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Remote sensing of three-dimensional clouds using multispectral measurements by SGLI

Hironobu Iwabuchi (PI), Hana Kato (Co-I)
Tohoku University
PI No.: ER2GCF204

Introduction

- Cloud properties (Cloud optical thickness; **COT**, cloud droplet effective radius (CDER) are globally retrieved by satellite observations using LUT itaration method (Nakajima and King, 1990).
- The method approximates clouds as a plane plate and is based on a **1-D radiative transfer** calculation.
- But radiation propagate three-dimensionally. → Errors in cloud property estimation (Várnai and Marshak, 2002; Marshak et al., 2006)
- Multipixel approach (e.g. convolutional neural network) is effective if trained based on **3-D radiative transfer** (Faure et al., 2001; 2002; Iwabuchi and Hayasaka, 2003; Cornet t al., 2004)
- However, the convolution kernel depends on various conditions (cloud thickness, inhomogeneity, wavelength, sun angles etc.), and it is hard to represent nonlinear relationships among them.
- Using **deep convolutional neural network** (CNN), Okamura et al (2017) showed the feasibility of more accurate COT and CDER estimation.

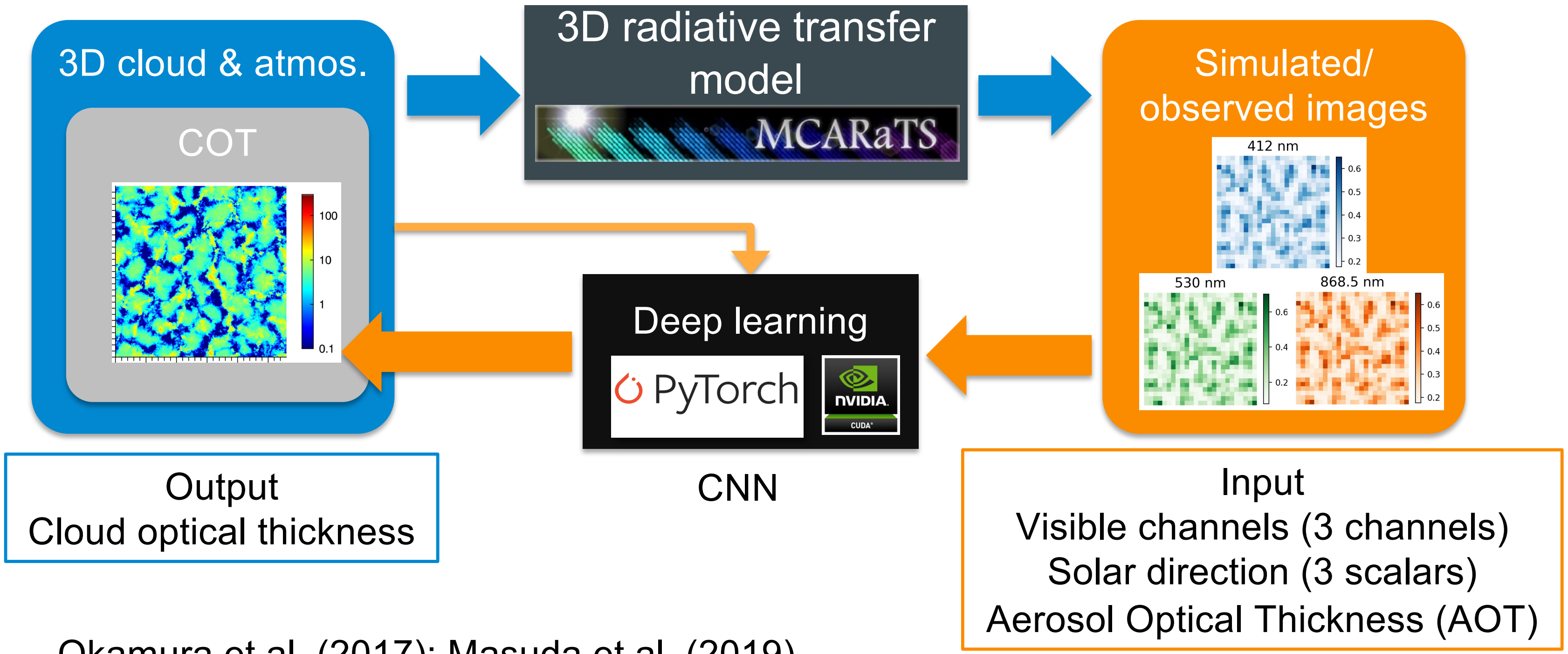
Objectives

1. 3D radiative transfer-based COT retrieval using deep learning for SGLI
    - To develop a method for COT retrieval taking into account cloud inhomogeneity and 3D radiative transfer using DNN and 3D radiative transfer model
    - To evaluate the 3D and inhomogeneity effects by applying this method to the GCOM-C SGLI observation data
2. Statistical retrieval for cloud properties (COT and cloud top height) from Himawari-8/AHI
    - Using only IR channels for consistent observation regardless to sunlight
    - Full-disk data analysis with 2-km resolution (6000 x 6000 pixels) within ~10 minutes

High accuracy, high computational efficiency

Approach

We train a deep learning model by simulation data based on physics models.



Okamura et al. (2017); Masuda et al. (2019)

Data and Method

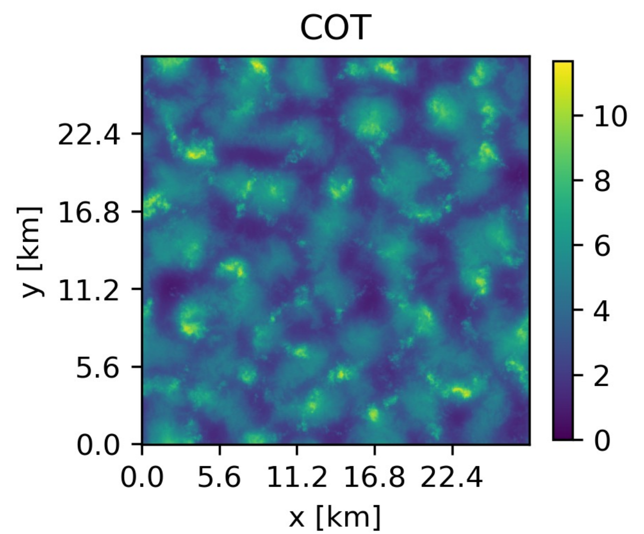
3D cloud data simulated by SCALE
(Sato et al., 2014; Nishizawa et al., 2016)

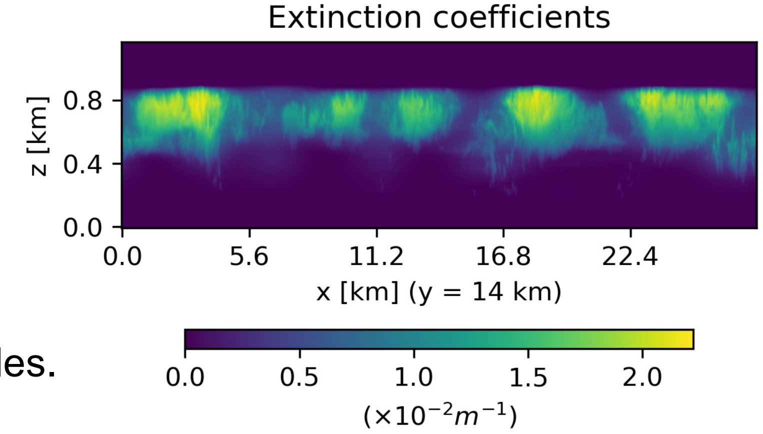
↓

3D radiative transfer simulation by MCARaTS

↓

Simulated SGLI multispectral images



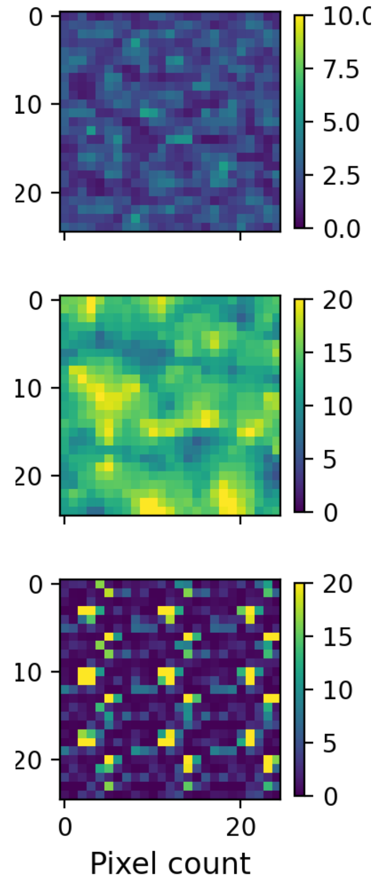


Simulations were performed for various cloud cases and sun angles.

Data and Method

Input Image	Reflectances (VN3:443 nm, SW1:1050 nm)
Input Vector	Solar zenith angle (0–70˚), Solar azimuth angles (0–360˚), Aerosol optical thickness (0.05–1)
Output Image	Cloud optical thickness (0.5 - 300)
Resolution	1 km × 1 km
Image Size	24 × 24 pixels
Samples	Training : 22,000 samples Validation : 4,880 samples Test : 2,400 samples
Augmentation	Horizontal and vertical stretching, extinction scaling (x1/2–2), cloud height

Examples of dataset (COT)



Data and Method

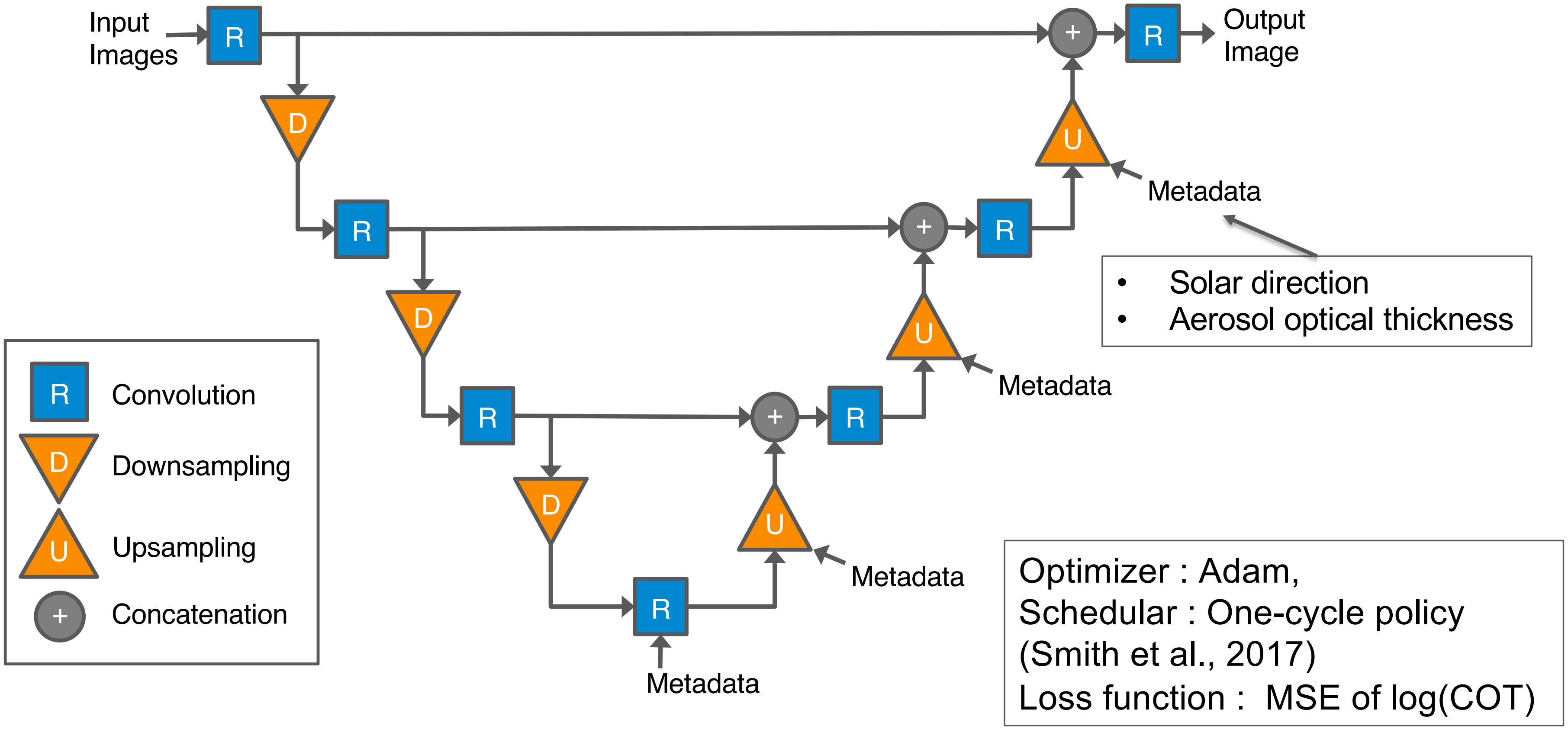
Model description

	Training data	Model
3D model	dataset from 3D radiative transfer calculation	Modified U-Net (including convolution)
1D model	dataset from 1D radiative transfer calculation	PixNet (pixel-by-pixel)

- The 1D model is for comparison and is designed to reproduce the current, operational algorithm.

Loss Function : Mean square error of log(COT)

CNN Model


Input
Images
R
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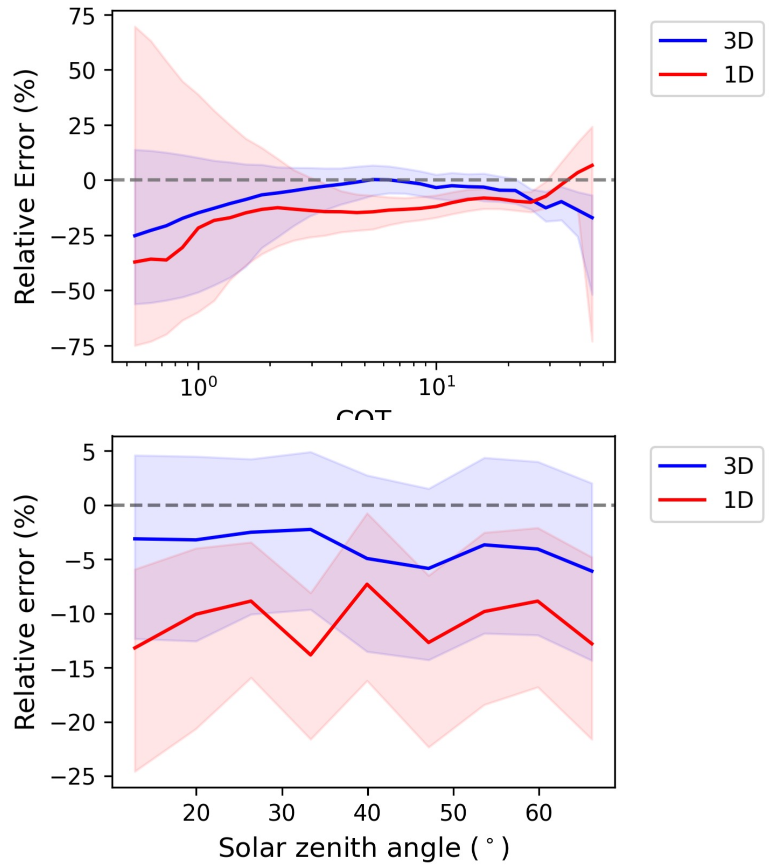
+
R
Output
Image
Metadata
Metadata
Metadata
Metadata
• Solar direction
• Aerosol optical thickness
R Convolution
D Downsampling
U Upsampling
+ Concatenation
Optimizer : Adam,
Schedular : One-cycle policy
(Smith et al., 2017)
Loss function : MSE of log(COT)

Results | evaluation

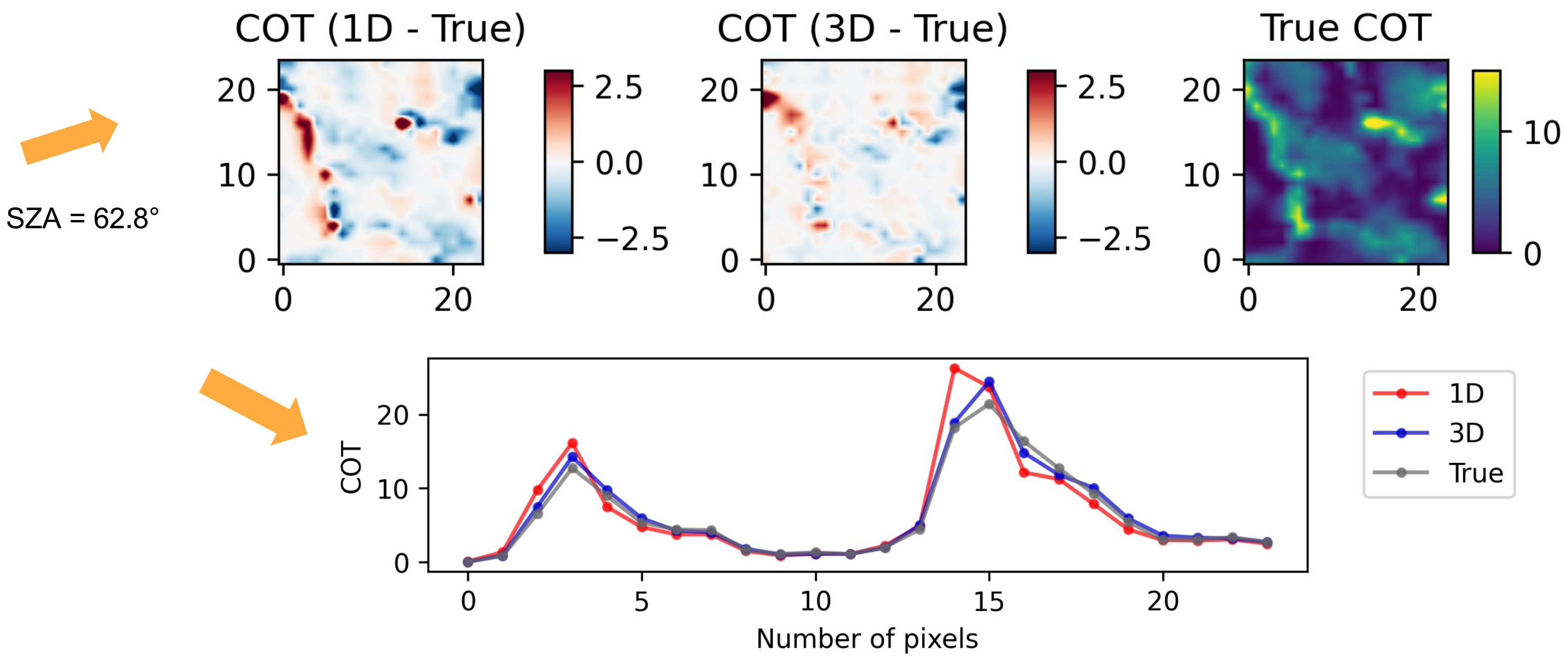
	RMSE (3D)	RMSE (1D)
All	67.8 (%)	74.4 (%)
COT [0.5, 1)	193 (%)	218 (%)
COT [1, 10)	46.5 (%)	46.5 (%)
COT [10, 300]	12.3 (%)	15.1 (%)

- Where COT ≧ 1,
  RMSE (3D) < RMSE (1D).
- The solar zenith angle dependence
  of the error is small for both models.



Solid line : 50 percentile
Dashed line : 25, 75 percentiles

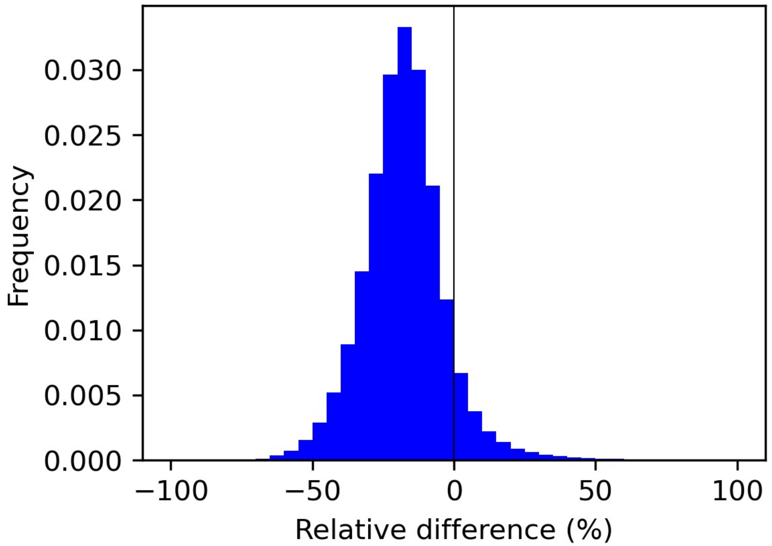
Results | case study



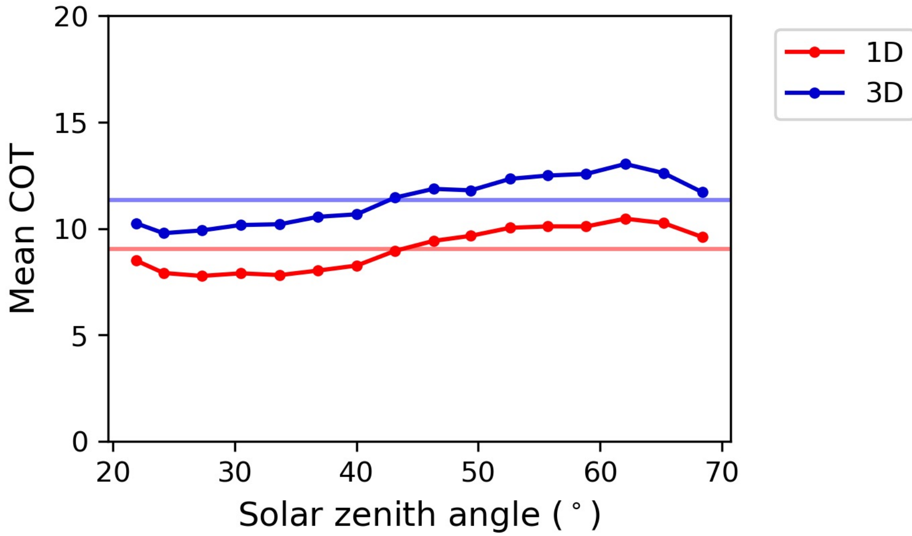
- For 1D model, cloud pixels on the sun side are overestimated and those on the opposite side of the sun are underestimated.

Results | SGLI

Data : October 2021 (1 month), 1 km resolution, Marine obeservation

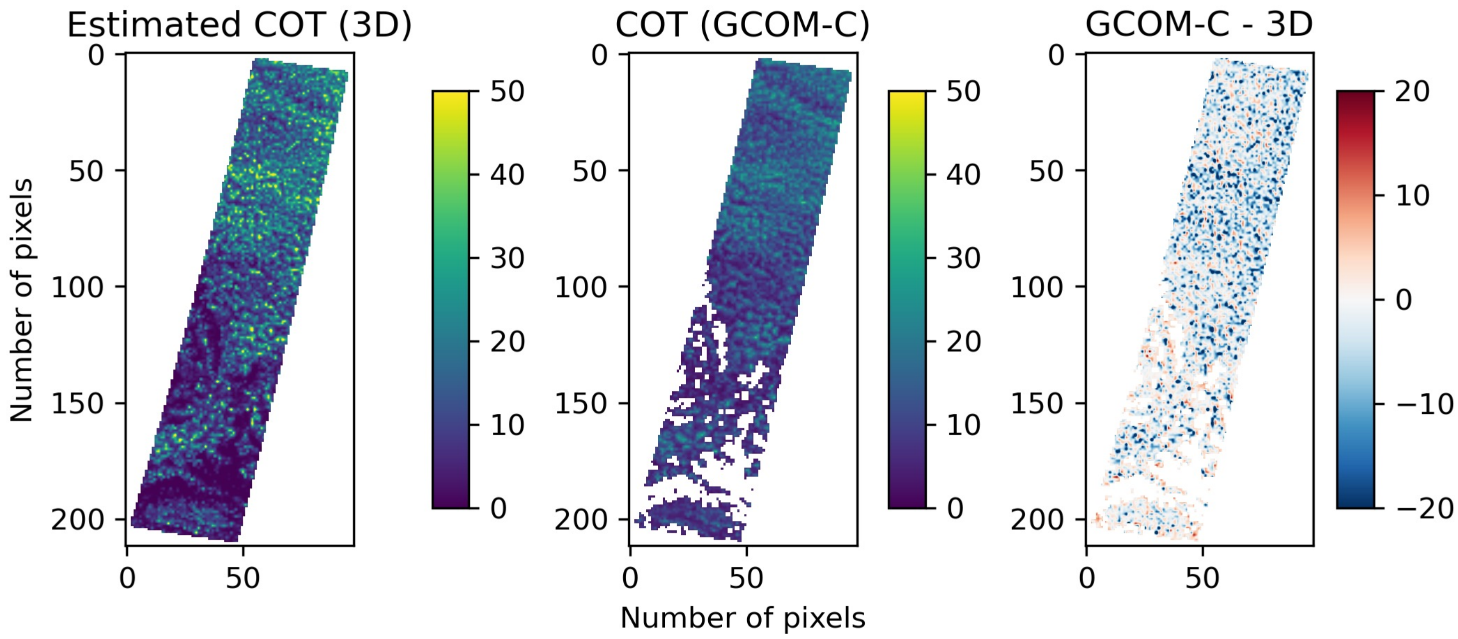


COT (1D) – COT (3D)



- The 1D model estimates the COT about 20% smaller than the 3D model.
- Its underestimation tendency does not depend on the solar zenith angle.

Results | SGLI case study

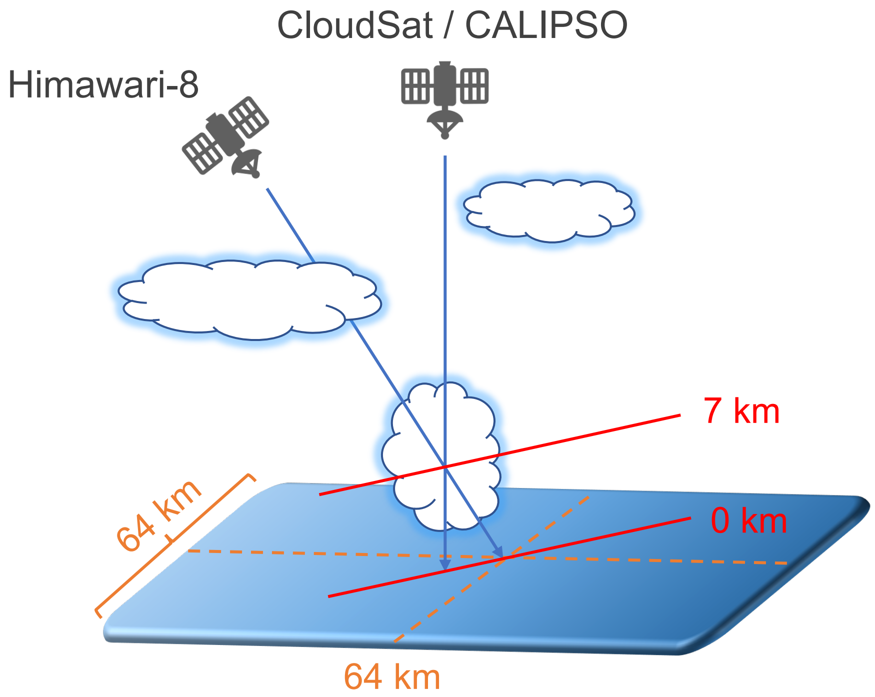


- Where the clouds are thick, COT (3D) > COT (GCOM-C)
- Some cloud pixels are overestimated at the edge of the clouds.

Part 2

Cloud identification and property retrieval from Himawari-8

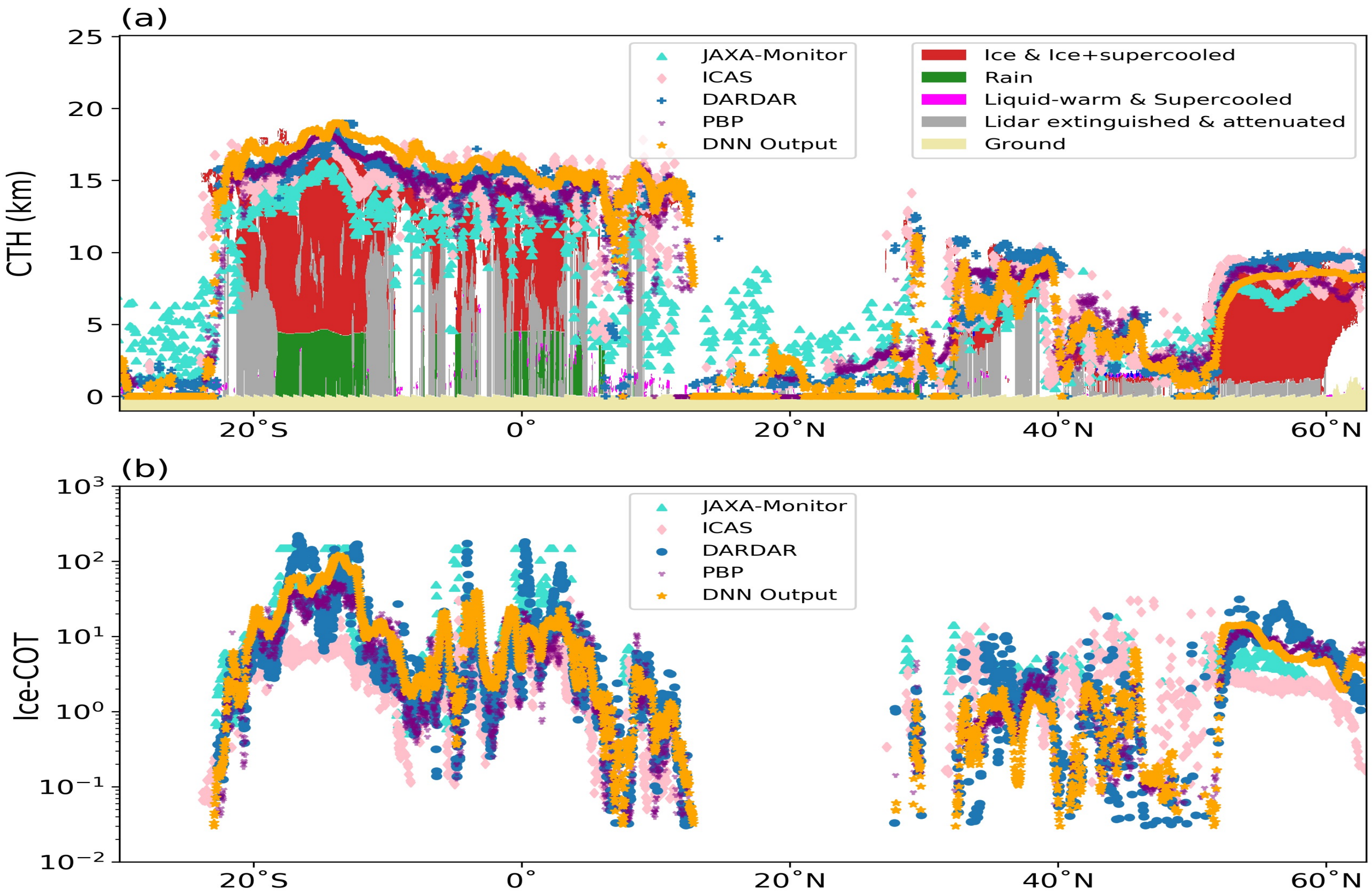
Model	Stack of convolution: image to vector MSE Loss Function + 0.5 × CrossEntropy Loss Function Adam optimizer and One-cycle policy scheduler
Input segment	Size: 32 × 32 pixel Train: 1,318,119 segments Test: 145,992 segments
Data period	4 months (Jan, Apr, Jul, Oct) of 2016
Input Image	Brightness Temperature from 4 infrared bands, [8.6, 10.4, 12.4, 13.3 μm] Sea Surface Temperature, Surface Elevation
Input Vector	Air Temperature on 8 pressure levels, Observation Time, Satellite Zenith Angle and Amuzith Angle
Target Vector	Cloud Top Height (CTH), Ice Cloud Optical Thickness (Ice-COT)
Resolution	~2 km, ~0.02˚ (60˚S – 60˚N)



Collocation over one segment

Part 2

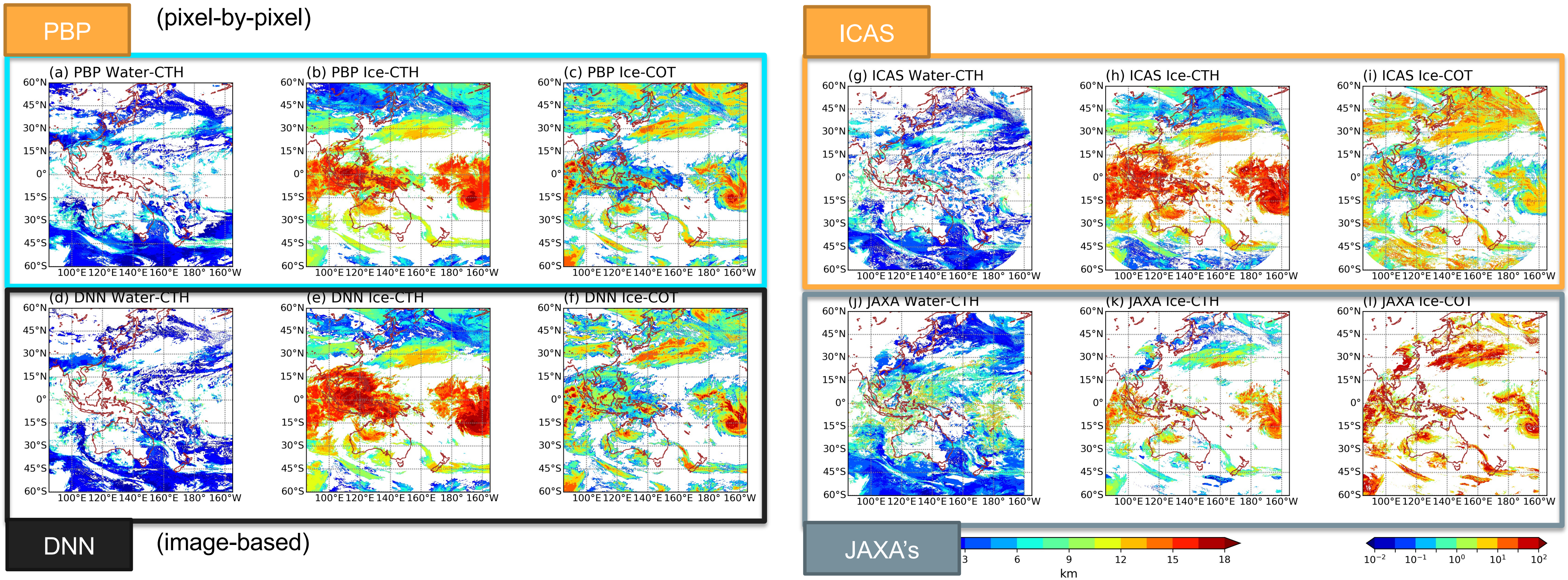
Case testing along a CloudSat/CALIPSO track



- The DNN result has the highest consistency with the DARDAR truth for both CTH and COT.
- The ICAS can be used as an reference for the full-disk **CTH** estimation, as an alternative of the DARDAR truth.
- DNN has the combined advantages of *ICAS* and *JAXA* on **COT** estimation, for *thin* and *thick* clouds respectively.

Part 2

Case testing over a full H8/AHI granule



- DNN can well reproduce the cloud systems, with specific values of CTH and COT.
- When compared to the DNN, the PBP model tends to underestimate high (>13km) and thick (τ>50) cloud.
- One full-disk retrieval takes about 20 minutes with one processor.

Conclusions

- We have developed a DNN approach for the retrieval of COT from a SGLI visible band and a SWIR band.
- The training and test data of the DNN are made by the 3D radiative transfer simulation whose input are 3D cloud fields from large-eddy simulations.
- Utilizing spatial features, our 3D method is able to estimate COT with higher accuracy than the 1D (IPA; independent pixel approximation) retrieval.
- A case study using SGLI observation data shows that our method tends to estimate **larger COT by 20% on average** than the IPA method and the operational COT retrieval method of GCOM-C/SGLI.
- Identification and property retrieval of cloud from Himawari-8/AHI is remarkably improved by using image-based neural networks. DNN is indeed accurate with helps by **spatial features**, which has not been explored well in traditional approaches.

Publications (FY2021)

- Wang, X., H. Iwabuchi, T. Yamashita: Cloud identification and property retrieval from Himawari-8 infrared measurements by a deep neural network. Remote Sensing of Environment, 2022 (under review).
- Nataraja, V., S. Schmidt, H. Chen, T. Yamaguchi, J. Kazil, K. Wolf, G. Feingold, H. Iwabuchi: Segmentation-Based Multi-Pixel Cloud Optical Thickness Retrieval Using a Convolutional Neural Network. Atmos. Meas. Tech., 2022 (submitted).
- 岩渕 弘信, Wang Xinyue, 加藤 葉菜, 山下 尭也: 深層ニューラルネットを用いた衛星画像解析による雲と気象状態の推定 (Estimation of cloud and meteorological state from satellite image by deep neural network). JpGU Annual Meeting 2021.
- Wang, X., H. Iwabuchi, and T. Yamashita: Retrieval of cloud properties from Himawari-8 measurement with a deep neural network method. [A-AS04] Machine Learning Techniques in Weather, Climate, Hydrology and Disease Predictions. JpGU 2021.

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