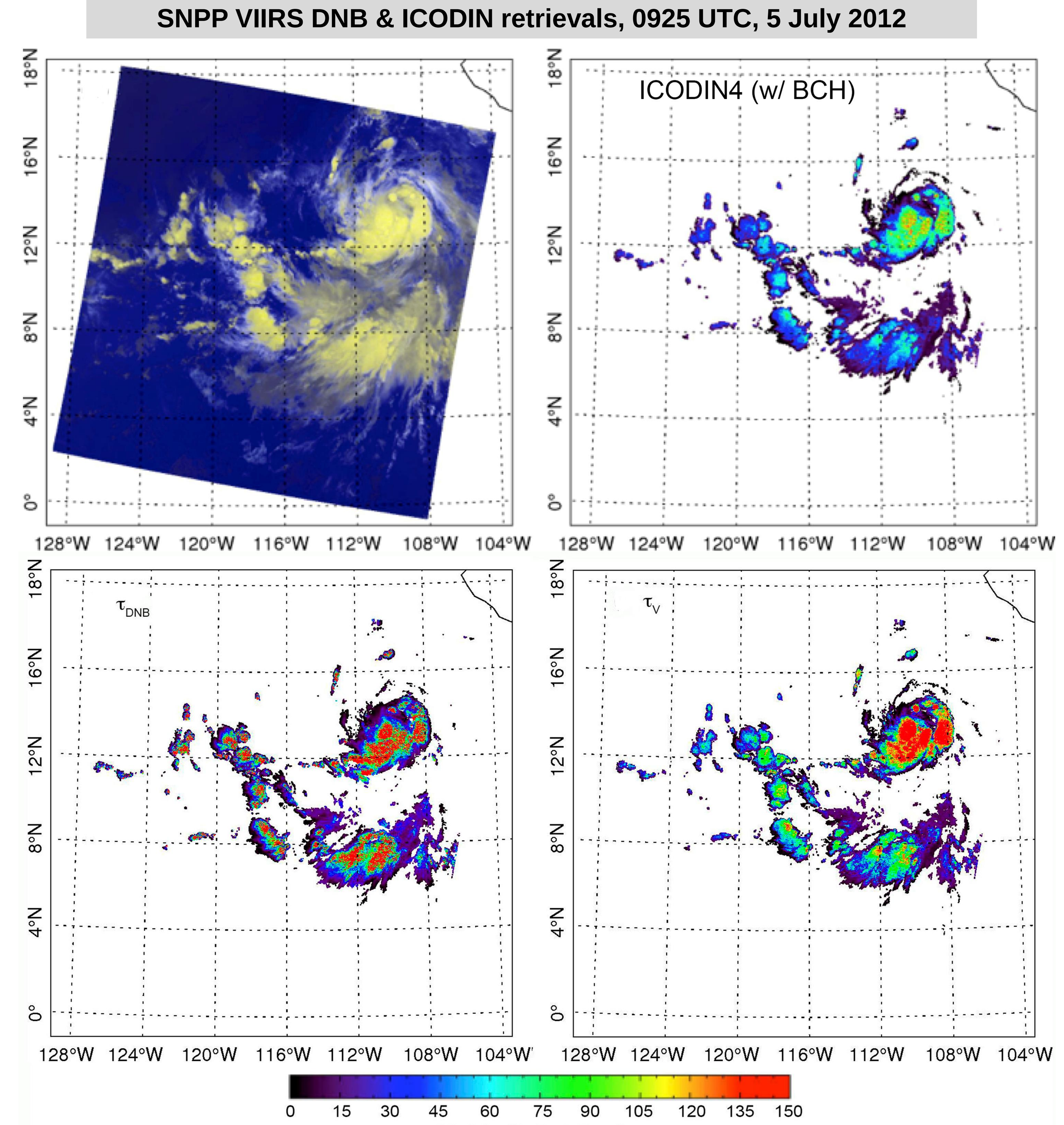
- BCH training includes many optically thin clouds and dampens the upper end of the COD range
- training with $\tau_{CS} > 8$ (ideal) produces much more realistic results over a large range (some trouble on low end?)
- applying ICODIN with $\tau_{CS} > 8$ in practice would require improved methods for identifying opaque ice clouds

Correlation of 3-ch w/ 4-ch results



3-channel ICODIN3b compares best with ICODIN4 (τ_{CN4}) indicating that 6.7-µm contains less information that 3.8 and 12 µm. ICODIN3a, while not as accurate can be used during the day, perhaps for multilayer cloud retrievals.

SNPP VIIRS DNB & ICODIN retrievals, 0925 UTC, 5 July 2012



- ICODIN only retrieves ice COD, does not account for water cloud under ice cloud
- ICODIN underestimates total COD retrieved from DNB reflectance using VISST, τ_{DNB}
- Total COD, τ_V, can be estimated from parameterization of Smith (2014) using τ_{CN4}
  - $\tau_V < \tau_{DNB}$, mostly. Will likely be better if $\tau_{CS} > 8$ training is used

COD Difference Statistics ICODIN-CloudSat, BCH Training

Retrieval Method	Year	Mean	R	Bias	Bias (%)	SDD	SDD (%)
BCH opaque only							
ICODIN4	2007	8.85	0.80	-0.07	-0.8	8.73	99
3.7, 6.7, 11, 12 µm	2008	8.50	0.78	-0.10	-1.2	8.89	105
ICODIN3a	2007	8.95	0.79	-0.05	-0.6	9.20	103
6.7, 11, 12 µm	2008	8.60	0.75	-0.07	-0.8	9.45	110
ICODIN3b	2007	8.83	0.79	-0.09	-1.0	8.91	101
3.7, 11, 12 µm	2008	8.51	0.78	-0.10	-1.2	8.94	105
ICODIN3c	2007	8.86	0.80	-0.05	-0.6	8.80	99
3.7, 6.7, 11 µm	2008	8.51	0.77	-0.10	-1.2	9.13	107
SIST	2007	7.40	0.63	-2.42	-24.6	12.2	124.4
	2008	7.16	0.64	-2.19	-23.4	11.6	124.4
Ideal (BCH & CloudSat opaque)							
Ideal ICODIN4	2007	21.8	0.73	-0.07	-0.3	13.2	61
3.7, 6.7, 11, 12 µm	2008	21.3	0.71	-0.33	-1.5	13.5	63

Summary

- Neural network using multispectral IR data can improve ice COD estimates at night
  - unbiased results, on average, and 21% reduction in random error
  - SDD ~ 100% when BCH or SIST selects opaque clouds
  - using $\tau_{CS} > 8$ to train yields bias of 0% and SDD of 63% for true opaque cloud
    - *using BCH gives 20% bias and 80% SDD*
  - can be used for any modern imager dataset
- Need improved method for diagnosing optically thick ice clouds from multispectral IR
- Improvements can be be made
  - use T, RH profiles, Zsfc, cloud heterogeneity
  - use to discriminate contiguous vs. high ice over low water clouds
  - test and adjust for non-nadir views

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