Retrieval of Atmospheric Aerosol Properties for geostationary and JAXA polar-orbital Satellite Imaging Sensors

Mayumi Yoshida *, Maki Kikuchi, Takashi M. Nagao, Hiroshi Murakami, Keiya Yumimoto, Taichu Tanaka

*Earth Observation Research Center (EORC), Japan Aerospace Exploration Agency (JAXA)

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Motivation

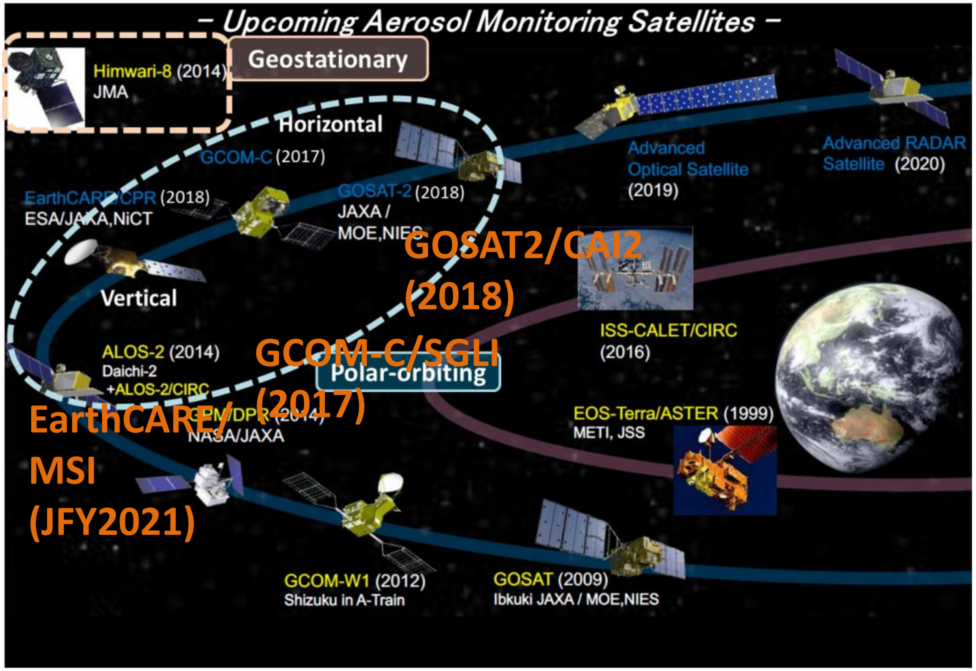
Our final goal

- produce synergistic global aerosol data set
  - using **JAXA Polar-orbiting** and **geostationary** satellites
  - Provided in near real time

This study

- A **common aerosol retrieval algorithm** is developed
  - for various satellite imaging sensors
  - over both land and ocean

Current and Upcoming Aerosol Monitoring Satellite



Target sensors

Geostationary:
Himawari-8/AHI, GOES-R, Meteosat
Polar-orbiting:
Aqua, Terra/MODIS, **GCOM-C/SGLI,** GOSAT2/CAI2, EarthCARE/MSI

Sensor Characteristics

Himwari-8/AHI characteristics

CH	λ(nm)	IFOV (m)
1	471	1000
2	510	
3	639	500
4	857	1000
5	1610	2000
6	2257	
7	3885	
8	6243	
9	6941	
10	7347	
11	8592	
12	9637	
13	10407	
14	11240	
15	12381	
16	13311	

High temporal resolutions

16 bands in Visible-Infrared

10 minutes interval

GCOM-C/SGLI characteristics

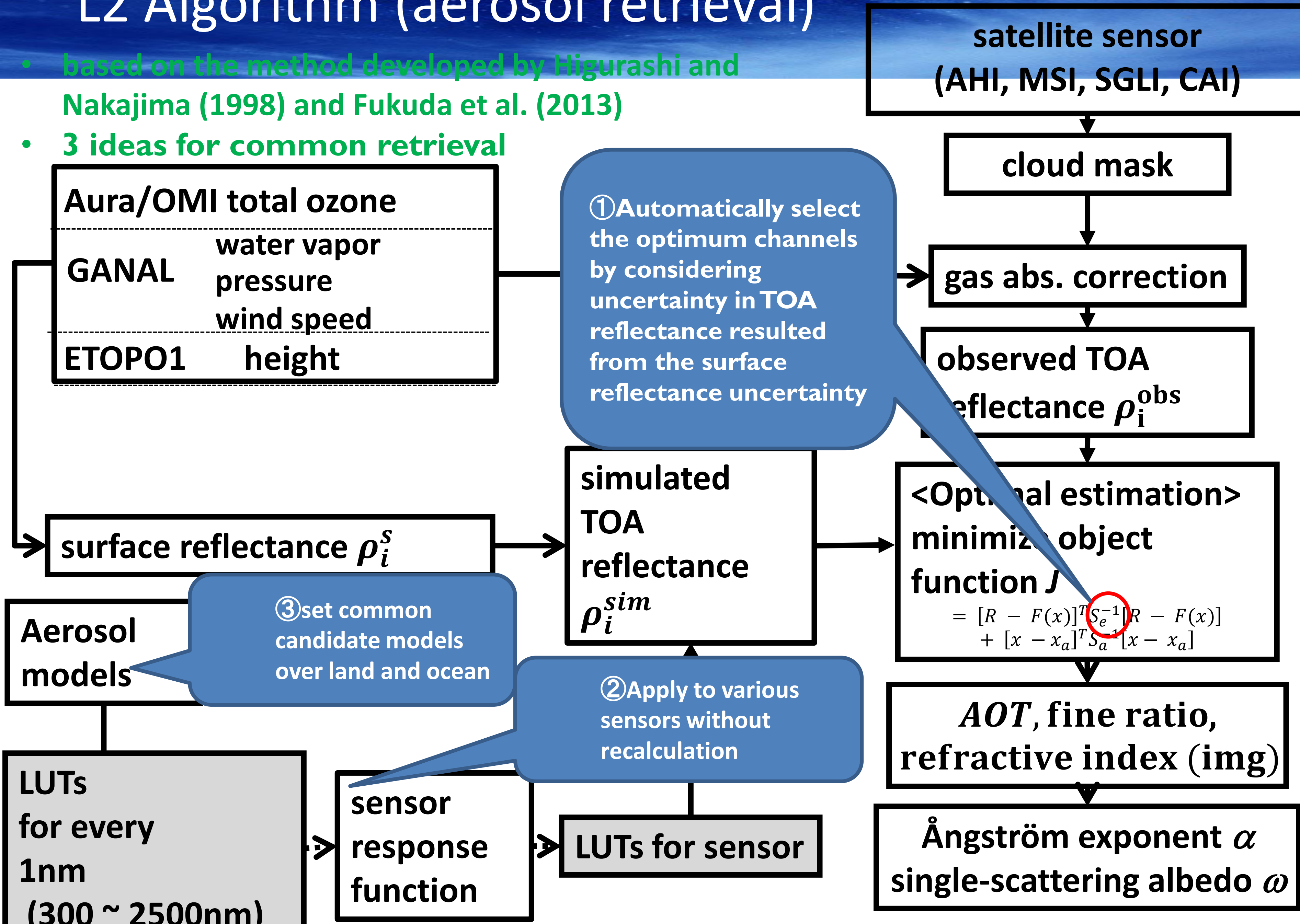
CH	λ(nm)	IFOV(m)
VN1	380	250
VN2	412	
VN3	443	
VN4	490	
VN5	530	
VN6	565	
VN7	673.5	
VN8	673.5	
VN9	763	
VN10	868.5	
VN11	868.5	
POL1	673.5	1000
POL2	868.5	
SW1	1050	
SW2	1380	
SW3	1630	250
SW4	2210	1000
TIR1	10800	250
TIR2	12000	250

High spatial resolutions

19 bands in Visible-Infrared

L2 Algorithm (aerosol retrieval)

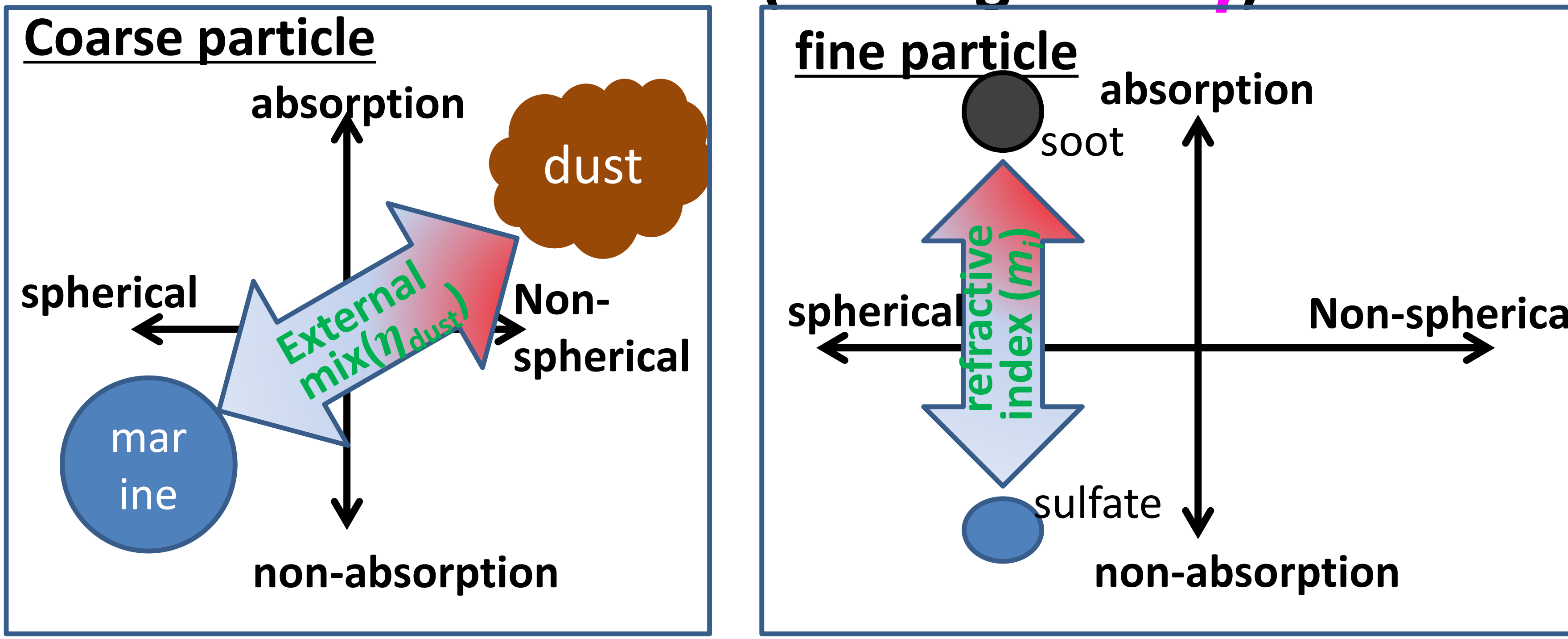
- based on the method developed by Higurashi and Nakajima (1998) and Fukuda et al. (2013)
- 3 ideas for common retrieval



Yoshida et al., 2018

Aerosol model

external mixture (mixing ratio η)



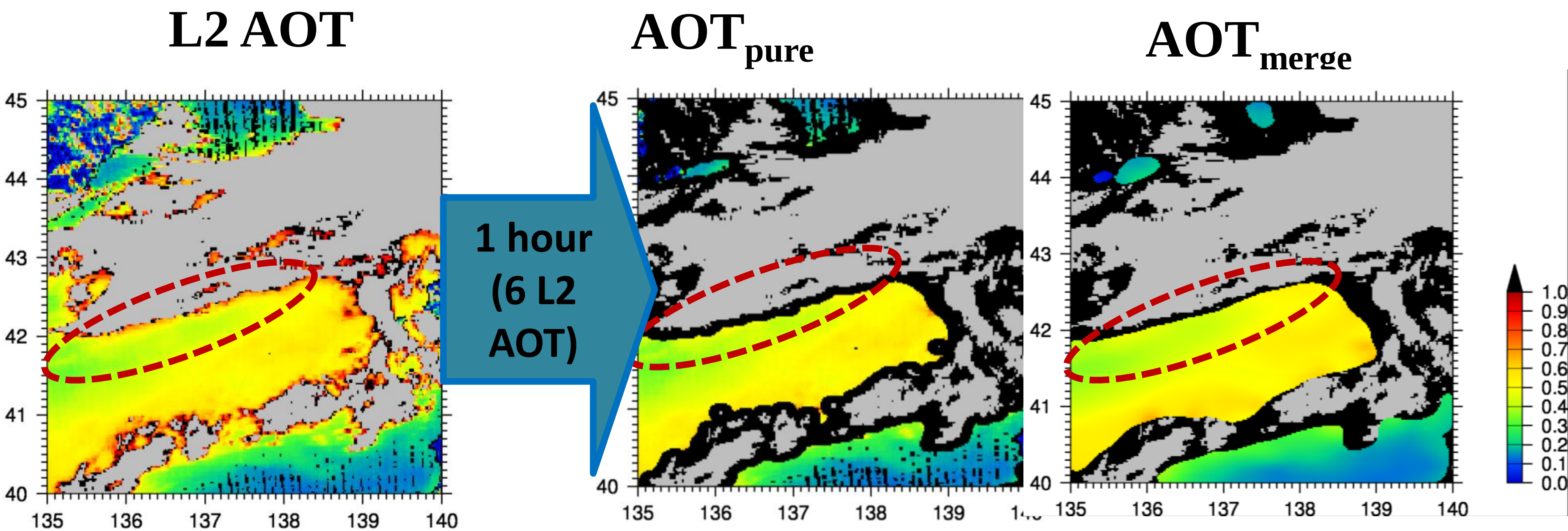
*each aerosol model is based on Omar et al., 2005 and Sayer et al., 2012.

□Estimated parameter

- **Aerosol optical thickness**
- **Fine ratio(η)**
- **Single scattering albedo** coarse: external volume mixing ratio (η_{dust})
  fine : imaginary part of the refractive index (m_i)

L3 Algorithm

01 : 00 UTC, 27 April 2015

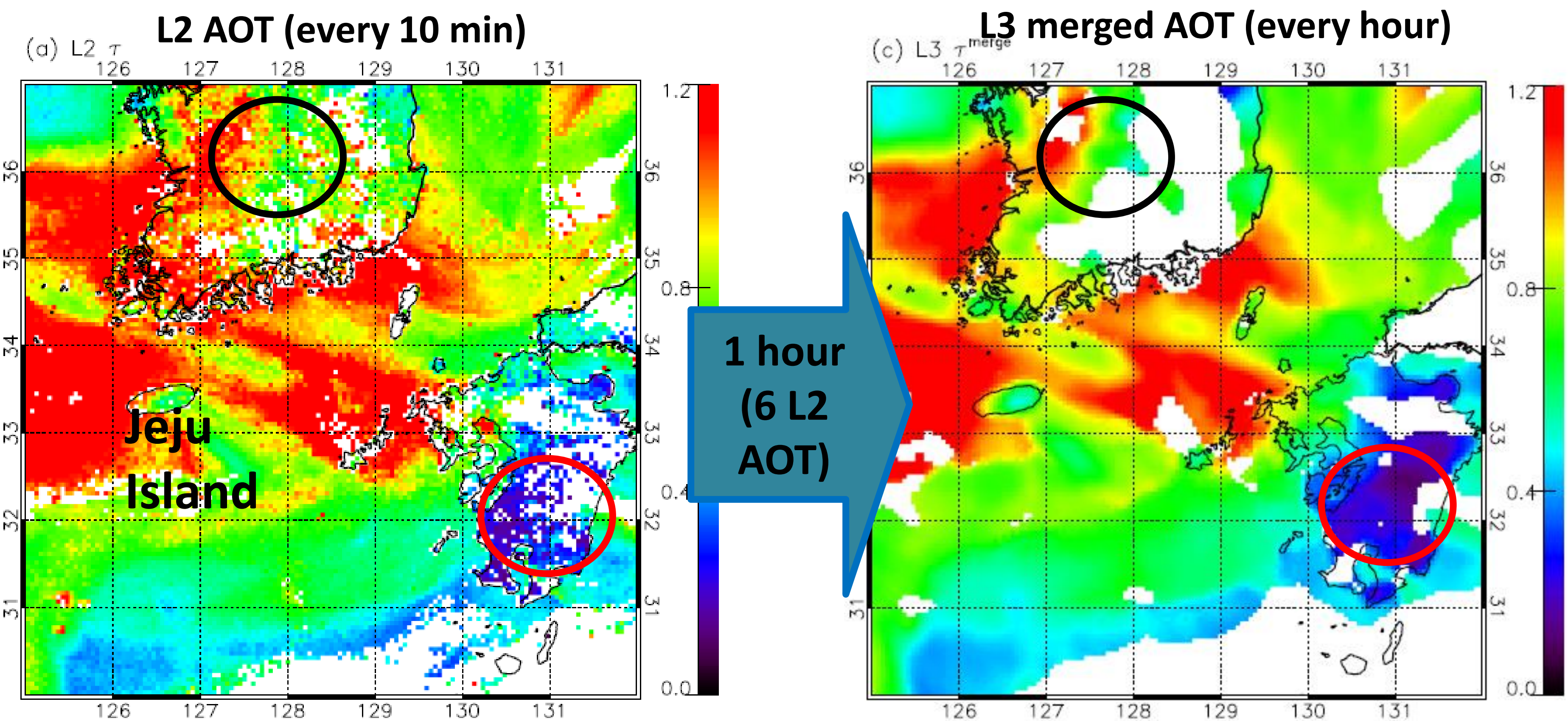


- Quality control (cloud screening) of AOT using difference in spatiotemporal variability between aerosol and cloud
- Minimize the missing data by using past and surrounding data

Kikuchi et al., 2018

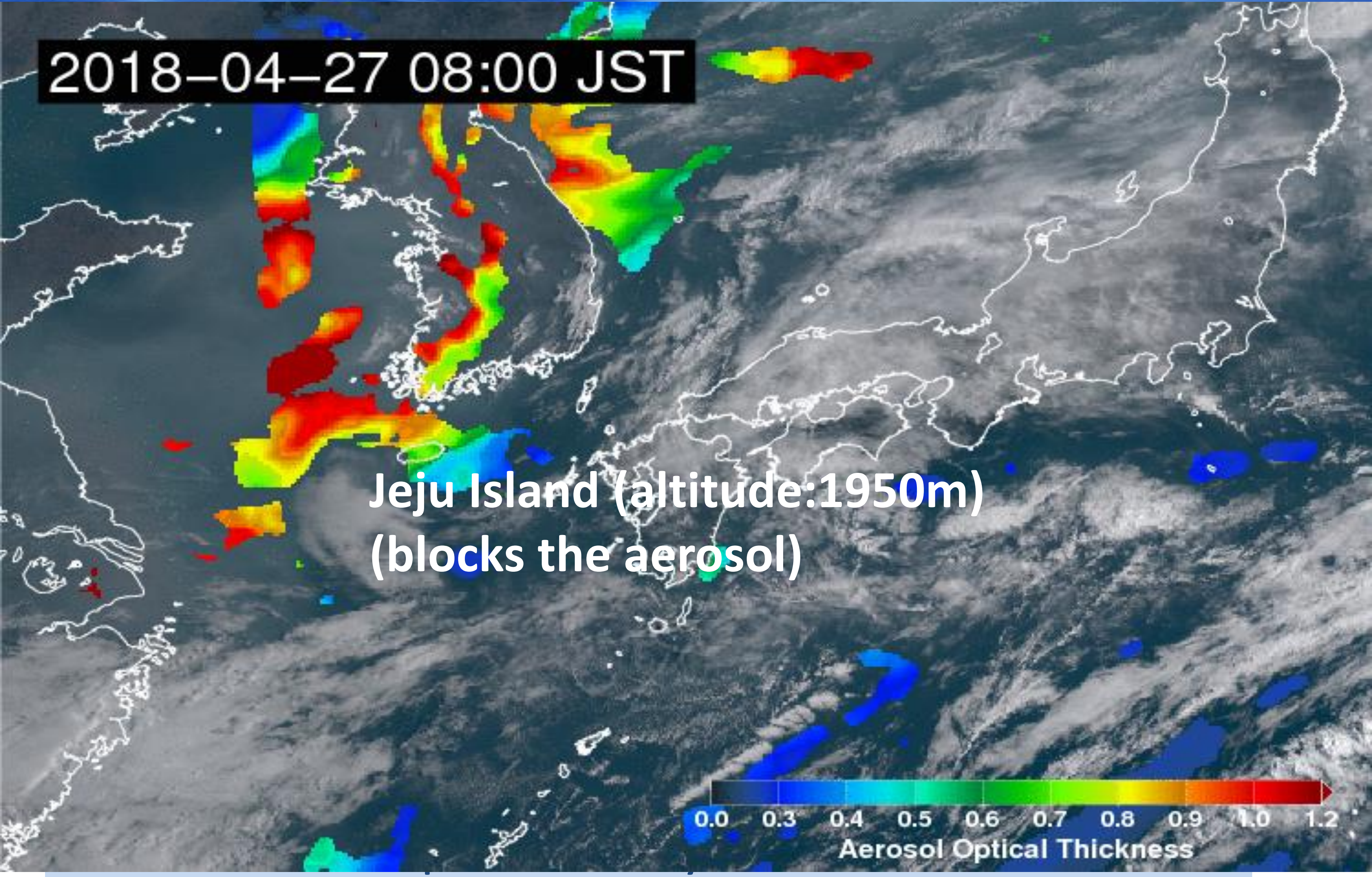
Retrieval Results (Himawar-8/AHI)

16 JST 27 Apr. 2018 : continental air pollutant transported to Kyusyu



- The high and nearly continuous AOT over land and ocean are estimated
- High AOT caused by local noise or insufficient cloud screening was eliminated and interpolated smoothly in L3

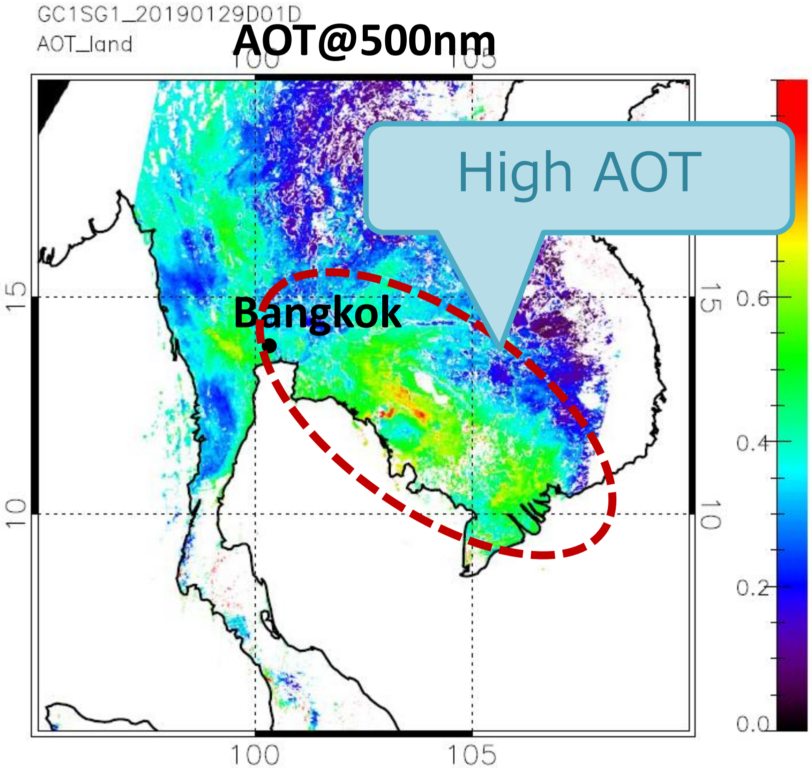
Retrieval Results (Himawar-8/AHI)

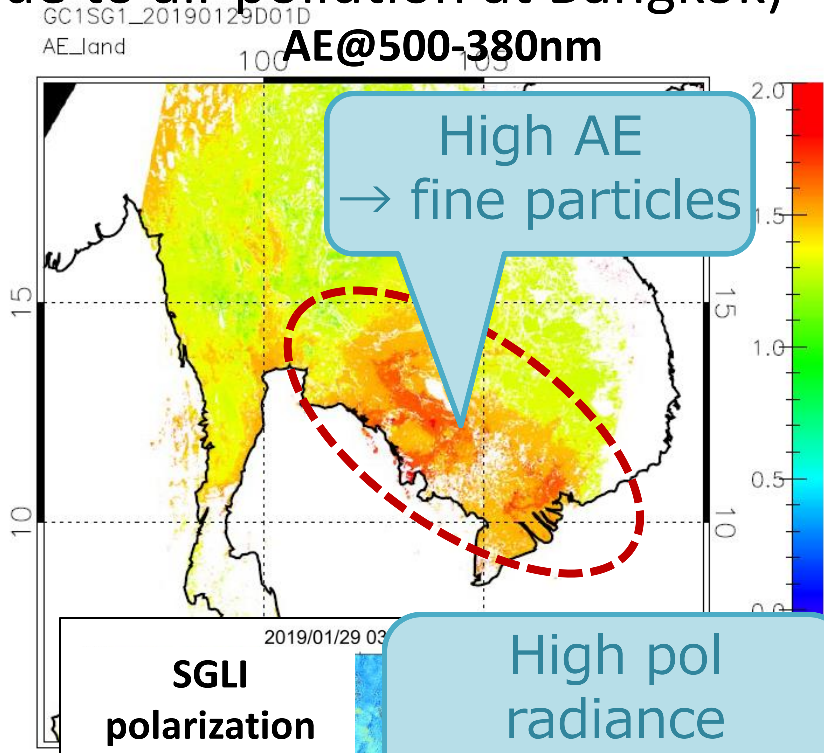


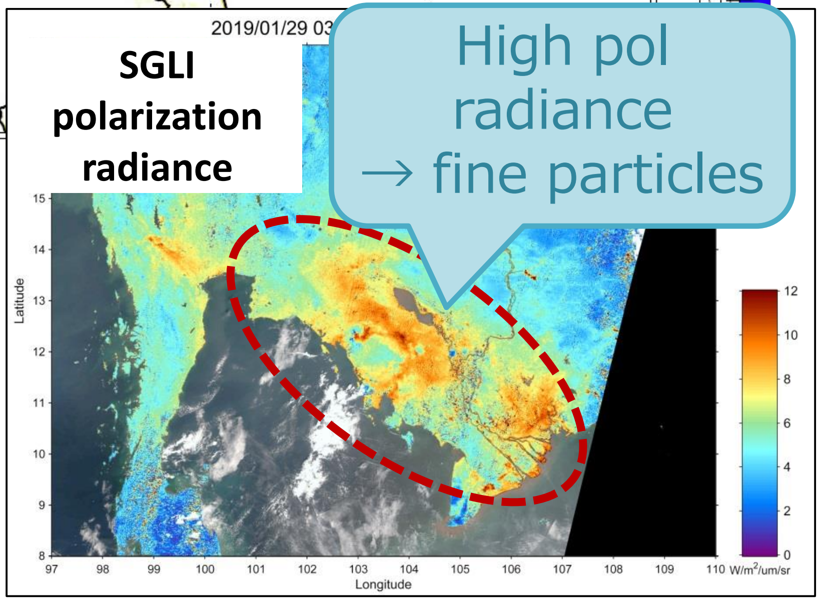
- **Aerosol transport are captured using frequent observation from AHI**

Retrieval Results (GCOM-C/SGLI)

29 Jan. 2019 Thailand (school closed due to air pollution at Bangkok)





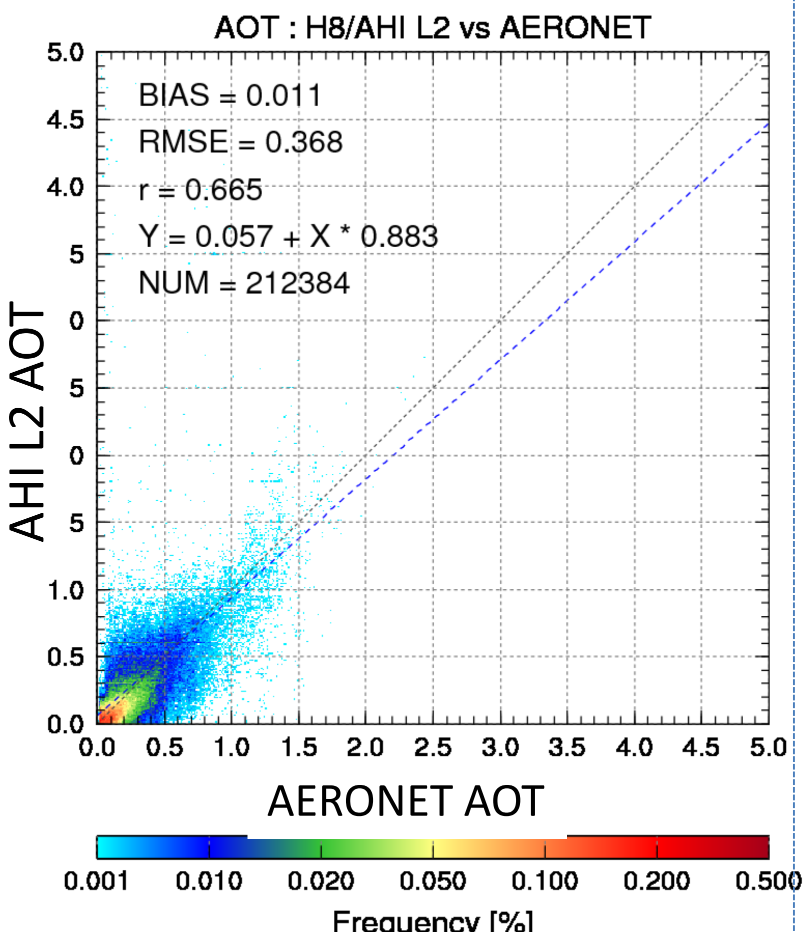


- The high AOT and AE (i.e. fine particles) are estimated corresponding to local air pollution report
- Estimated AOT and AE are consistent with SGLI polarization observation

Validation (AHI vs AERONET)

Frequency distributions
: 1 year, all AERONET site

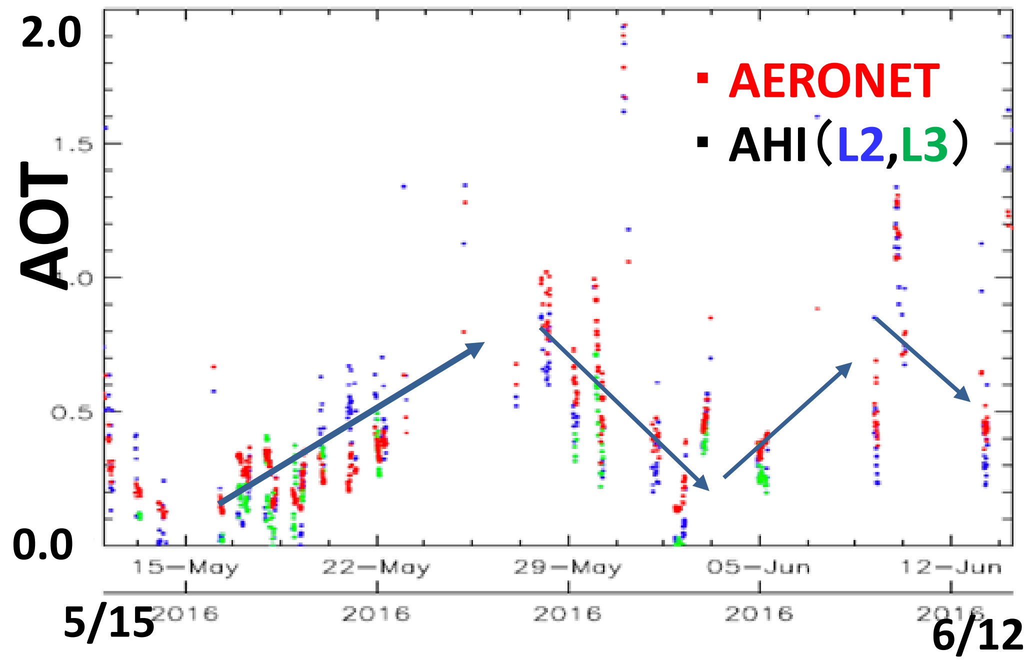
L2 Ver.020 2017/5 – 2018/4



- **AHI AOT is generally consistent with AERONET**

Time variation

Baeksa in Korea

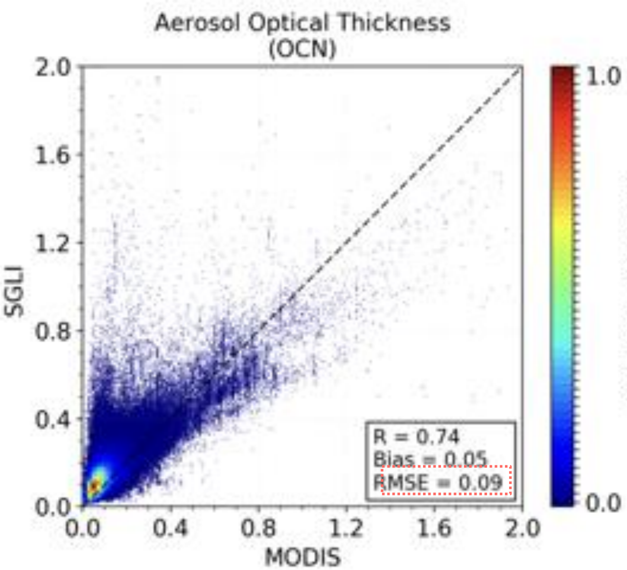


L2: snapshot retrievals every 10 min
L3: cloud screening data using 1hour data

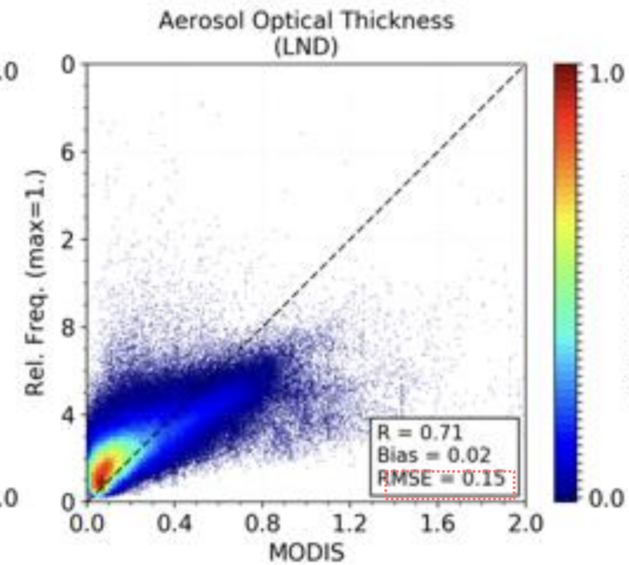
- **AHI AOT successfully represent the time variation of AERONET**

Validation (SGLI) : preliminary

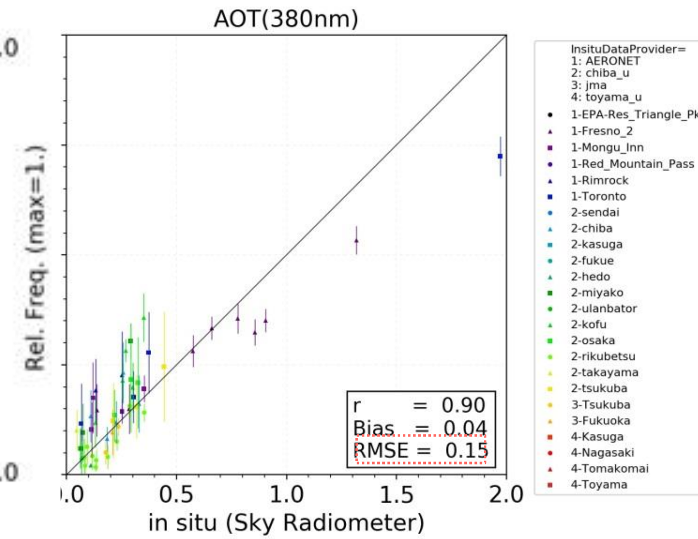
AOT over Ocean (Monthly)
vs. MODIS (DT method)



AOT over Land (Monthly)
vs. MODIS (DT method)



AOT over Land (instantaneous)
SGLI 0.1 deg. Grid average
vs. In-situ (SKYNET, AERONET)



RMSE

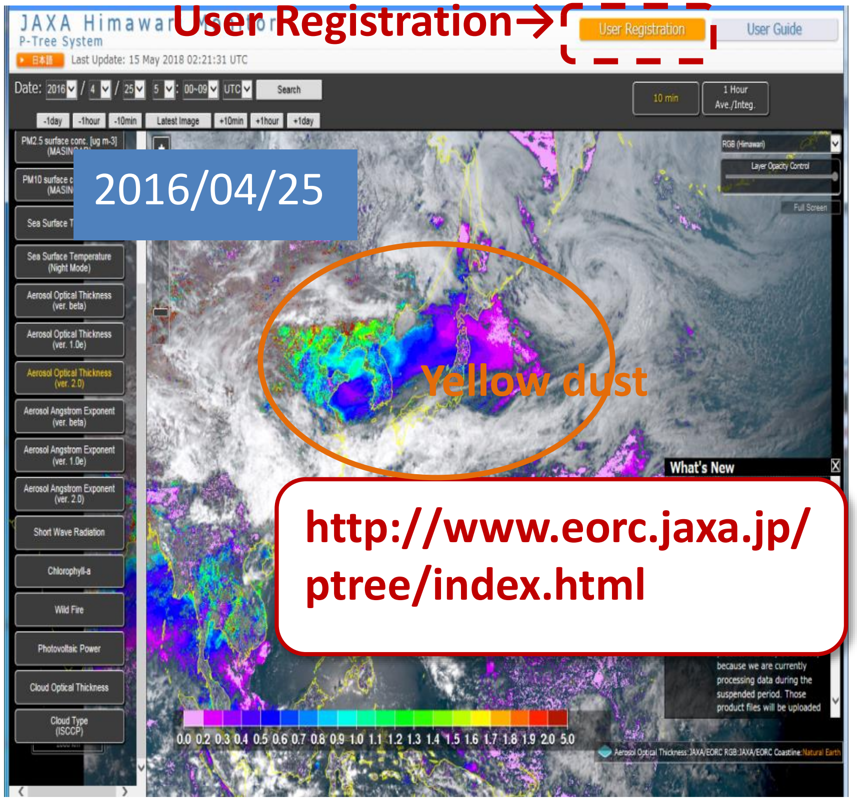
Estimated errors	Release threshold	Standard accuracy	Target accuracy
0.09 (ocean-other sat., monthly ave.)	0.10 (monthly ave.)	0.10 (scene)	0.05 (scene)
0.15 (land-other sat., monthly ave.) 0.15 (land-in-situ, scene)	0.15 (monthly ave.)	0.15 (scene)	0.10 (scene)

Release threshold is achieved

Data distribution

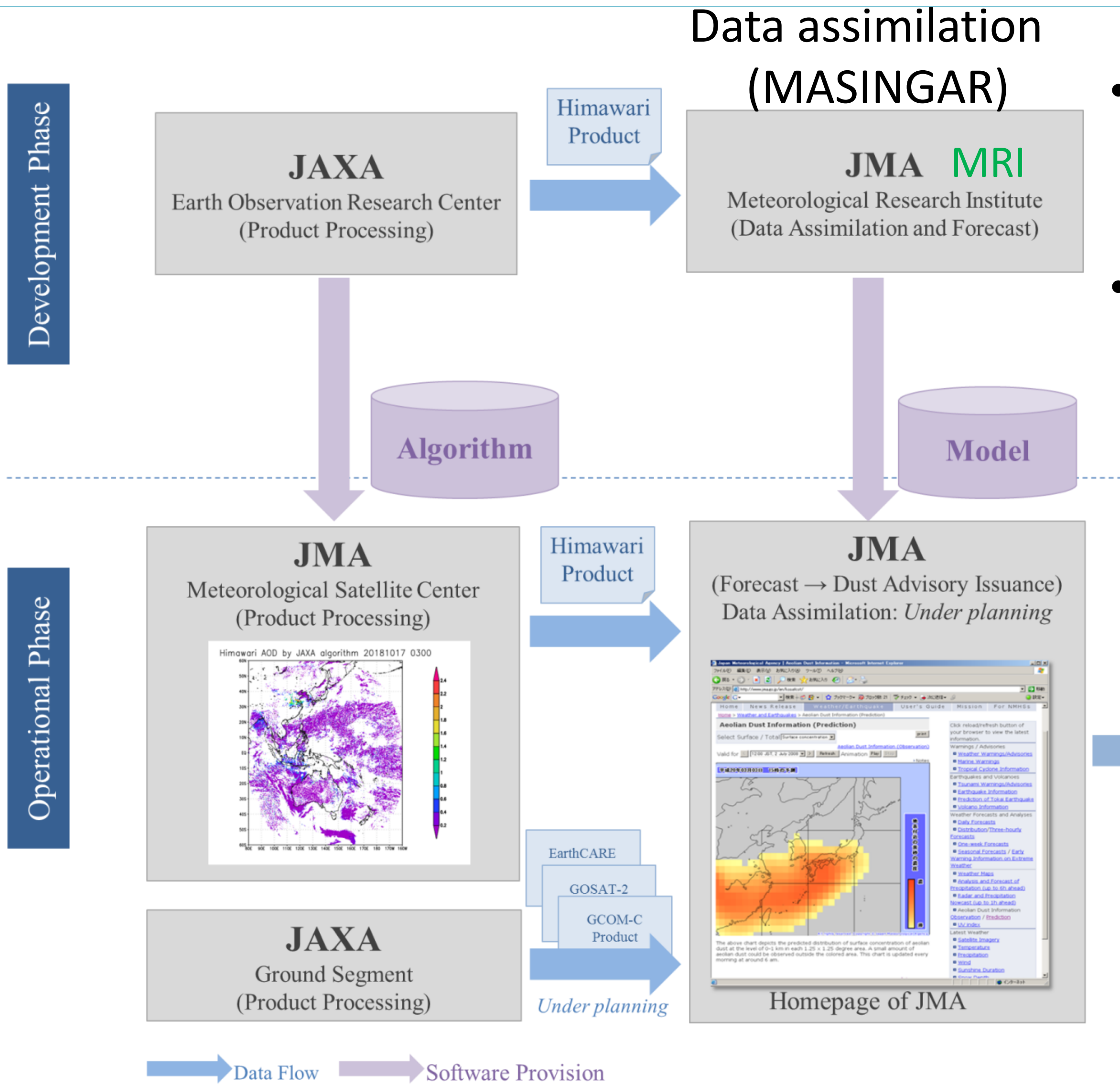
Himawari-8/AHI :
JAXA Himawari Monitor

GCOM-C/SGLI:
G-Portal



- **distribute original (Level 1) and geophysical (Level 2) products**
- **Data can be achieved with simple user registration**

JMA-JAXA Collaboration Framework



- JAXA provided JMA the Himawari aerosol algorithm (L2, L3)
- JMA implemented the algorithm to its operational system and started its experimental operation since December 2018

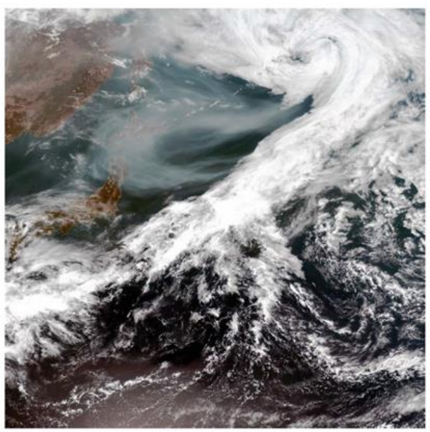
Next step: Utilization of aerosol transport model

aerosol data assimilation system collaborated with MRI and Kyusyu-Univ.

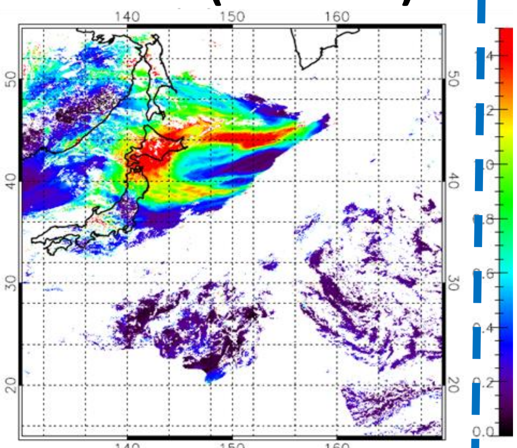
A priori

Sattellite observation → **retrieval** → Aerosol parameters → **Data assimilation** → Analysis → **forecast** → Forecast

Osberved RGB

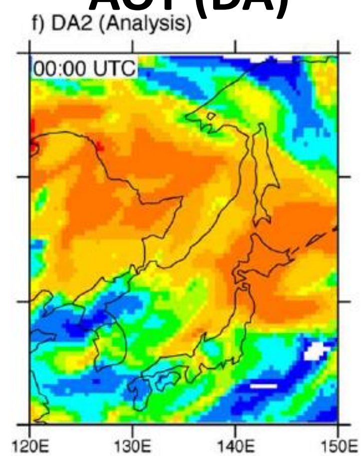


AOT (satellite)

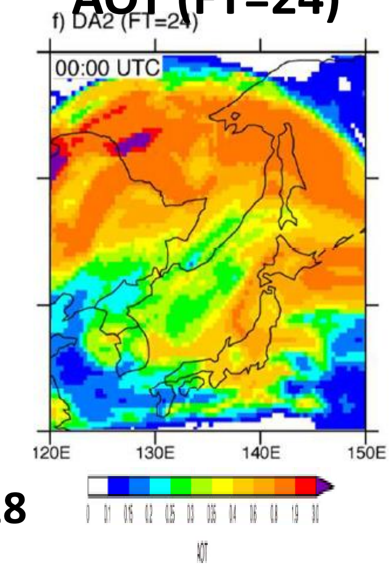


Yoshida et al.,2018

AOT (DA)



AOT (FT=24)



Yumimoto et al.,2018

Retrieval @JAXA

Data assimilation and forcast @MRI

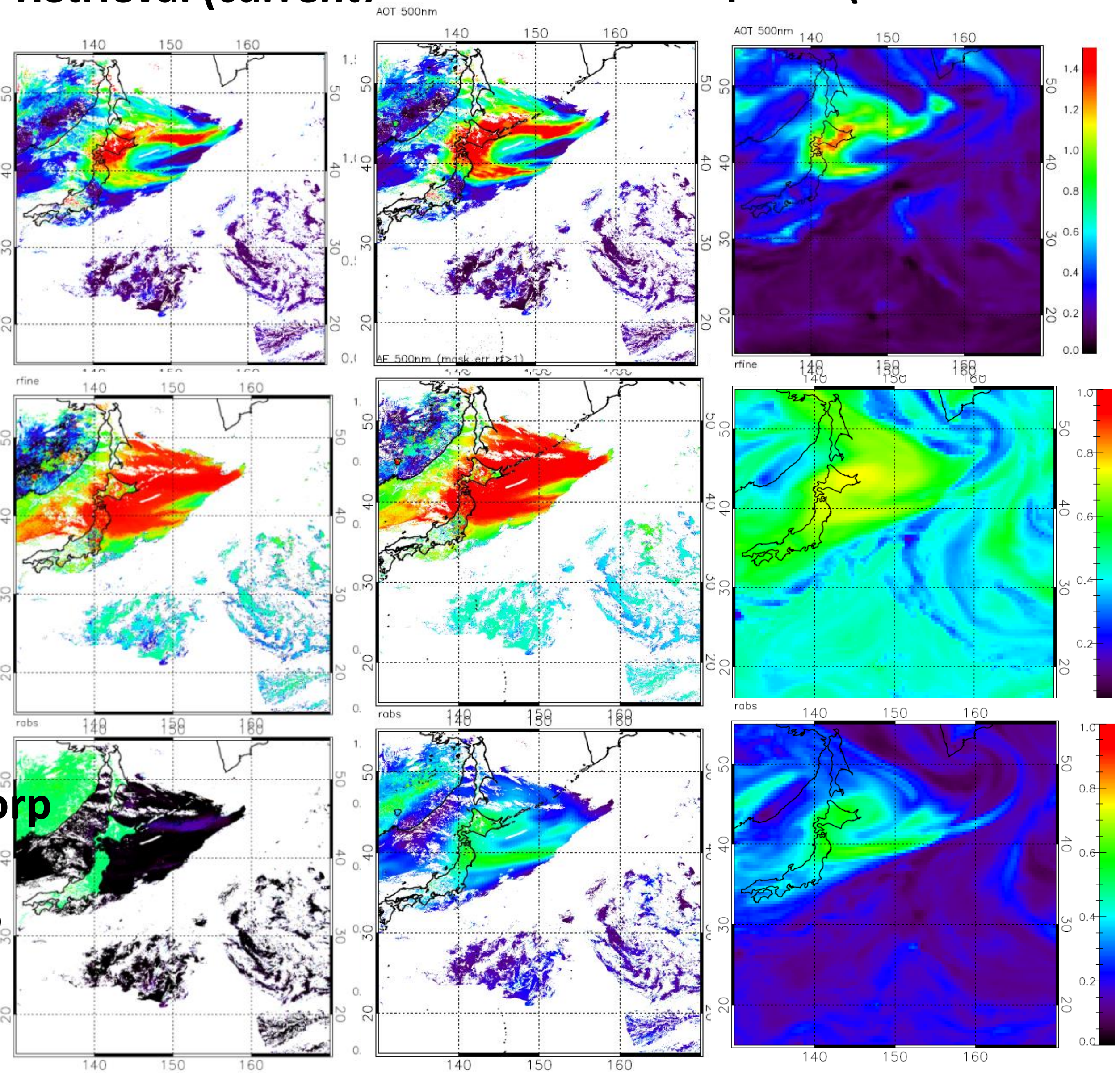
Preliminary Results

Retrieval (current) | New Results | A priori (model forcast)

AOT

Fine ratio

Absorption ratio



02UTC, 19 May 2016: Aerosol originated from wildfires

- Absorption ratio seems to be improved
- less noisy AOT and fine ratio
- AOT seems to well capture observed aerosol front
- Should be validated in future

Summary

- We developed **a common algorithm** to retrieve aerosol properties for various satellite sensors over land and ocean.
  - common aerosol models
  - common lookup tables
  - automatic selection of the optimum channels

- This method was applied to the **Advanced Himawari Imager (AHI) /Himawari-8** and **SGLI/GCOM-C**.

- The retrieved AOT are generally **consistent with MODIS and AERONET** product.

- The retrieved product is distributed at **JAXA Himawari Monitor and G-portal.**

- **The utilization of aerosol properties forecasted by a global aerosol transport model** as a priori seems to improve the retrieval, but should be validated in future.

Thank you

BackUp

L2 Algorithm

- we derived the aerosol parameters (τ, η_f, and m_i) using an optimal estimation method (Rodgers 2000).
- The state vector of a set of aerosol parameters $\boldsymbol{x} = \{\tau, \eta_f, m_i\}$ was derived by minimizing the object function *J* (Eq. 6). It uses the measurement vector of a gas-corrected observed reflectance set ***R*** = $\{\rho_{\mathrm{i}}^{obs\prime}, i = 1, \ldots, \mathrm{N}\}$ and simulated TOA reflectance ***F(x)*** = $\{\rho_{\mathrm{i}}^{sim}, i = 1, \ldots, \mathrm{N}\}$, where N is the channel number.

$$J = [\boldsymbol{R} - \boldsymbol{F}(\boldsymbol{x})]^T \boldsymbol{S}_{\boldsymbol{e}}^{-1} [\boldsymbol{R} - \boldsymbol{F}(\boldsymbol{x})] + [\boldsymbol{x} - \boldsymbol{x}_{\boldsymbol{a}}]^T \boldsymbol{S}_{\boldsymbol{a}}^{-1} [\boldsymbol{x} - \boldsymbol{x}_{\boldsymbol{a}}] \quad (6),$$

$\boldsymbol{x}_{\boldsymbol{a}} = \{\tau_a, \eta_{f_a}, m_{i_a}\}$: the vector of a prior estimate of $\boldsymbol{x}$

$\boldsymbol{S}_{\boldsymbol{e}}$ and $\boldsymbol{S}_{\boldsymbol{a}}$: the covariance matrices of ***R*** and $\boldsymbol{x}_a$

$$\boldsymbol{S}_{\boldsymbol{e}} = \begin{bmatrix} {\sigma_1}^2 & & 0 \\ & \ddots & \\ 0 & & {\sigma_N}^2 \end{bmatrix}, \quad (7)$$

- the uncertainty in TOA reflectancere $\sigma_i^2 = \sigma_s^2 + \sigma_n^2$,
  - σ_s : the uncertainty in the TOA reflectance that results from $\Delta\rho_i^s$.
  - σ_n :sensor noise (calculated from the signal-to-noise ratio)
- We assume $\Delta\rho_i^s$ to be some percentage of the surface reflectance (ρ_i^s) at each channel. The percentage is calculated at each pixel from the standard deviation of surface reflectance for 1 month at a channel whose ρ_{i}^{sim} is most sensitive to ρ_i^s (i.e., $\rho_{\mathrm{i}}^{sim}/\rho_i^s$ is the largest), when ρ_i^s at 470 nm is lower than ρ_i^s at 640 nm (i.e., the reflectance should be minimally influenced by heavy aerosol loading).
- the uncertainties of the three aerosol parameters (τ, η_f, and m_{i}) $\mathbf{S}_{\hat{\mathbf{x}}}$ were calculated using the law of error propagation, as follows:

$$\boldsymbol{S}_{\hat{\mathbf{x}}} = \left(\boldsymbol{A}^T \mathbf{S}_{\mathbf{e}}^{-1} \mathbf{A}\right)^{-1}, \quad (10)$$

A: the Jacobian matrix

Surface reflectance

- adopt the **second lowest reflectance** (ρ_i^s) at 470 nm within one month
- In the case of $\rho_i^s@470nm > \rho_i^s@640nm$
  - ✓ influenced by residual aerosol contamination
  - ✓ **adopt the modified Kaufman method (Fukuda et al. 2013)**

$$\rho_i^s = \sum_{k=0}^{4} a_k NDVI^k ,$$

$$\mathrm{NDVI} = \frac{R_{band4} - R_{band3}}{R_{band4} + R_{band3}}$$

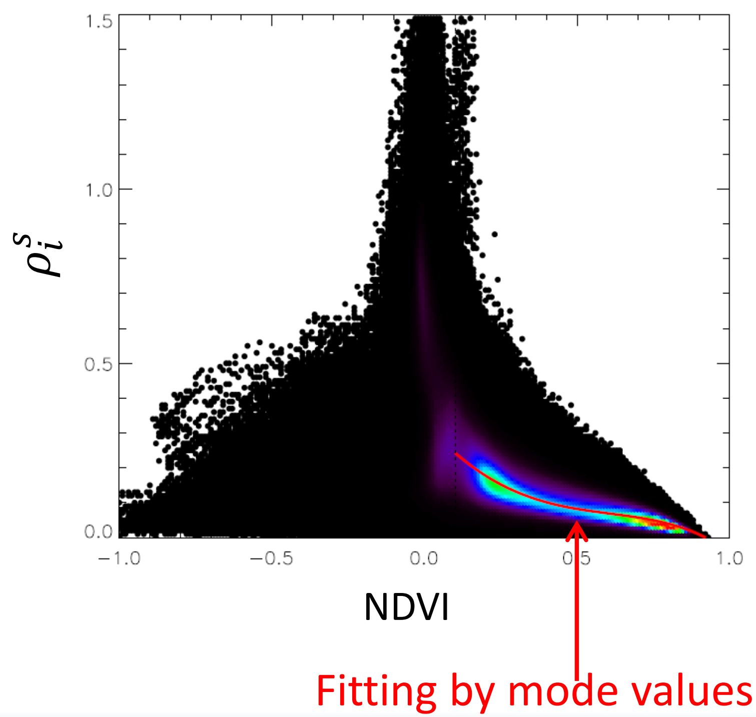
- **The standard deviation of surface reflectance in one month** is used for the reference of the $\boldsymbol{\rho_i^s}$ **estimation error** for the AOT retrieval

Probability density distribution

- ✓ all AHI area
- ✓ 1 year data in 2016
- ✓ $\rho_i^s@470nm < \rho_i^s@640nm$

(less influenced by heavy aerosol loading)

band3(0.64µm)



L3 algorithm

Described aerosol temporal/spatial variance in RMSD from the target

$$\sigma_{\Delta L,\Delta t} = \sqrt{\frac{1}{N}\sum_1^N \{AOT(x',y',t') - AOT(x_0,y_0,t_0)\}^2}$$

AOT where ΔL, Δt away from the target   AOT at the target

<u>Derived 2 types of AOT</u>

1. AOTmerge

Estimated the target AOT by the optimum interpolation using the surrounding and the past one hour data, including the target AOT

AOTmerge is an AOT dataset with minimum missing retrieval

$$AOT_{merge}(x_o, y_0, t_0) = \sum_{i=0}^{n} w_i\, AOT(x_i, y_i, t_i) \qquad w_i = \frac{\frac{1}{\sigma(x_i,y_i,t_i)^2}}{\frac{1}{\sigma_{merge}(x,y,t)^2}}$$

w_i: weighted according to AOT difference induced from the distance and time difference

$AOT(x_i, y_i, t_i)$: surrounding and past AOT

2. AOTpure

Estimated the target AOT by the optimum interpolation using the surrounding and the past one hour data, excluding the target AOT

→ selected to be AOTpure if it was within the 99% of confidence interval[*1]

[*1]defined to be within 2.58σ assuming the error was in normal distribution

AOTpure is a highly accurate AOT dataset with minimum cloud contamination

$$AOT_{pure}(x_o, y_0, t_0) = \begin{cases} AOT(x_o, y_0, t_0) & \text{if } AOT_{est}(x_o, y_0, t_0) - 2.58\sigma_{pure}(x_o, y_0, t_0) \le AOT(x_o, y_0, t_0) \le AOT_{est}(x_o, y_0, t_0) + 2.58\sigma_{pure}(x_o, y_0, t_0) \\ N/A & \text{else} \end{cases}$$

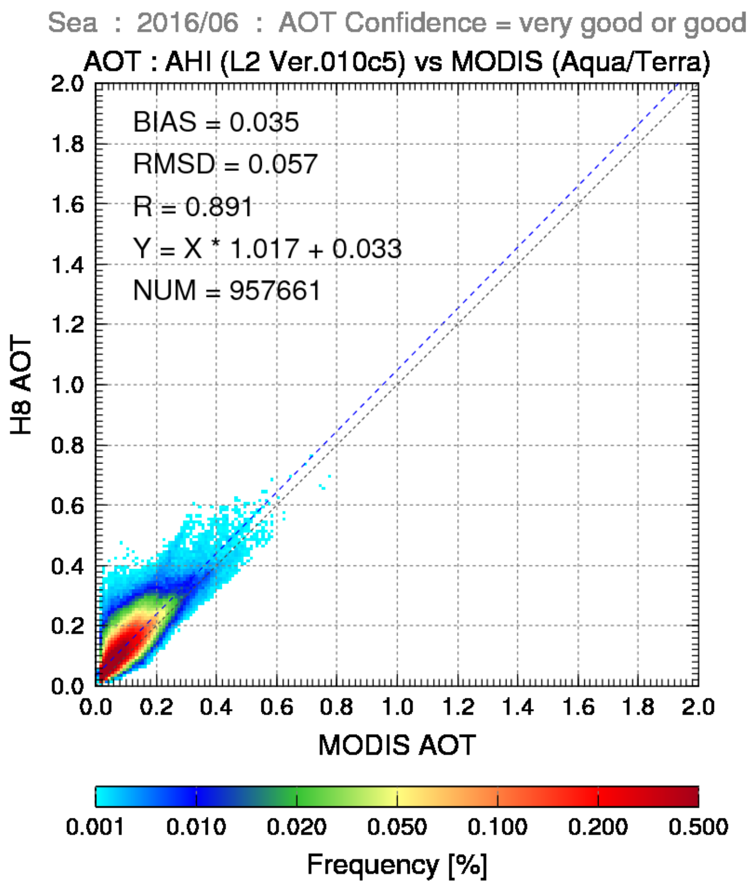
AOT_{est}: estimated AOT; $2.58\sigma_{pure}$: 99% confidence int.; $AOT(x_o, y_0, t_0)$: observed AOT

Kikuchi, M., H. Murakami, K. Suzuki, T. M. Nagao, and A. Higurashi, 2018: Improved Hourly Estimates of Aerosol Optical Thickness using Spatiotemporal Variability Derived from Himawari-8 Geostationary Satellite, *IEEE Transactions on Geoscience and Remote Sensing*, 10.1109/TGRS.2018.2800060

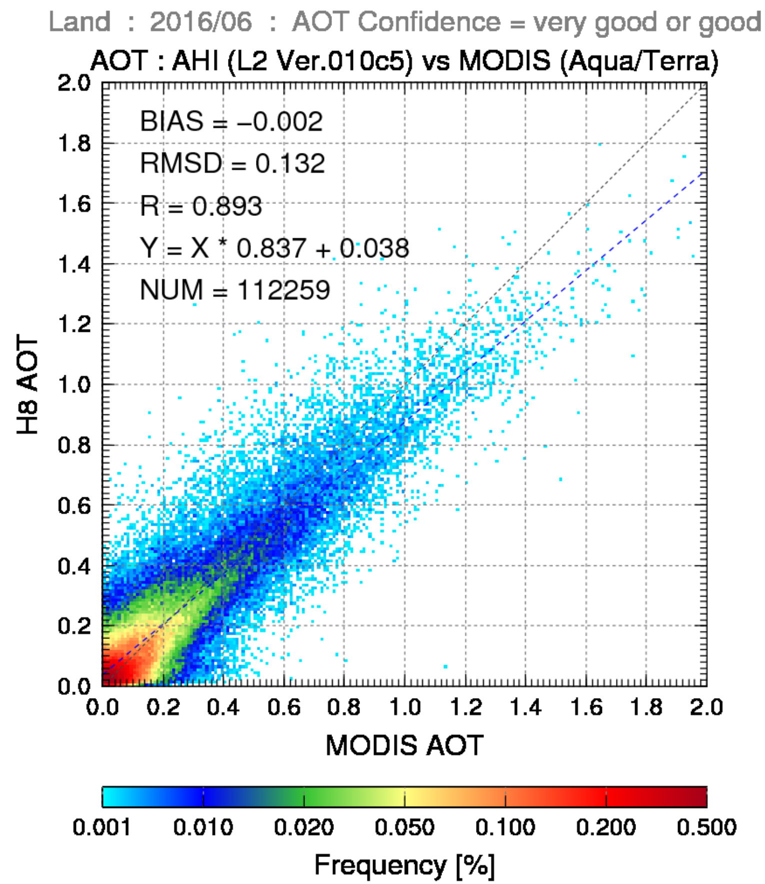
L2 Evaluation with MODIS

June 2016

Ocean



Land

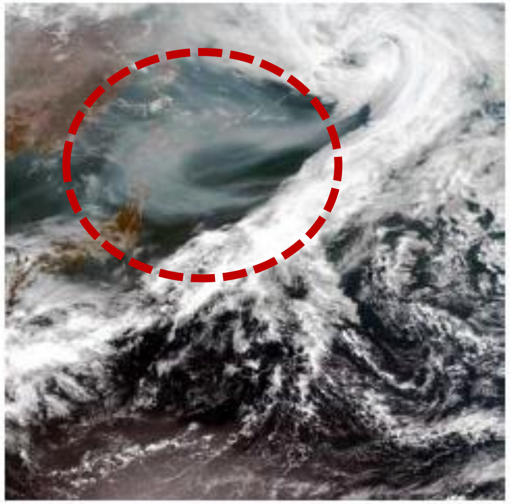


Retrieval Results (H8/AHI)

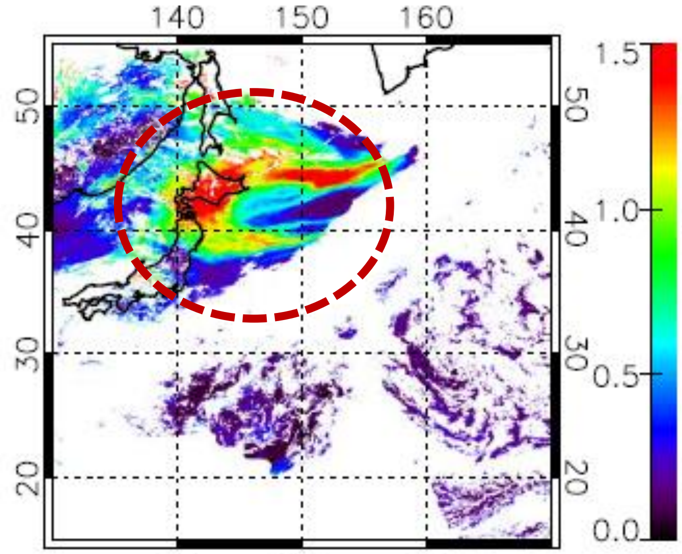
02UTC, 19 May 2016

Aerosol originated from wildfires at a proximity to Lake Baikal in Russia

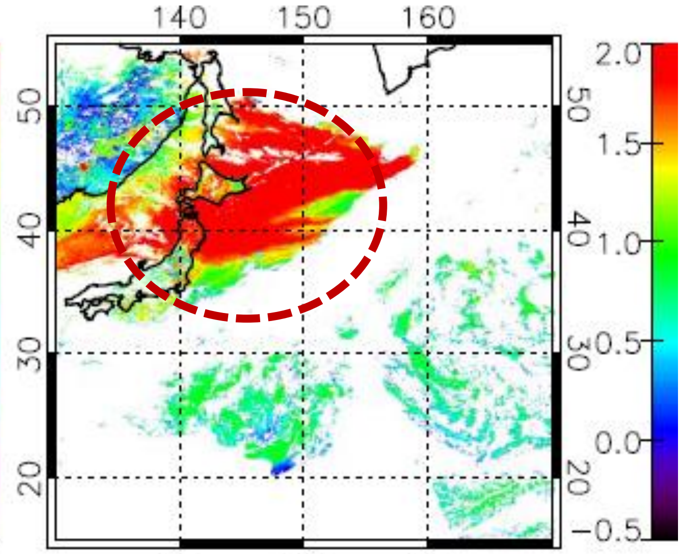
RGB



AOT@500nm



AE@400-600nm



- **The high AOT and AE (fine particles) are estimated over land and ocean, corresponding to aerosol transport from the continent**
- **nearly continuous AOT over land and ocean**

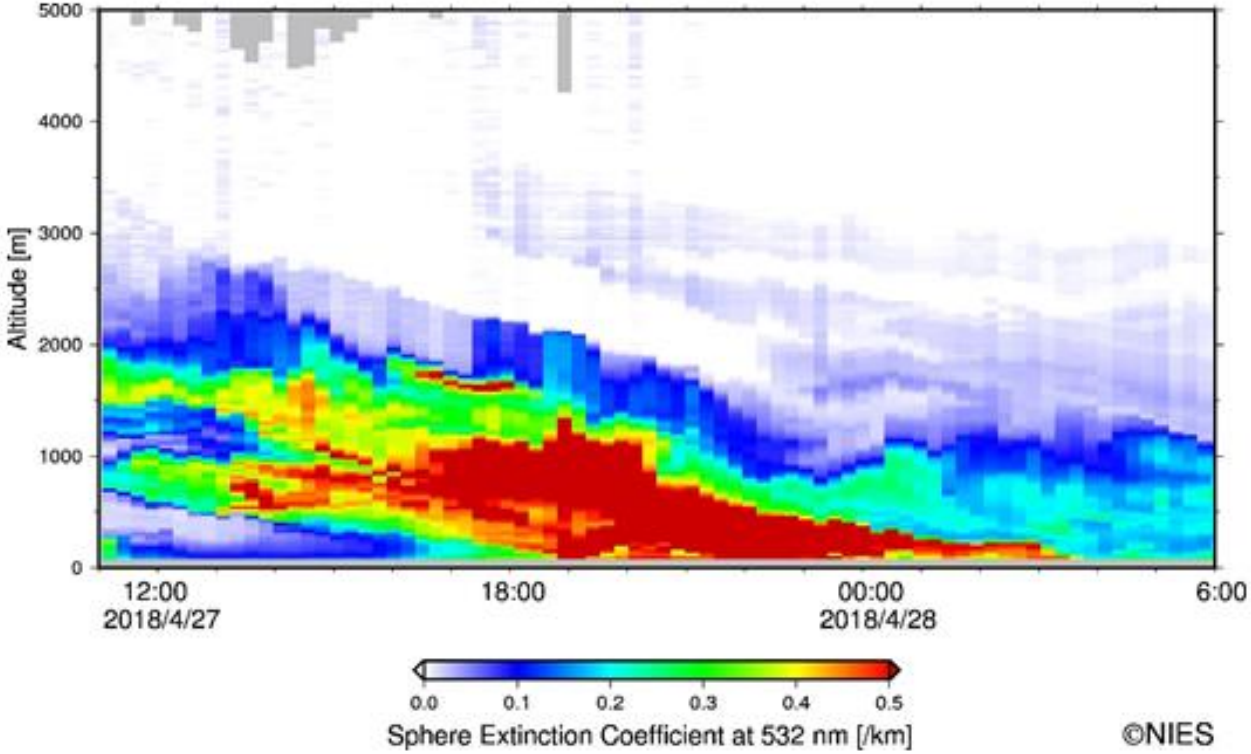


図4　2018年4月27日の済州島におけるライダの観測結果。横軸は時刻（日本時刻）、縦軸が高度（メートル）。赤い色ほど濃い大気浮遊物質が観測されている*4。