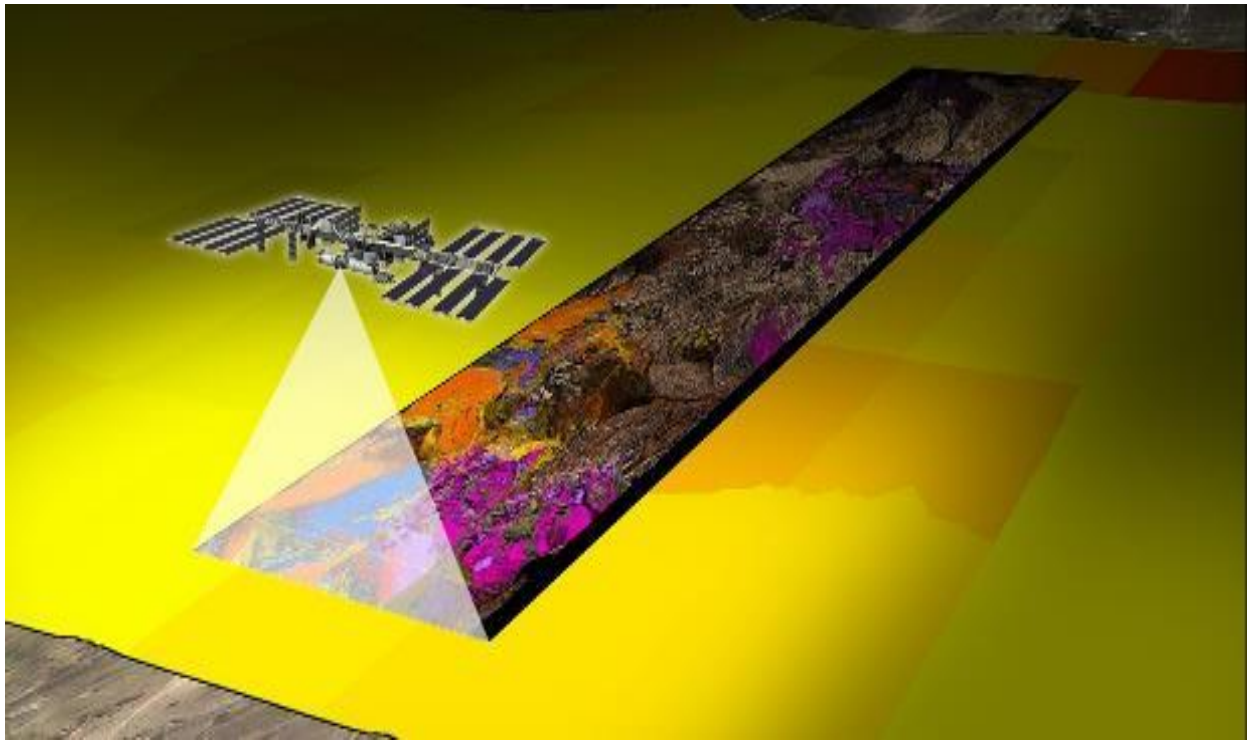
The NASA Earth Surface Mineral Dust Source Investigation (EMIT)



Robert O. Green[1], Natalie Mahowald[2], David R. Thompson[1], Roger Clark[3], Bethany Ehlmann[4], Paul Ginoux[5], Olga Kalashnikova[1], Ron Miller[6], Greg Okin[7], Thomas H. Painter[7], Carlos Perez Garcia-Pando, Vincent Realmuto[1], Gregg Swayze[9], Eyal Ben Dor[10], Philip G. Brodrick[1], Longlei Li[2], Nimrod Camron[1], Benjamin Phillips[11], and Kevin Reath[11]

[1]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA, [2]Cornell University, Ithaca, NY, USA, [3]Planetary Science Institute, Tucson, AZ, USA, [4]California Institute of Technology, Pasadena, CA, USA, [5]Princeton University, Princeton, NJ, USA, [6]NASA Goddard Institute for Space Studies, New York, NY, USA, [7]University of California Los Angeles, Los Angeles, CA, USA, [8]Barcelona Supercomputing Center, Barcelona, Spain, [9]US Geological Survey, Golden, CO, USA, [10]University of Tel Aviv, Tel Aviv, Israel, [11]NASA Headquarter, Washington, DC, USA

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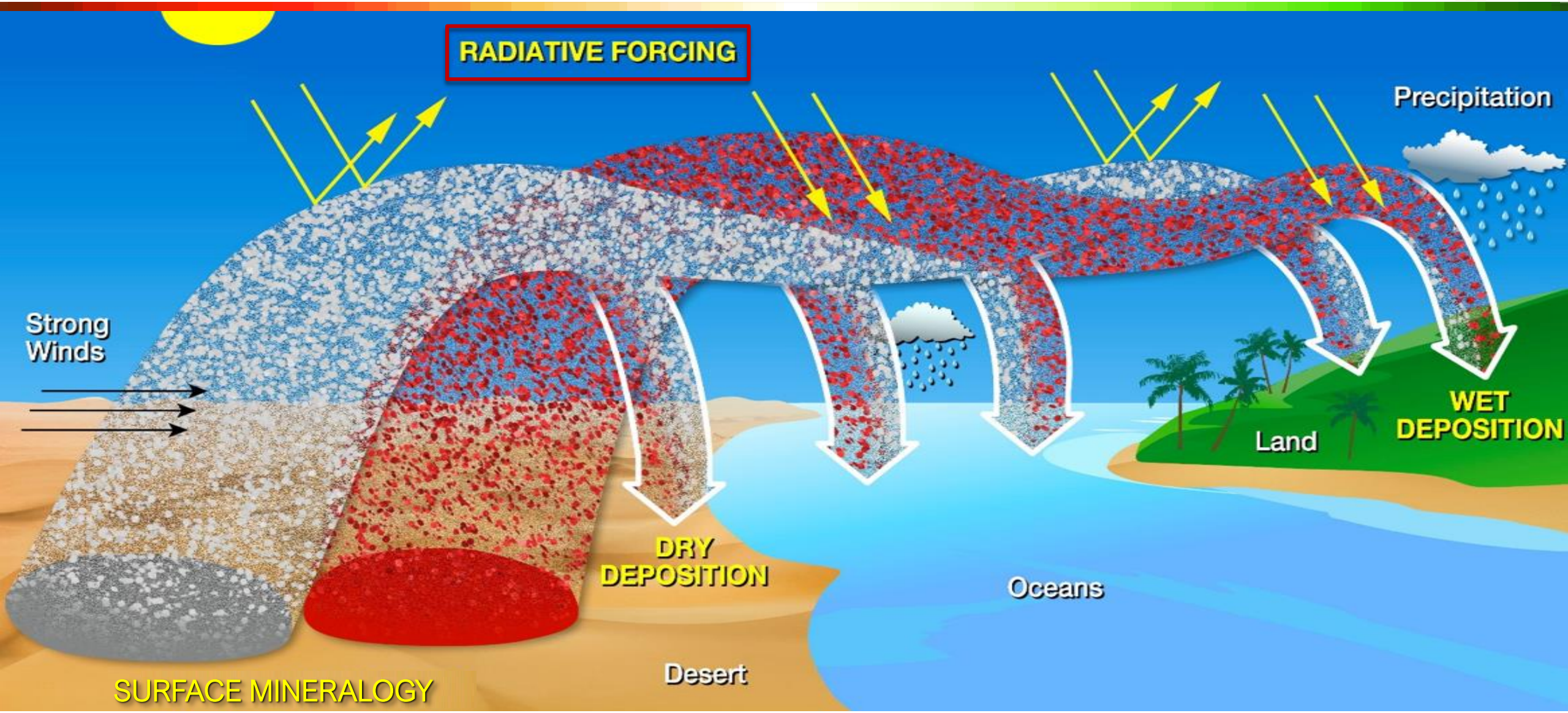
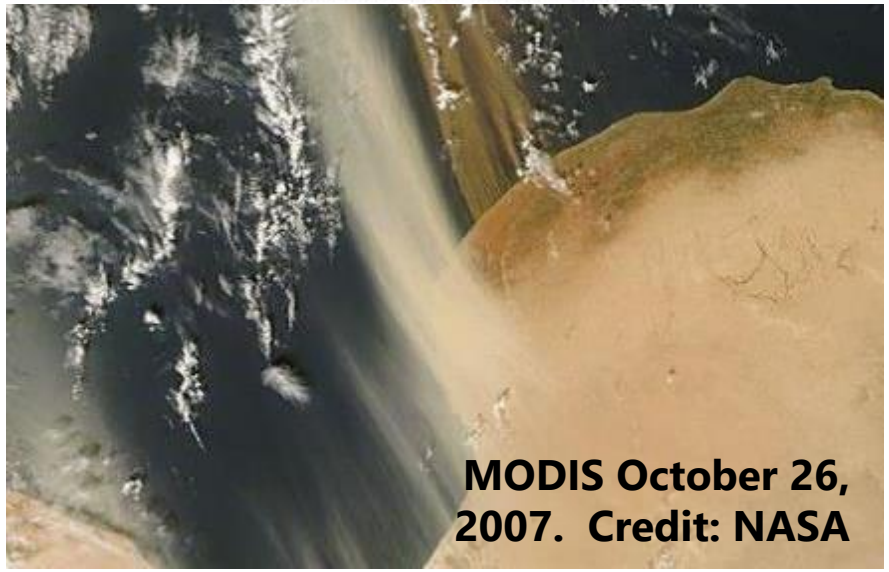
Earth's Mineral Dust Cycle



EMIT Science Objectives

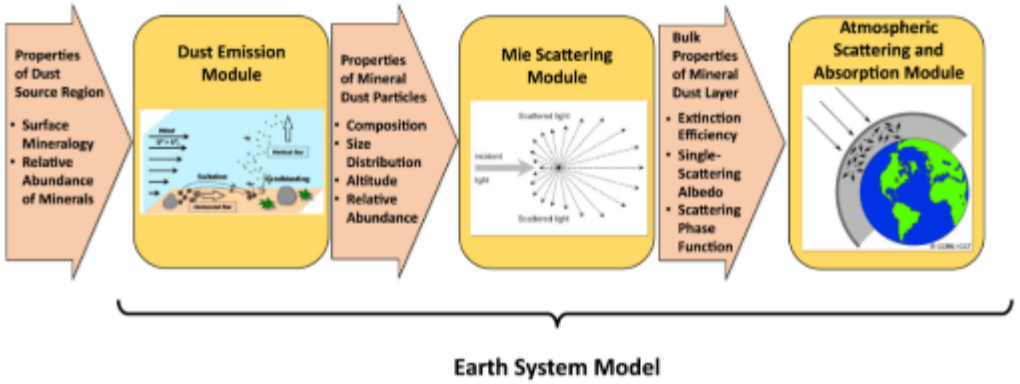


1) Constrain the sign and magnitude of dust-related RF at regional and global scales.

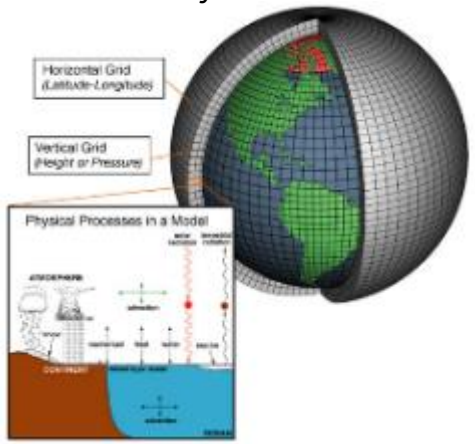
EMIT achieves this objective by acquiring, validating and delivering updates of surface mineralogy used to initialize Earth System Models.

2) Predict the increase or decrease of available dust sources under future climate scenarios.

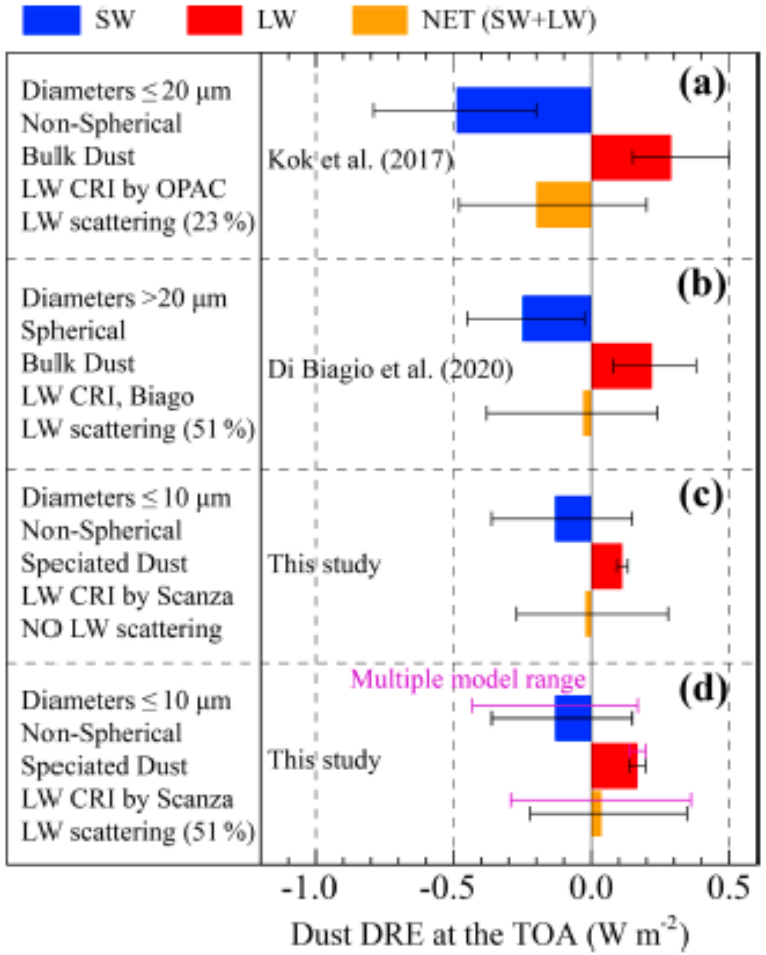
EMIT achieves this objective by initializing Earth System Model forecast models with the mineralogy of soils exposed within at-risk lands bordering arid dust source regions.



Earth System Models



DRE uncertainty due to soil mineralogy



Today, when using mineral speciation in models:

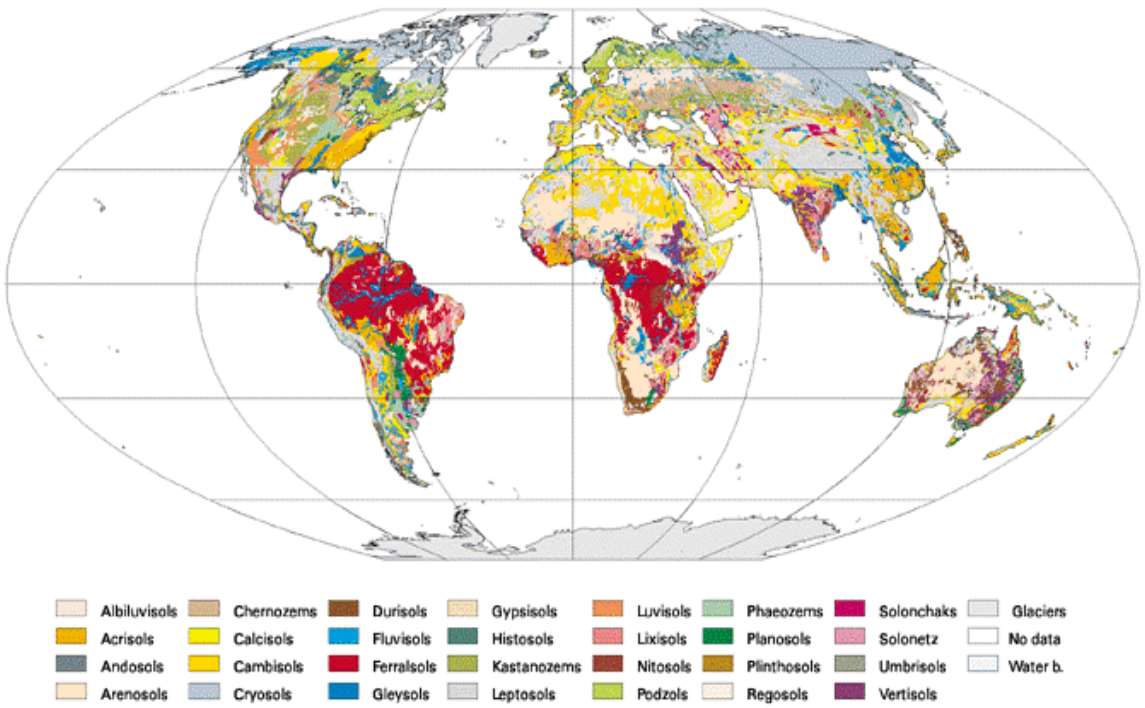
- The global net TOA DRE is estimated to be -0.23 to +0.35 W/m^2 due to soil mineralogy uncertainty

- 97 % of this range is related to the abundance of iron oxides

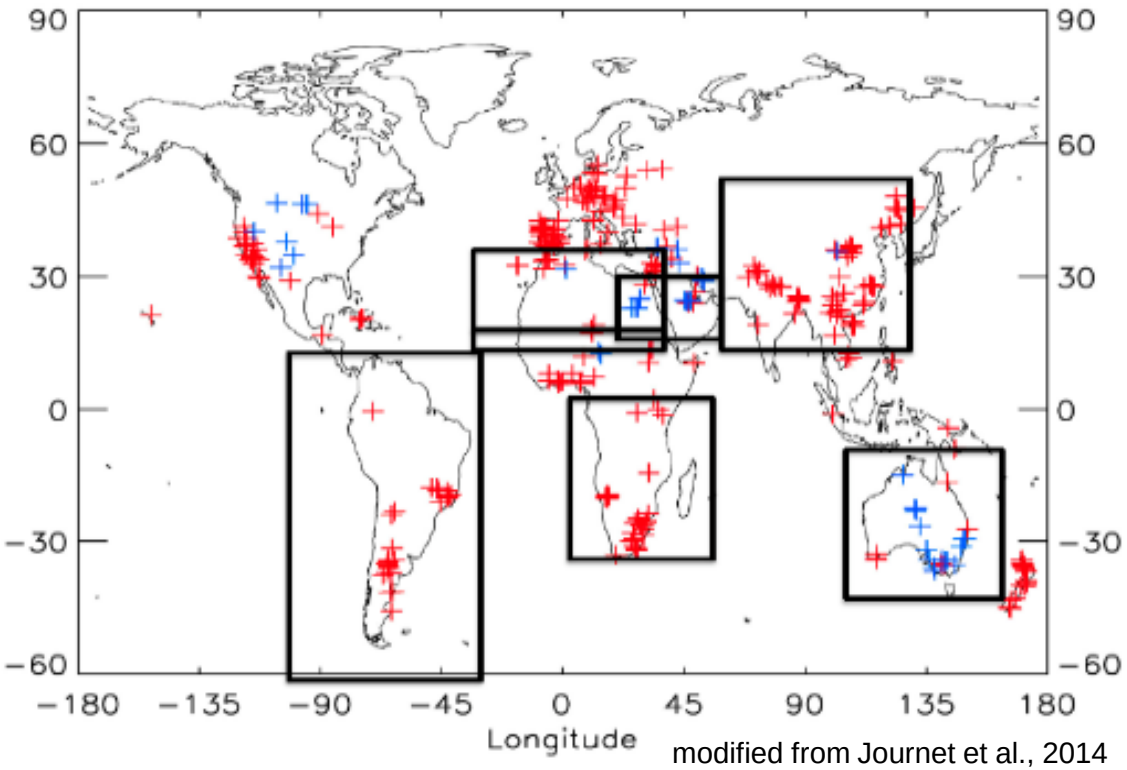
Li, L., Mahowald, N. M., Miller, R. L., Pérez García-Pando, C., Klose, M., Hamilton, D. S., Gonçalves Ageitos, M., Ginoux, P., Balkanski, Y., Green, R. O., Kalashnikova, O., Kok, J. F., Obiso, V., Paynter, D., and Thompson, D. R.: Quantifying the range of the dust direct radiative effect due to source mineralogy uncertainty, Atmos. Chem. Phys., 21, 3973–4005, https://doi.org/10.5194/acp-21-3973-2021, 2021.

Example: Current Mineral Dust Source Information

UN Food and Agriculture Organization (FAO)
Soil Map Interpolated/Extrapolated



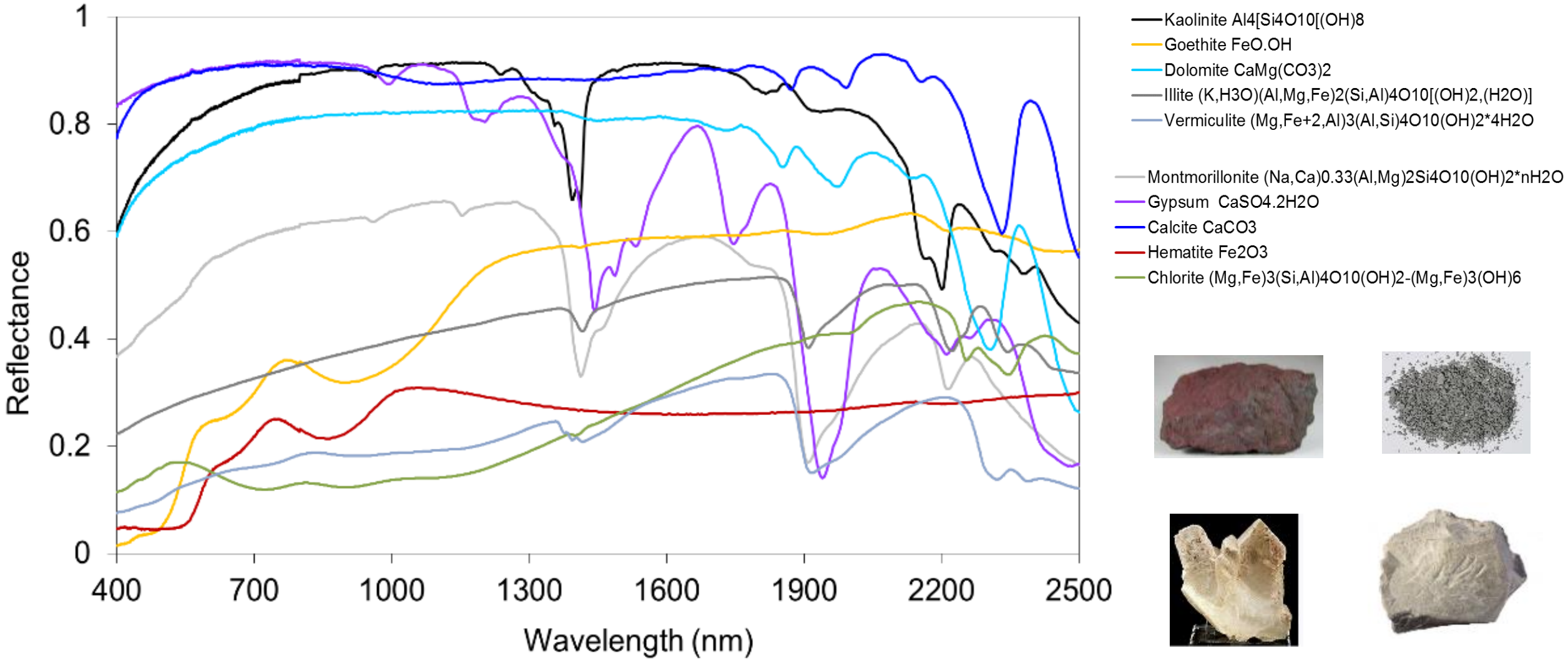
Current Soil Sample Locations



modified from Journet et al., 2014

Challenge: Using FAO soil data sets and “Average” soil properties from ≤5000 soils samples (mostly not in deserts) doesn’t fully capture actual distribution and diversity of the mineral dust source regions.

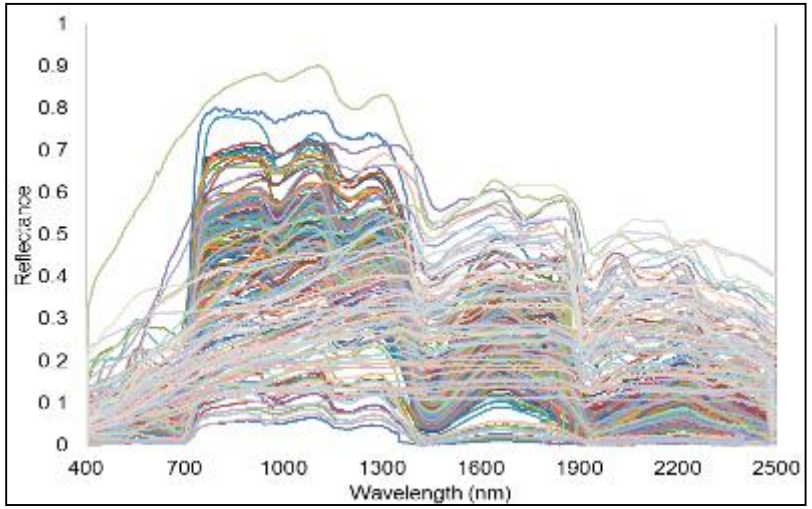
EMIT Will Use Imaging Spectroscopy
Dust Minerals have Distinct Spectral Signatures



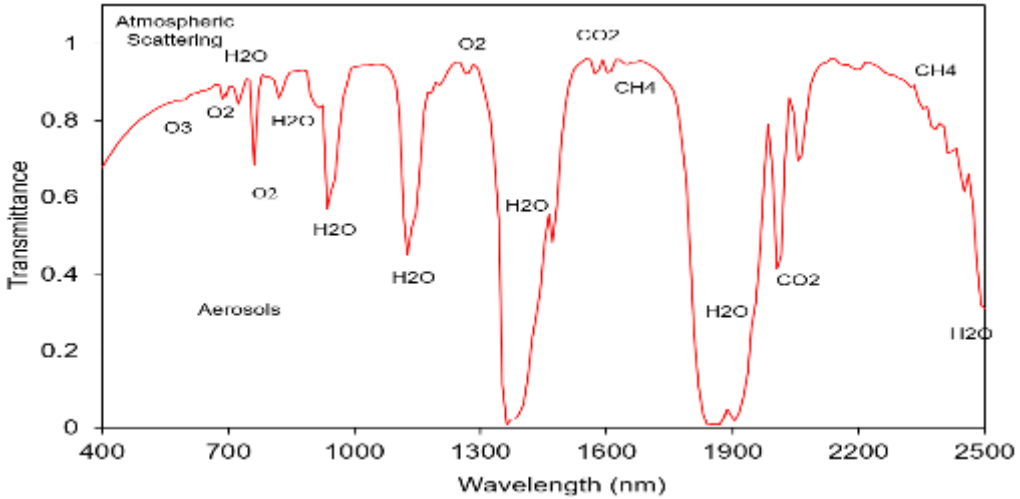
Visible to Short Wavelength Infrared Spectral Range (VSWIR) [400 to 2500 nm]

The Earth System is Rich with Spectral Signatures

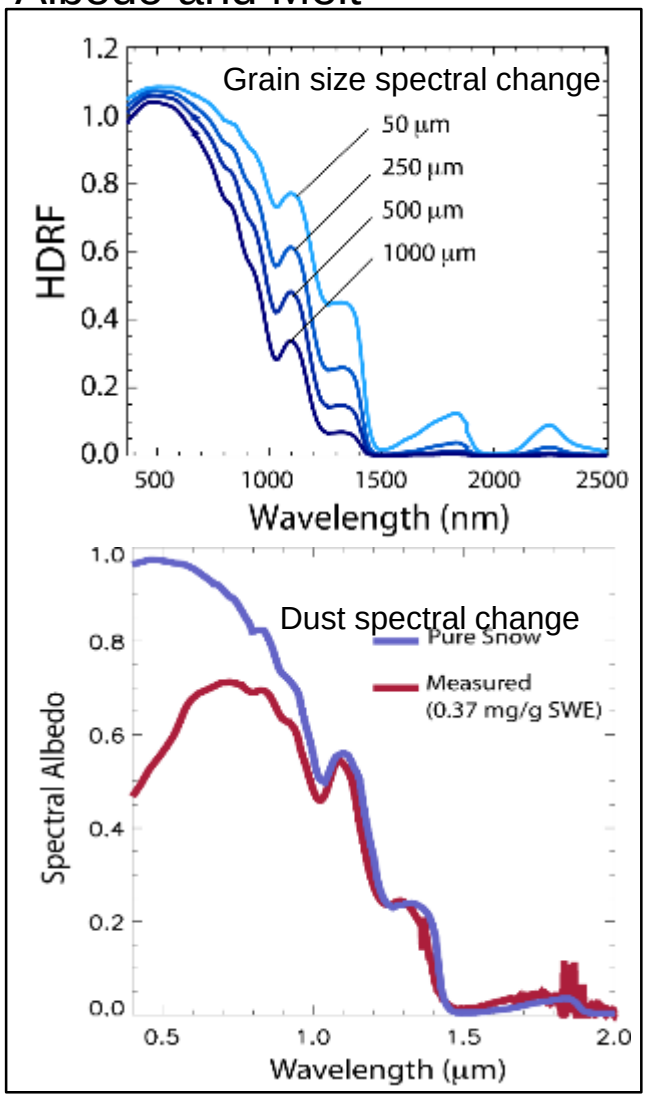
Ecosystems: Diversity of Signatures



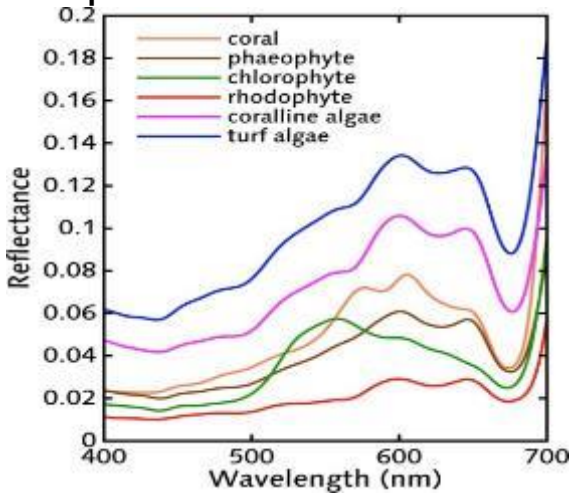
Atmosphere: Gases, Aerosols, Clouds



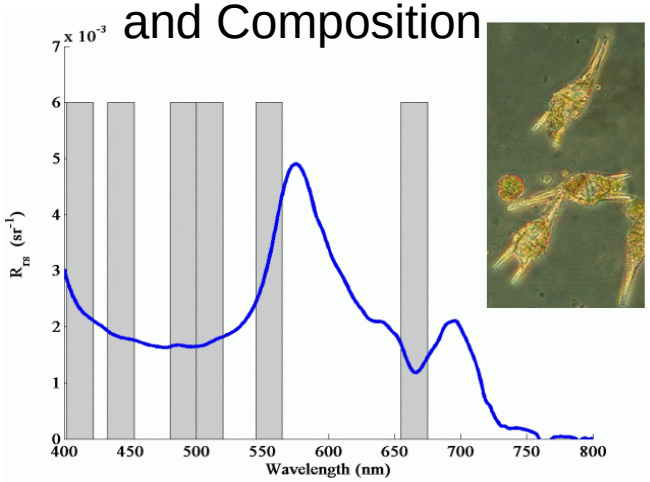
Snow/ice: Grain size, Dust, Albedo and Melt



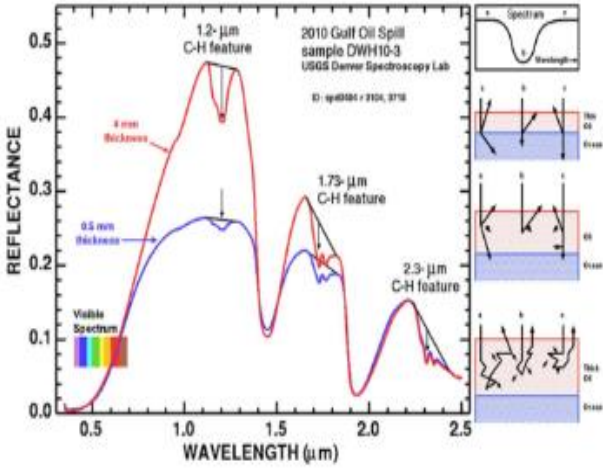
Aquatic: Benthic Materials



Aquatic: Algal Biomass and Composition



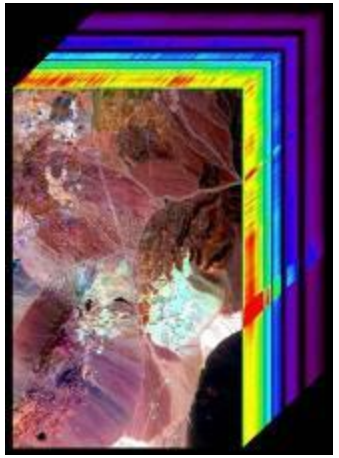
Oil Spill



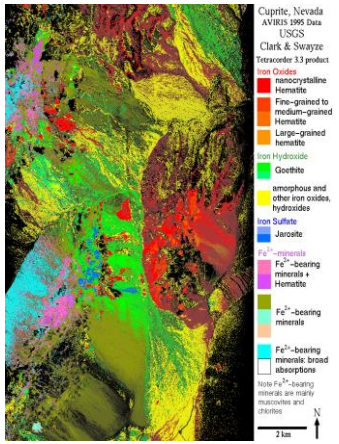
NASA Imaging Spectroscopy Offers a Tested Approach to Measure Surface Mineralogy

Jet Propulsion Laboratory
California Institute of Technology

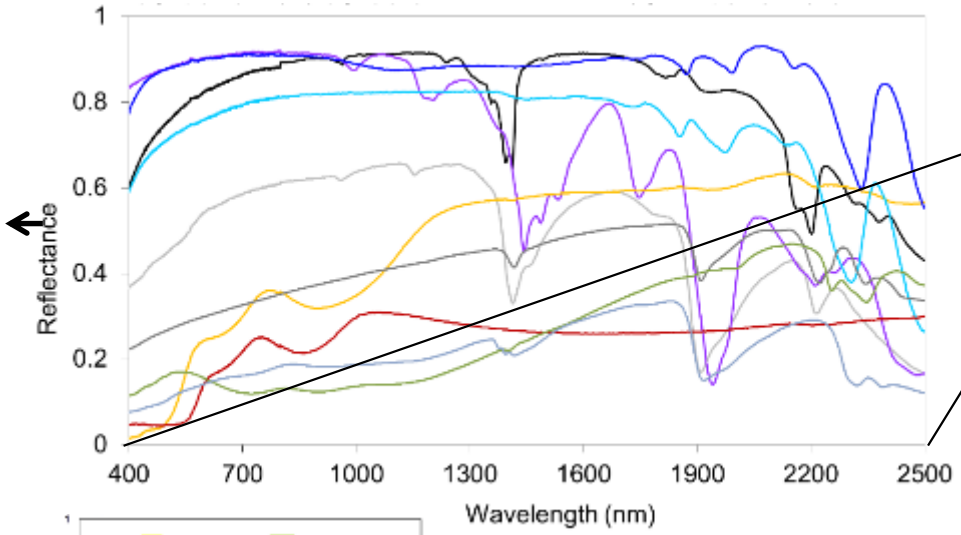
Calibrated Image Cube

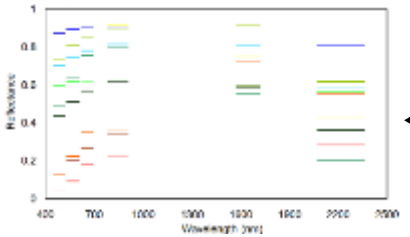


Material Map

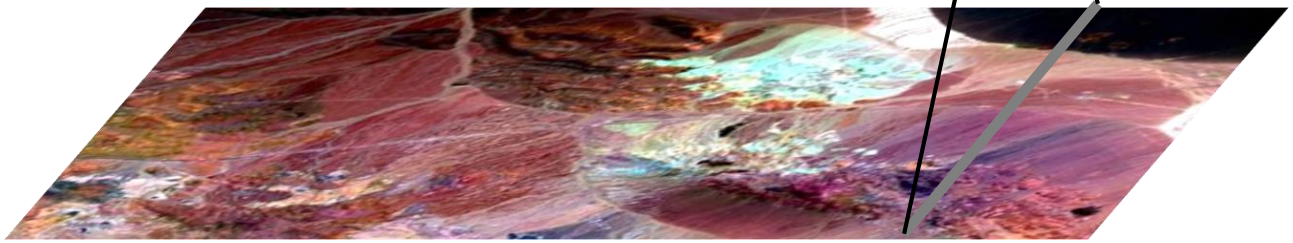


1000s of Parallel Spectrometers





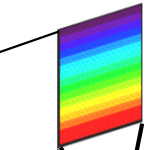
Multispectral



Space

Airborne

Ground



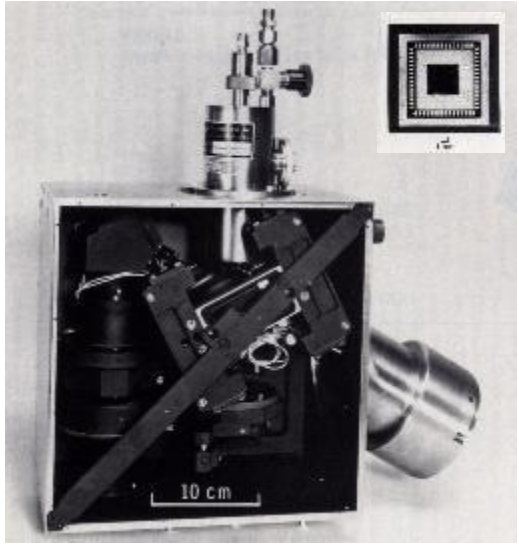
Detector Array

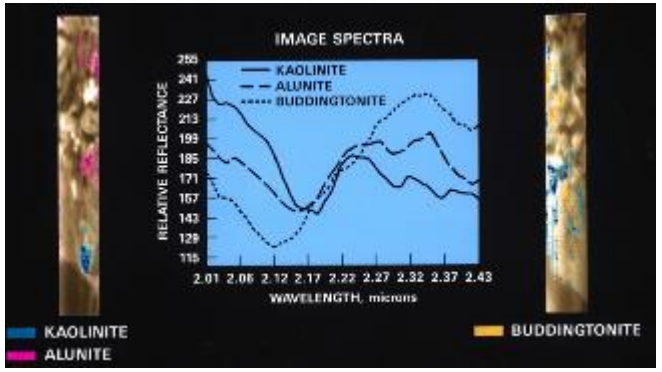
Spectrometer

Slit

Telescope

First Imaging Spectrometer (AIS)

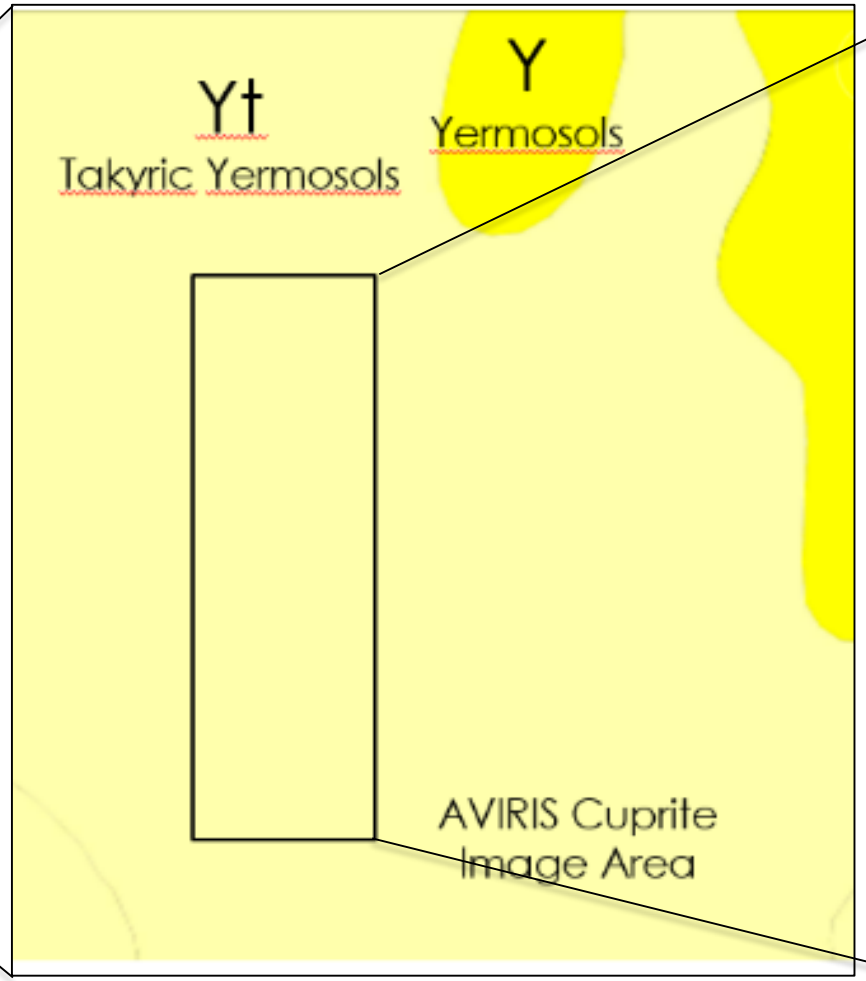




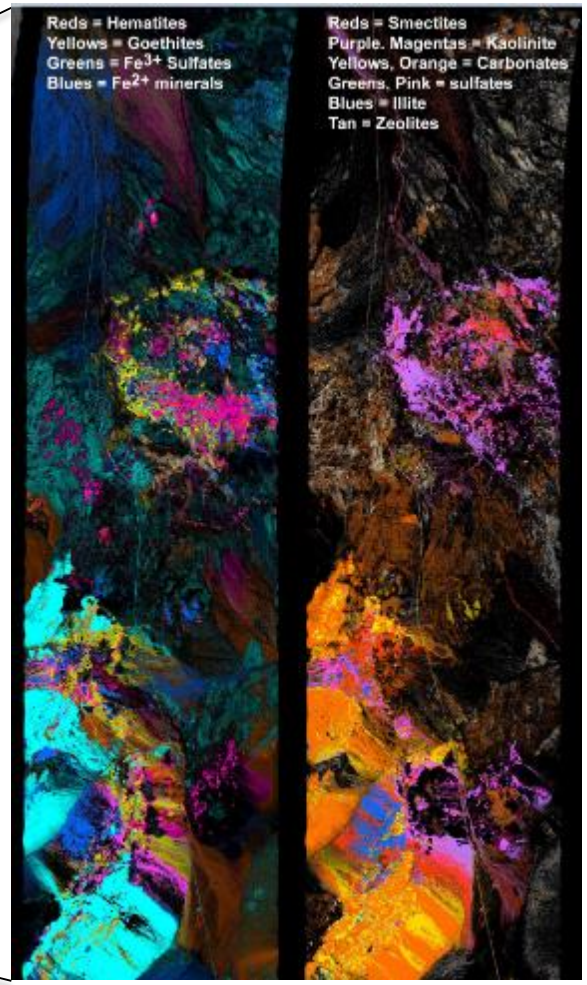
FAO Soil Map Compared to Airborne VSWIR Imaging Spectroscopy at Cuprite, Nevada

Cuprite, Nevada Region

FAO Soil Map



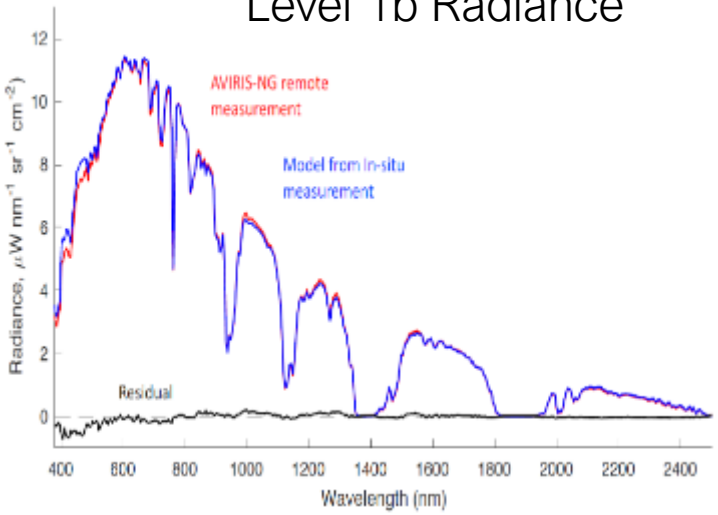
VSWIR Imaging Spectroscopy



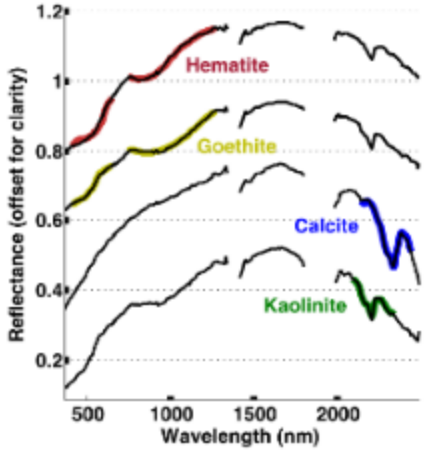
EMIT Data Products and Testing Builds on Decades of Airborne Imaging Spectrometer Measurements

Jet Propulsion Laboratory
California Institute of Technology

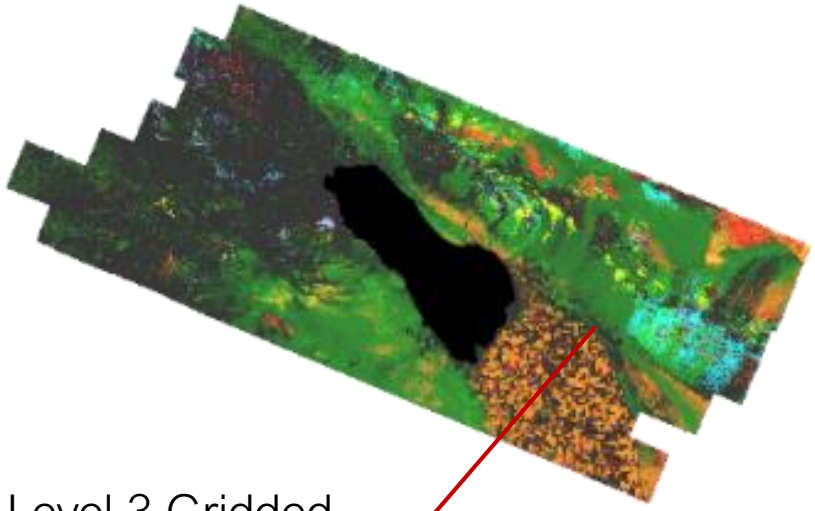
Level 1b Radiance



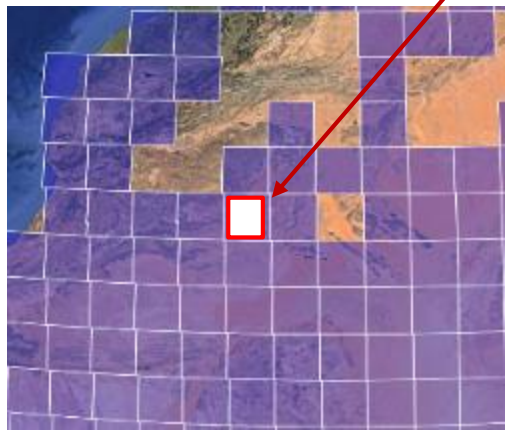
Level 2a Reflectance



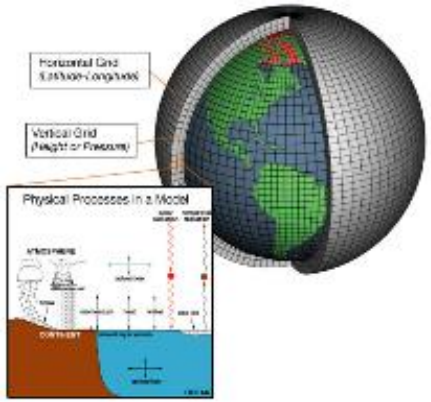
Level 2b Mineralogy



Level 3 Gridded



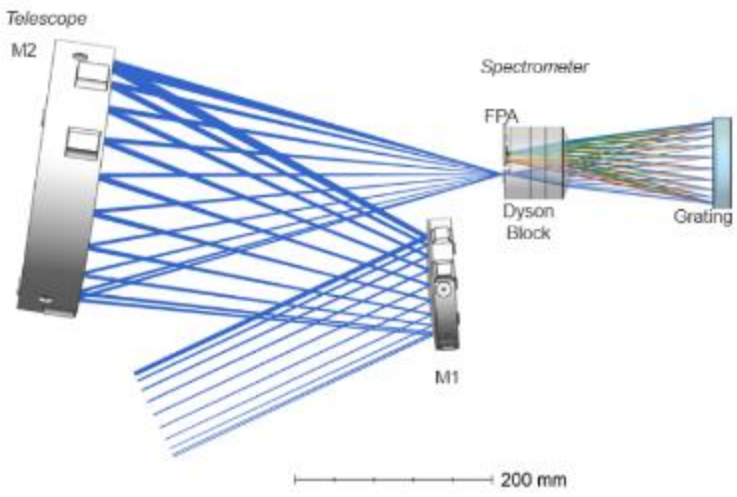
Level 4 Model Runs

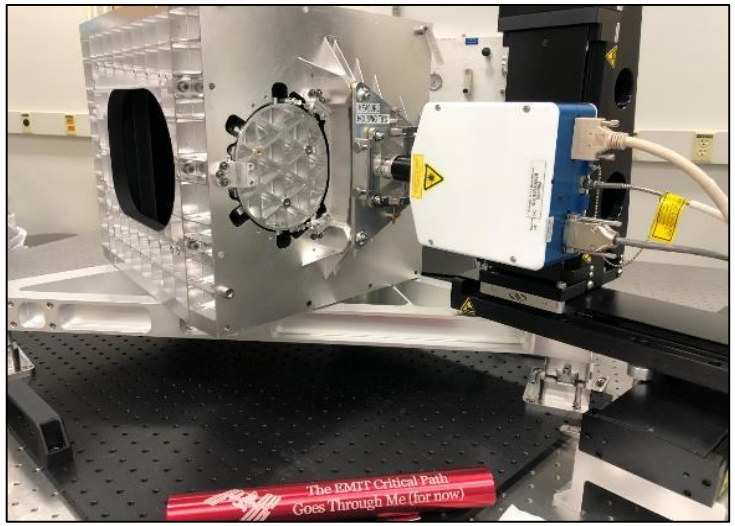


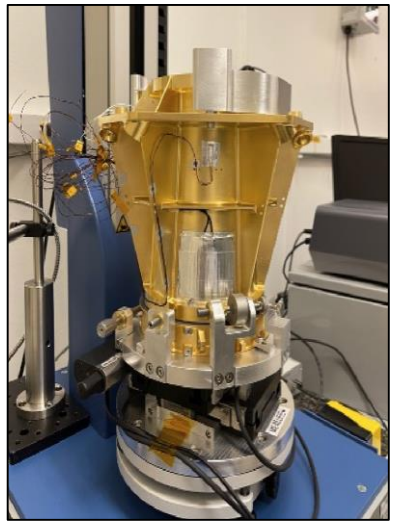
Field Spectroscopy with Laboratory/Analyses

The EMIT Instrument is Well Along in Development

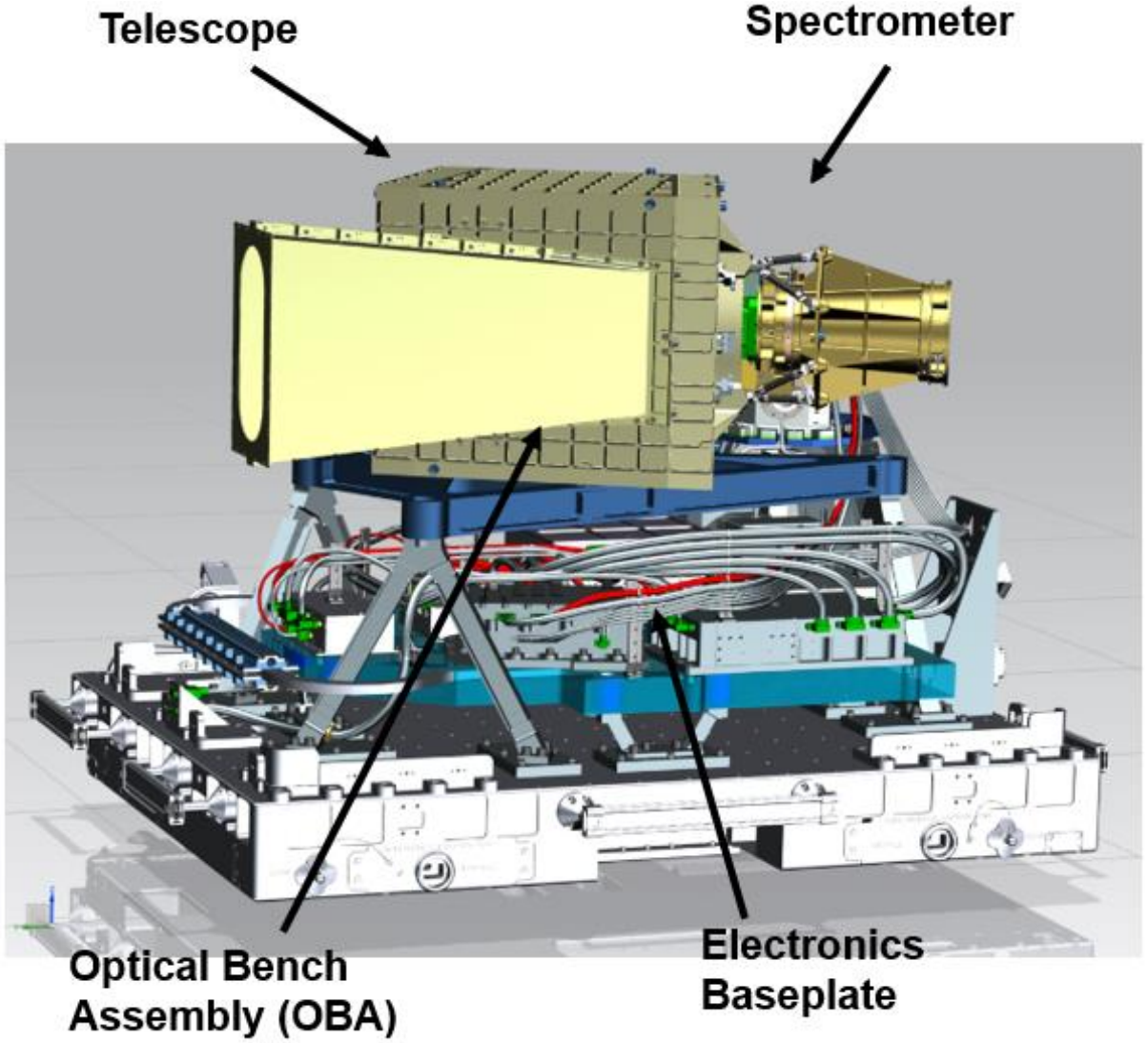
Telescope and F/1.8 Dyson Imaging Spectrometer







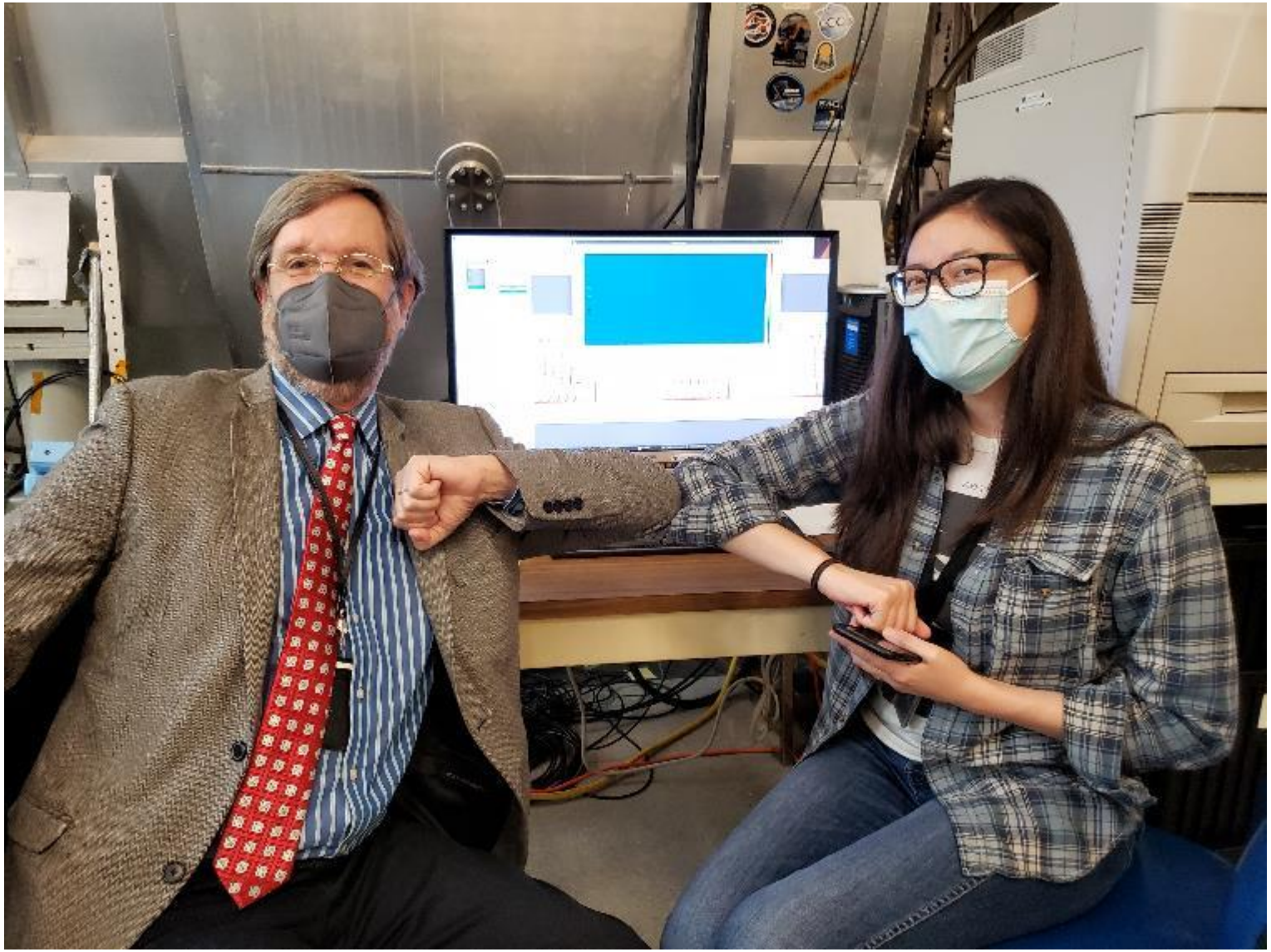
Payload Design

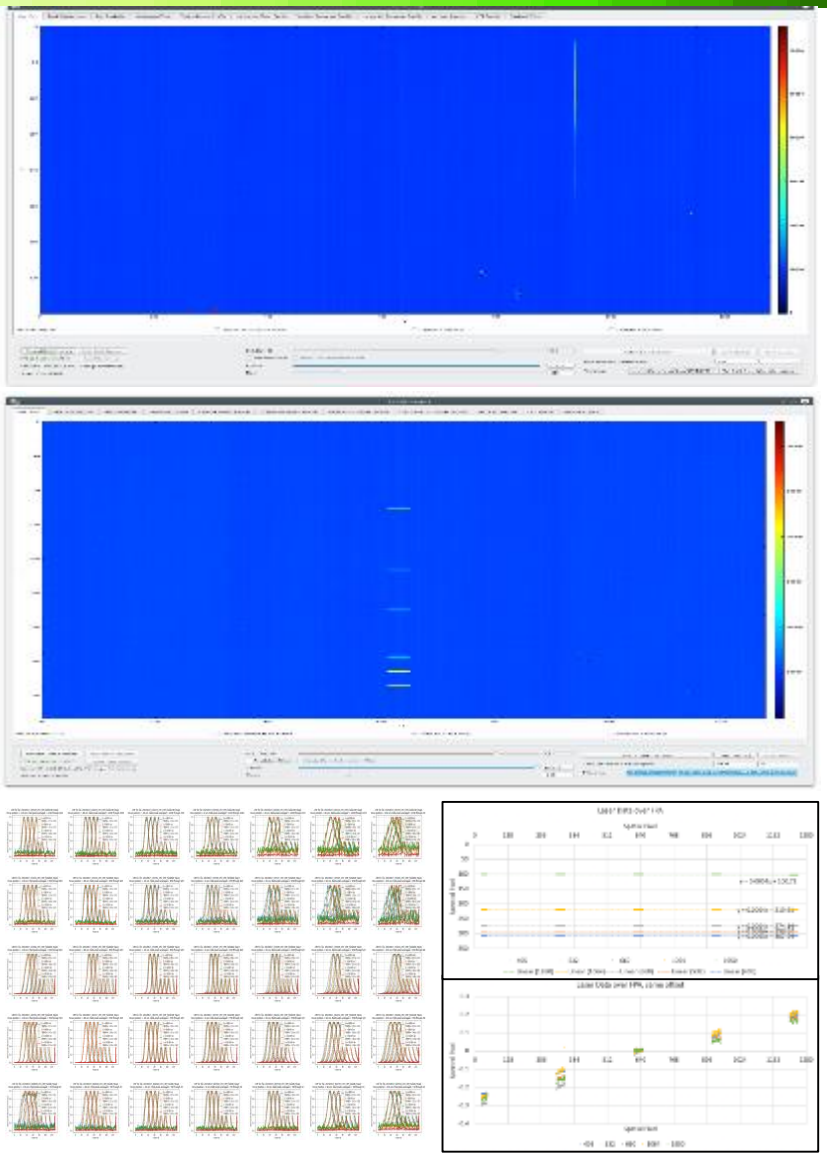


Imaging Spectrometer Alignment

- Review of alignment criteria for each requirement
- Review TVAC1a ARF cold measurement results
  - Assess the opportunity or risk of each adjustment from
    - Optics SME perspective
    - Optomechanical adjustment perspective
    - Project perspective
    - Science perspective
- Review TVAC1a CRF cold measurement results
  - Assess the opportunity or risk of each adjustment from
    - Optics SME perspective
    - Optomechanical adjustment perspective
    - Project perspective
    - Science perspective
- Review TVAC1a Keystone cold measurement results
  - Assess the opportunity or risk of each adjustment from
    - Optics SME perspective
    - Optomechanical adjustment perspective
    - Project perspective
    - Science perspective
- Review TVAC1a Laser centroid cold measurement results
  - Assess the opportunity or risk of each adjustment from
    - Optics SME perspective
    - Optomechanical adjustment perspective
    - Project perspective
    - Science perspective
- Concurrence on path forward

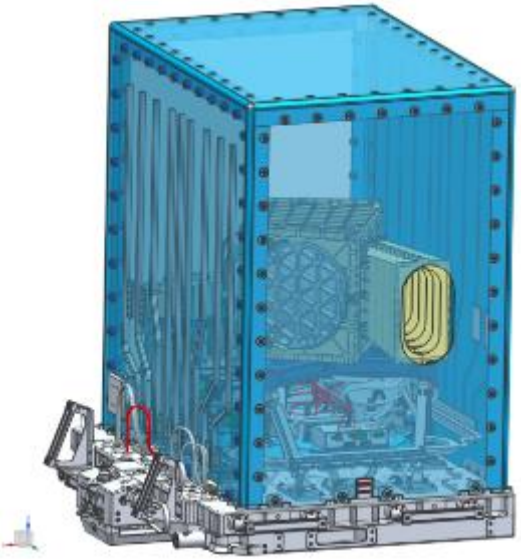
Live EMIT Spectra with Christine Bradley 20210817





EMIT will Begin Measuring Spectra from the ISS in 2022

EMIT in Enclosure

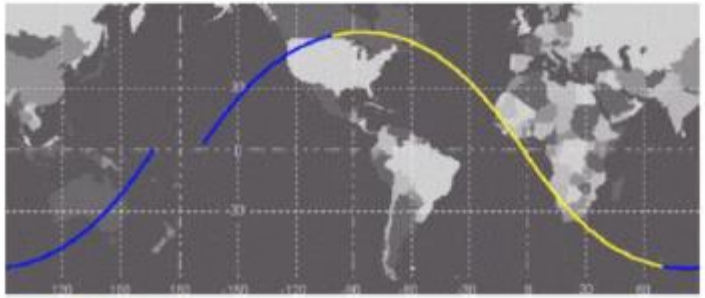


Planned SpaceX Launch

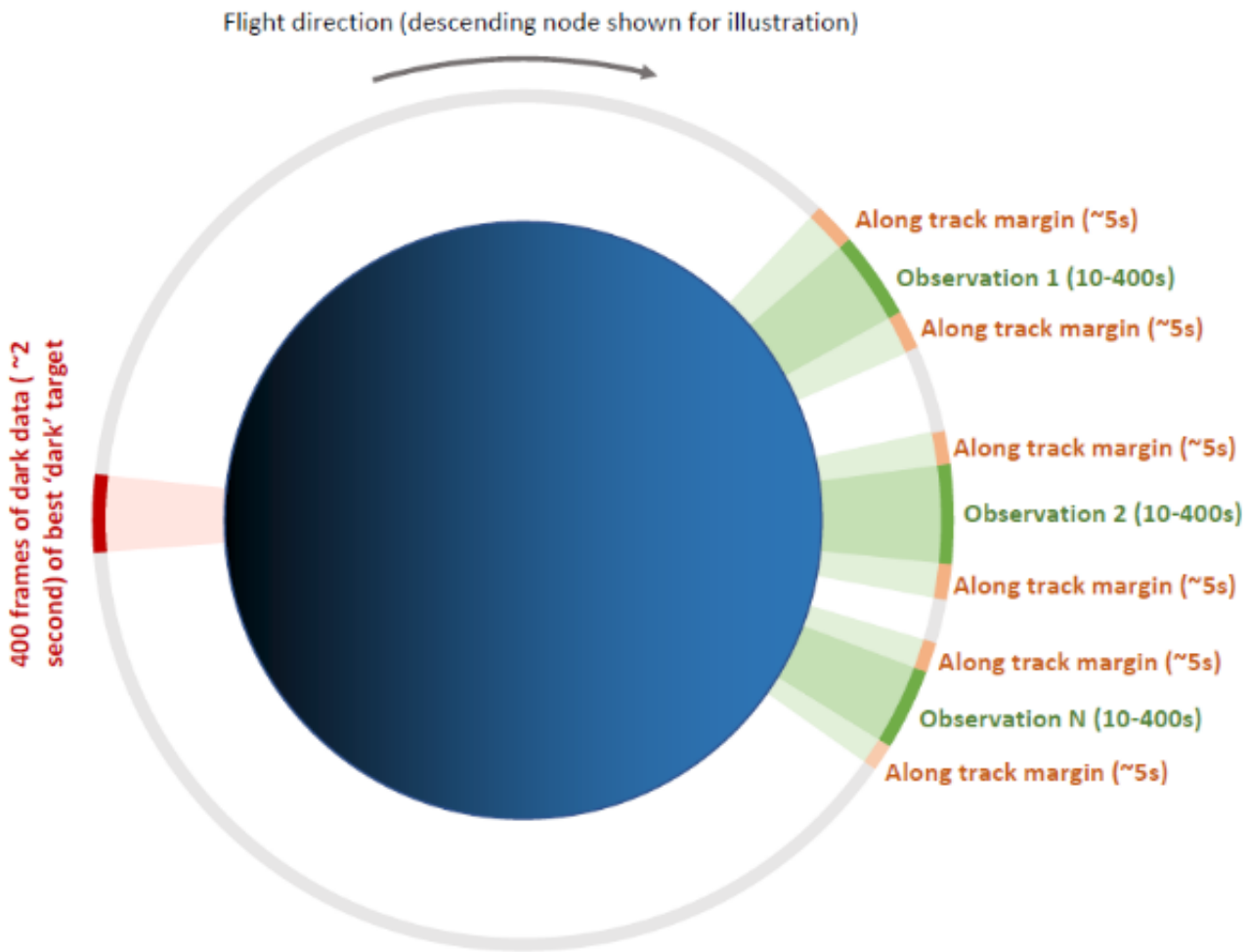
Acquisition Analysis and Example Orbit

Science Mask

Cloud Statistics



ISS Orbit



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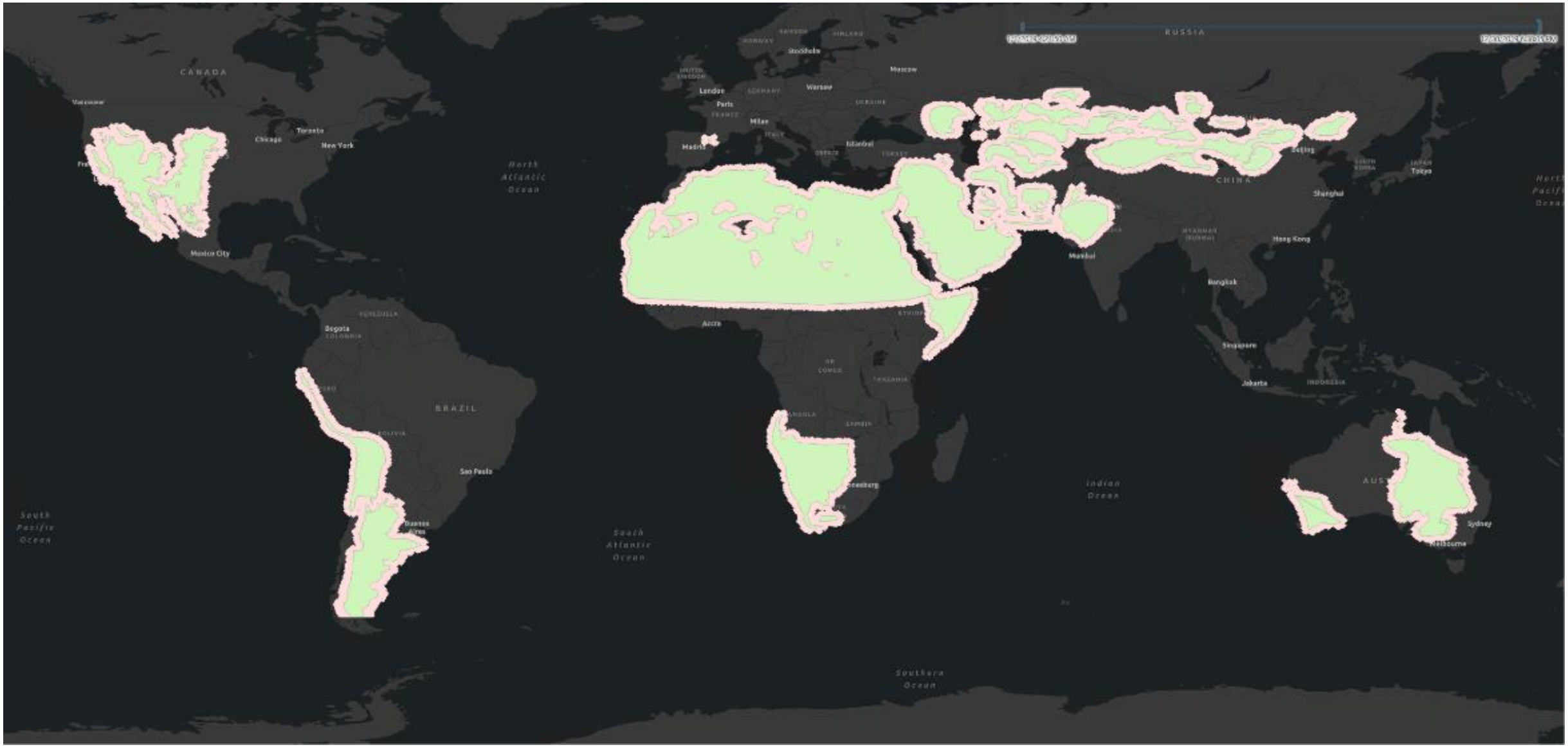
California Institute of Technology

EMIT Planned Arid Land Coverage Area



EMIT Dust Source Surface Mineralogy

EMIT on the ISS delivers >10^9 direct spectroscopic observations of arid land surface

EMIT Data Products to NASA LP DAAC

Data Product	Description	Initial Availability to NASA DAAC	Median Latency in Product Availability to NASA DAAC after Initial Delivery	NASA DAAC Location
Level 0	Raw collected telemetry	4 months after IOC	2 months	LP DAAC
Level 1a	Reconstructed, depacketized, uncompressed data, time referenced, annotated with ancillary information reassembled into scenes.	4 months after IOC	2 months	LP DAAC
Level 1b	Level 1a data processed to sensor units including geolocation and observation geometry information	4 months after IOC	2 months	LP DAAC
Level 2a	Surface reflectance derived by screening clouds and correction for atmospheric effects.	8 months after IOC	2 months	LP DAAC
Level 2b	Mineralogy derived from fitting reflectance spectra, screening for non-mineralogical components.	8 months after IOC	2 months	LP DAAC
Level 3	Gridded map of mineral composition aggregated from level 2b with uncertainties and quality flags	11 months after IOC	2 months	LP DAAC
Level 4	Earth System Model runs to address science objectives	16 months after IOC	2 months	LP DAAC

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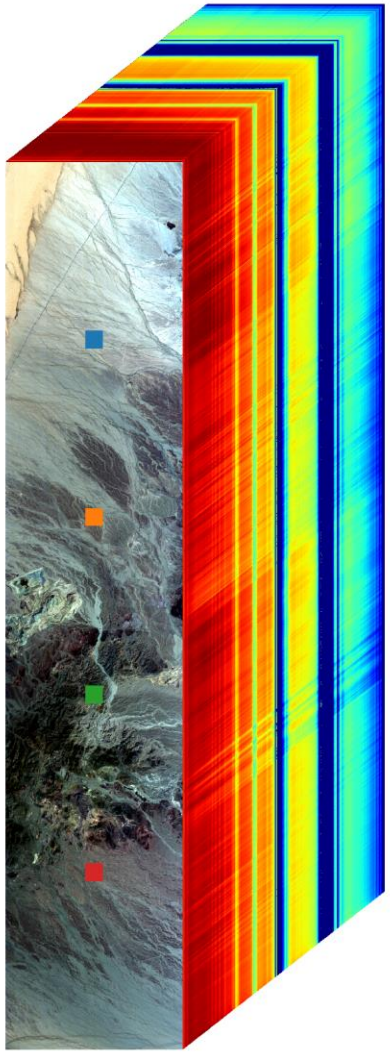
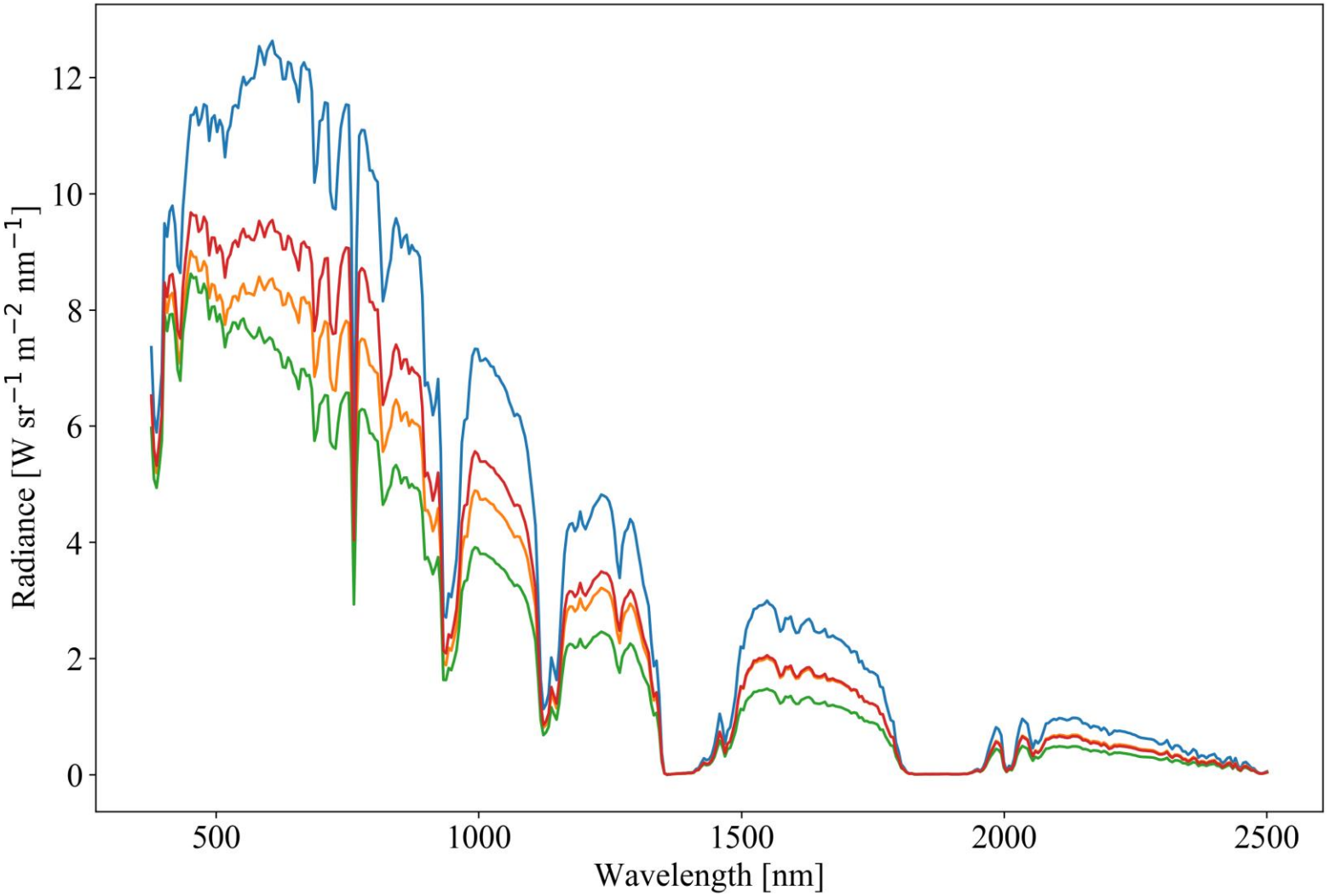
L1B Outputs (Radiance)





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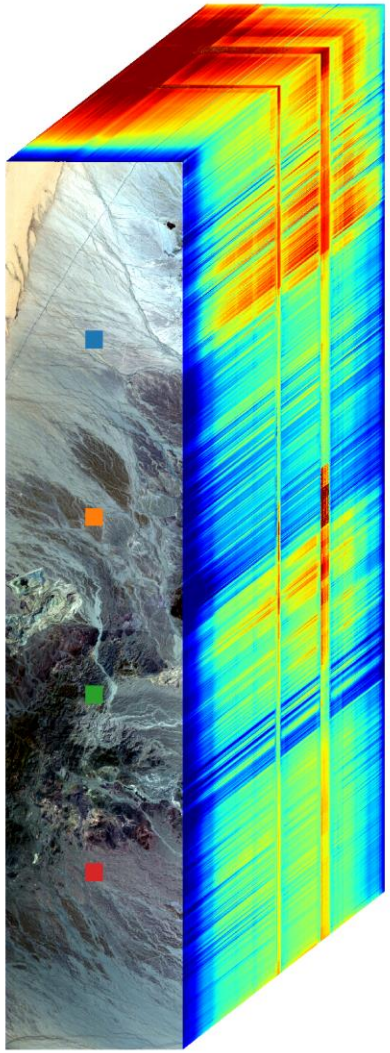
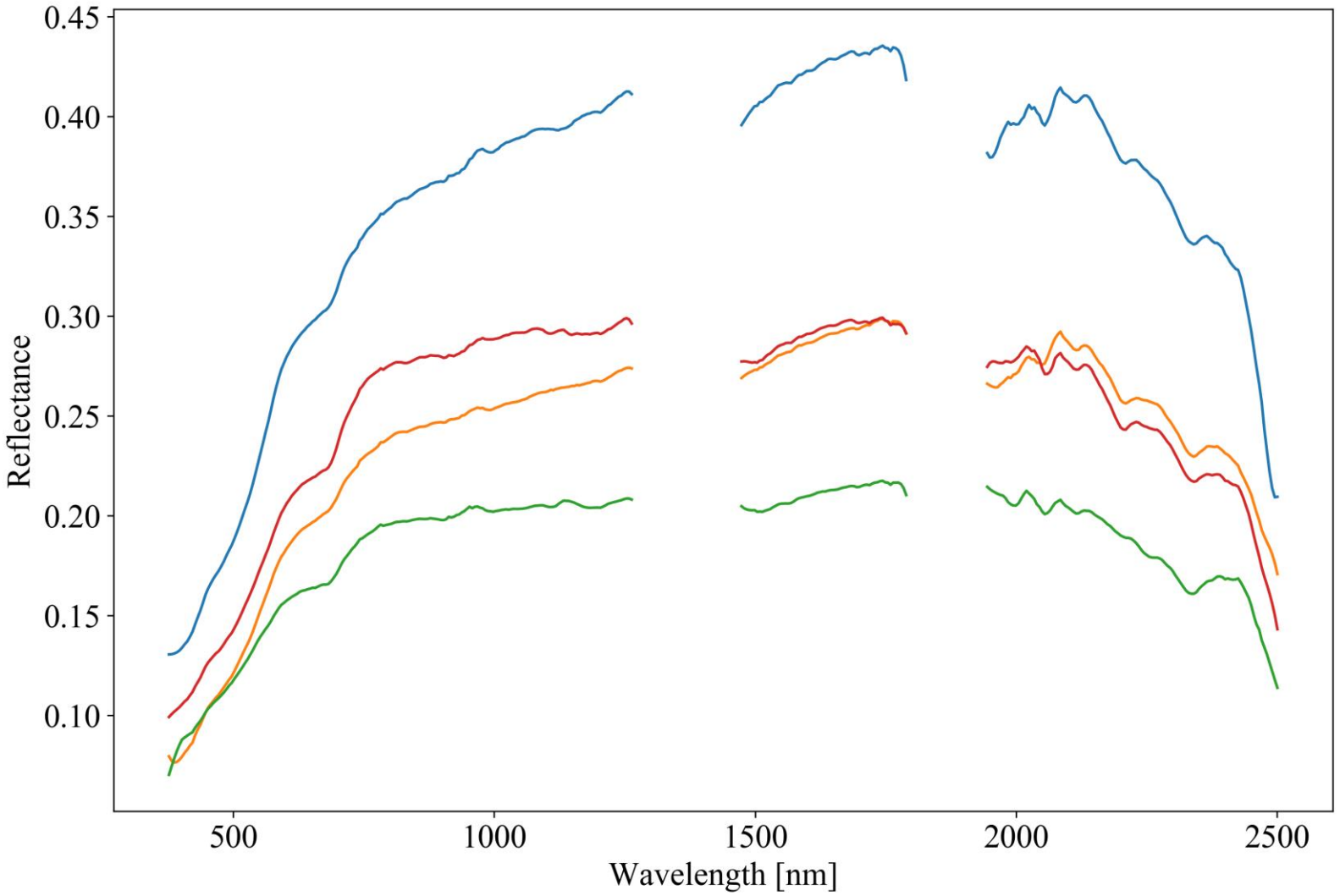
L2A Outputs (Reflectance)





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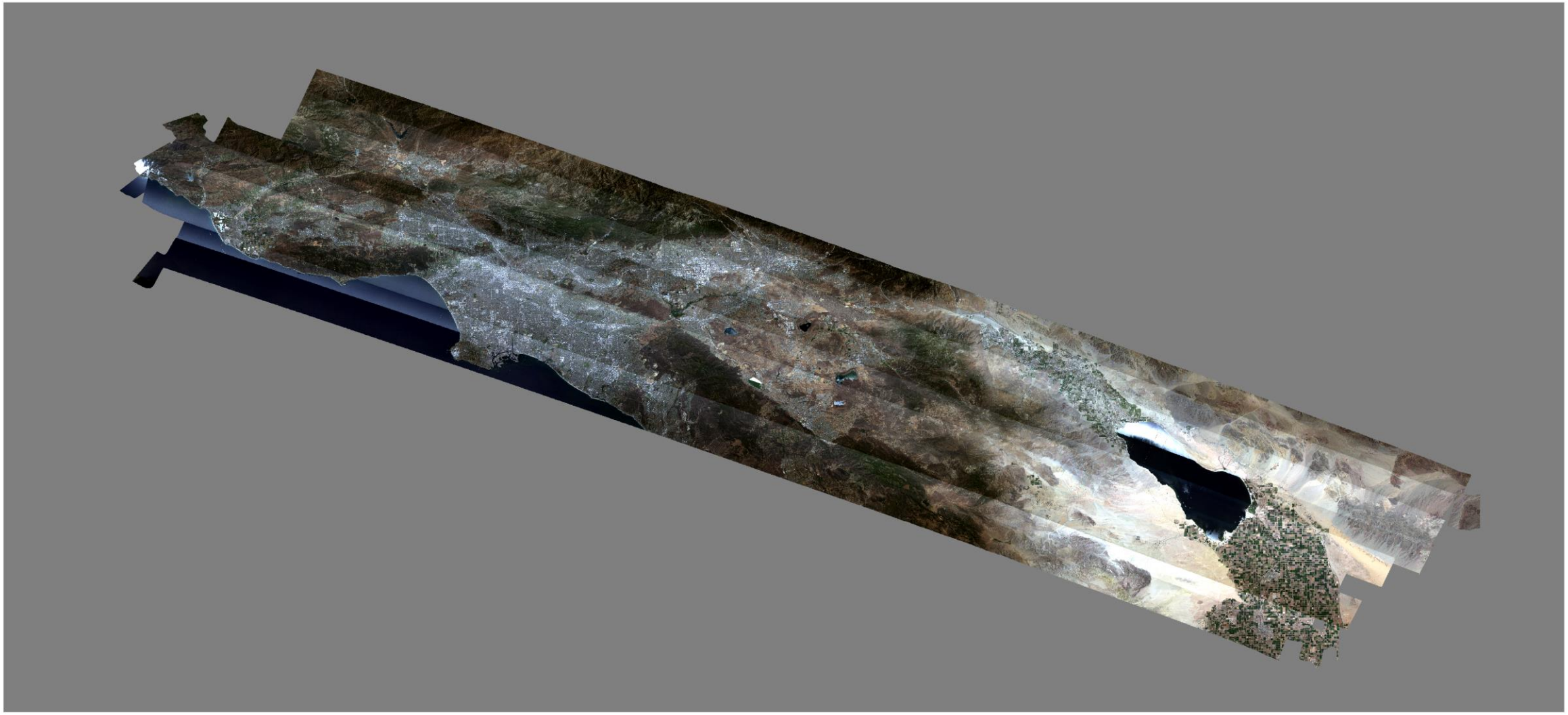
L2A Outputs (RGB, orthorectified)

RGB



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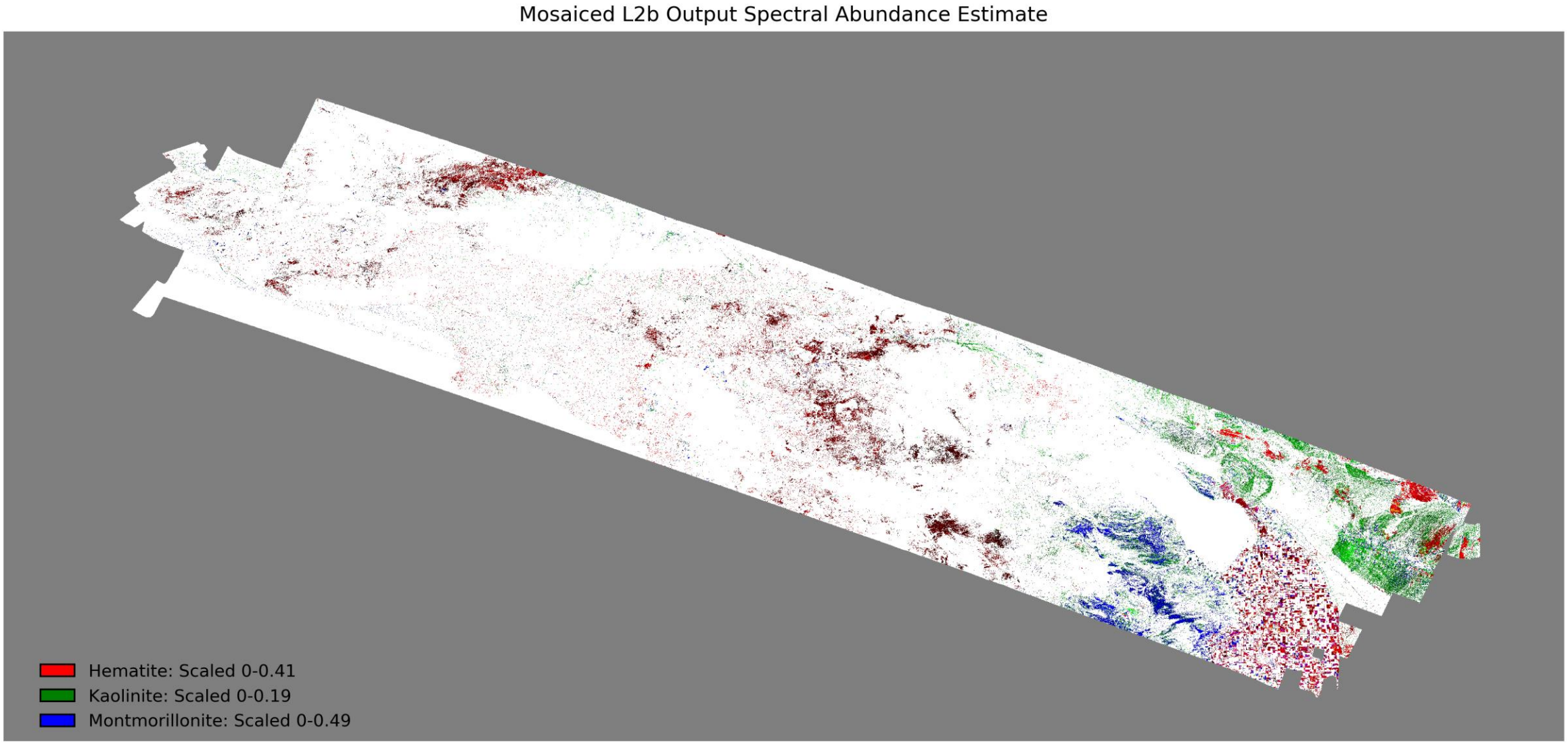
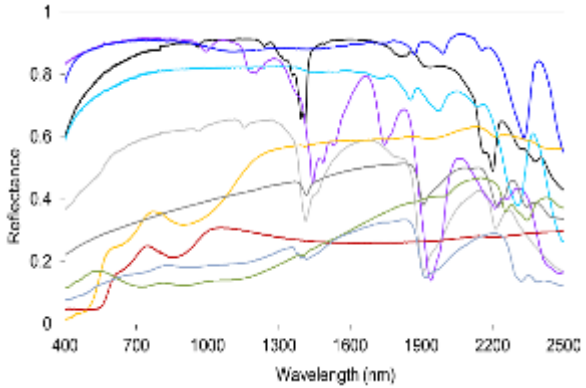
L2B Outputs (orthorectified)



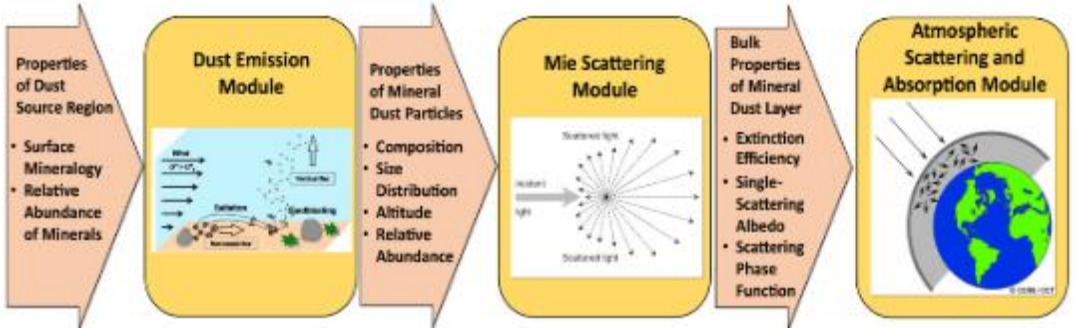
Summary: EMIT Science Flow to Objectives

Surface Spectroscopy

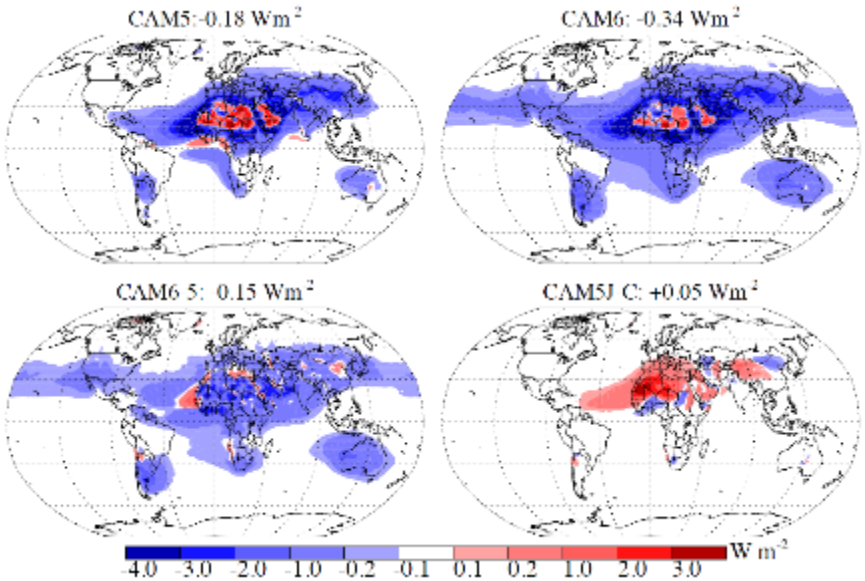


Mineral composition for models

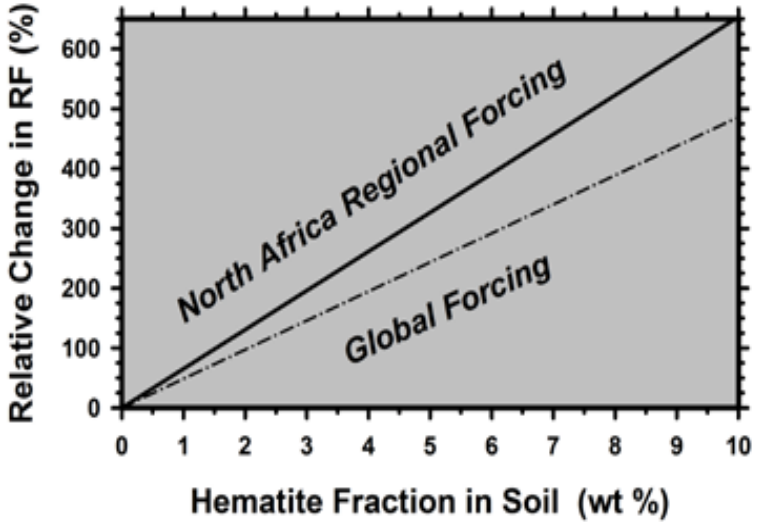
Update mineralogy in ESMs



Model Runs



RF Predictions



Objectives

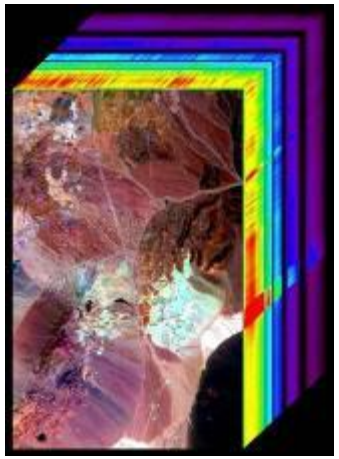
1) Constrain the sign and magnitude of dust-related RF at regional and global scales.

2) Predict the increase or decrease of available dust sources under future climate scenarios.

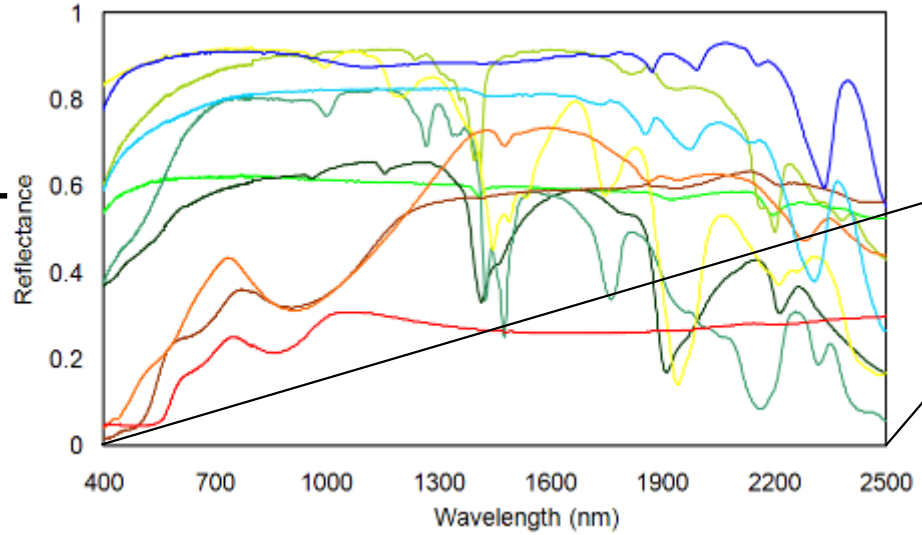
JPL's Sustained Commitment to Imaging Spectroscopy

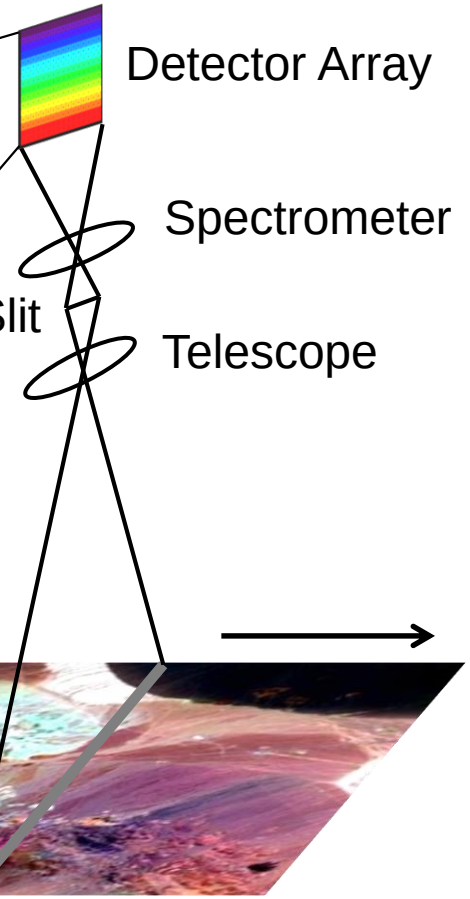
Jet Propulsion Laboratory
California Institute of Technology

Calibrated Image Cube

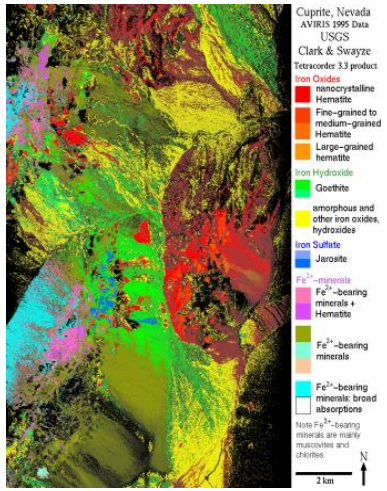


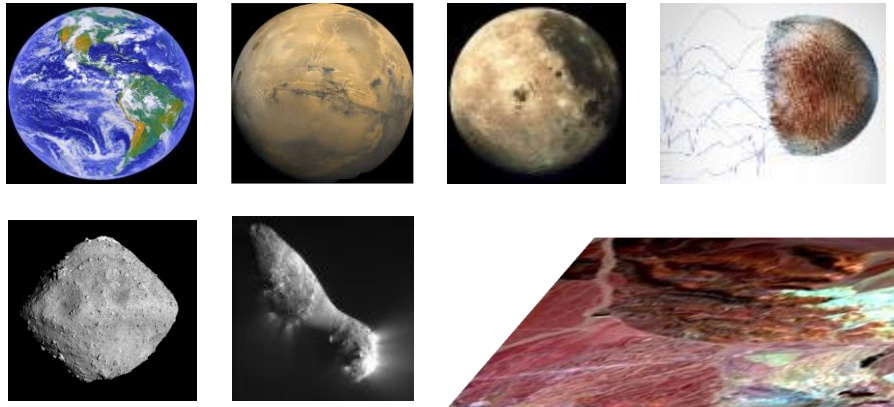
Targeting the most demanding science and applications requirements

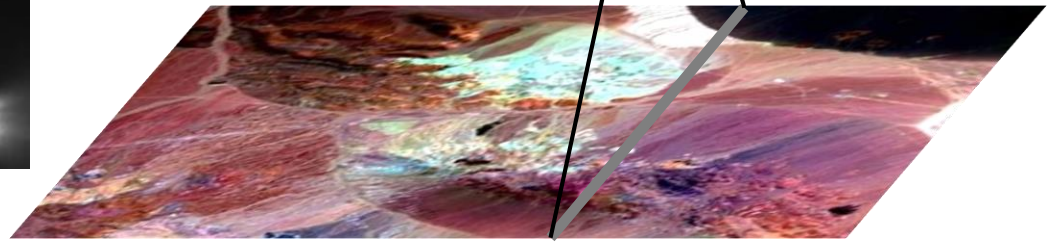


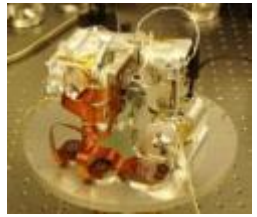


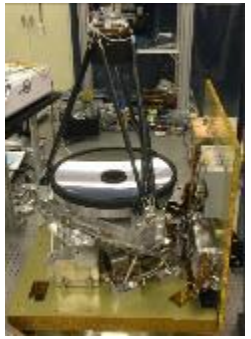
Material Map











Each imaging spectrometer is different based on requirements and technologies.

Comparing assumptions for dust optical properties in various Goddard-based aerosol retrieval algorithms

Robert Levy (NASA/GSFC)

Goddard's "Dust" Science Task (STG) leads: Patricia Castellenos, Peter Colarco

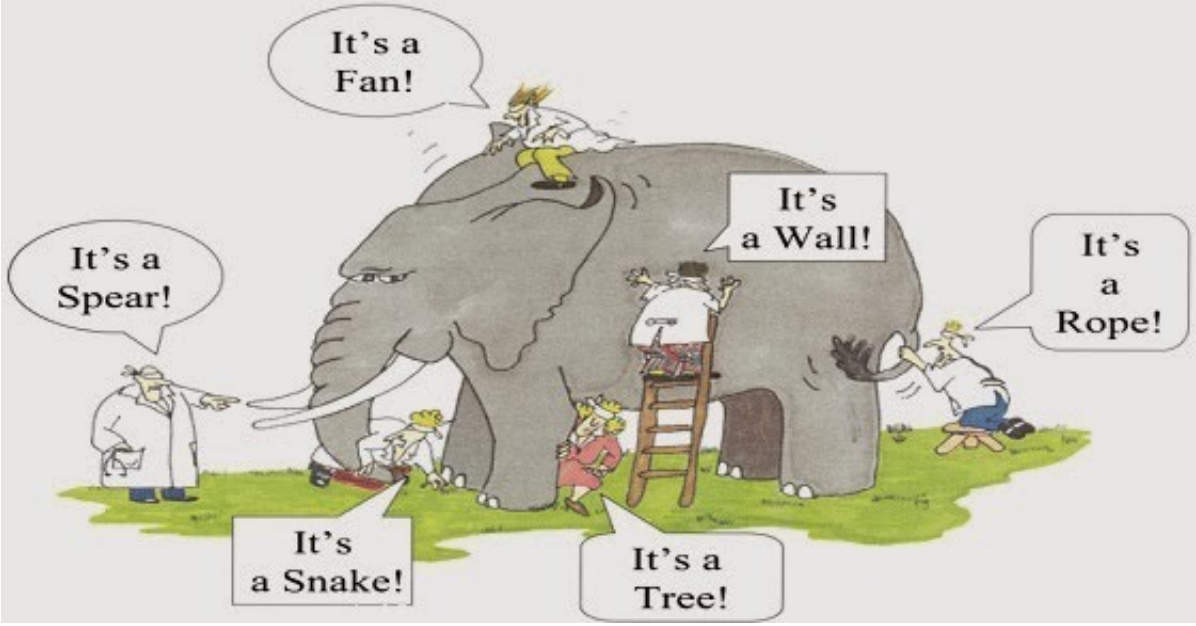
Algorithm contacts:

- AERONET: David Giles
- Dark Target: Yaping Zhou
- Deep Blue / SOAR: Jaehwa Lee
- MISR: Ralph Kahn, Olga Kalashnikova
- OMIAERUV: Hiren Jethva
- MAIAC: Yujei Wang
- Dust on Mars: Scott Guzewich

Background (Satellite remote sensing of dust)

- Dust aerosol is quite *variable* when it comes to vertical loading, size distribution, shape distribution and composition.
- In fact, the definition of 'dust' is not fixed, but let's assume dust means particles lifted from arid land surfaces by wind processes.
- There are many remote sensing techniques, developed and tuned for a diverse set of sensor/platform combinations,
- In general, satellite remote sensing is an ***under-determined problem*** – no single measurement is sufficient for determining all properties of the dust.

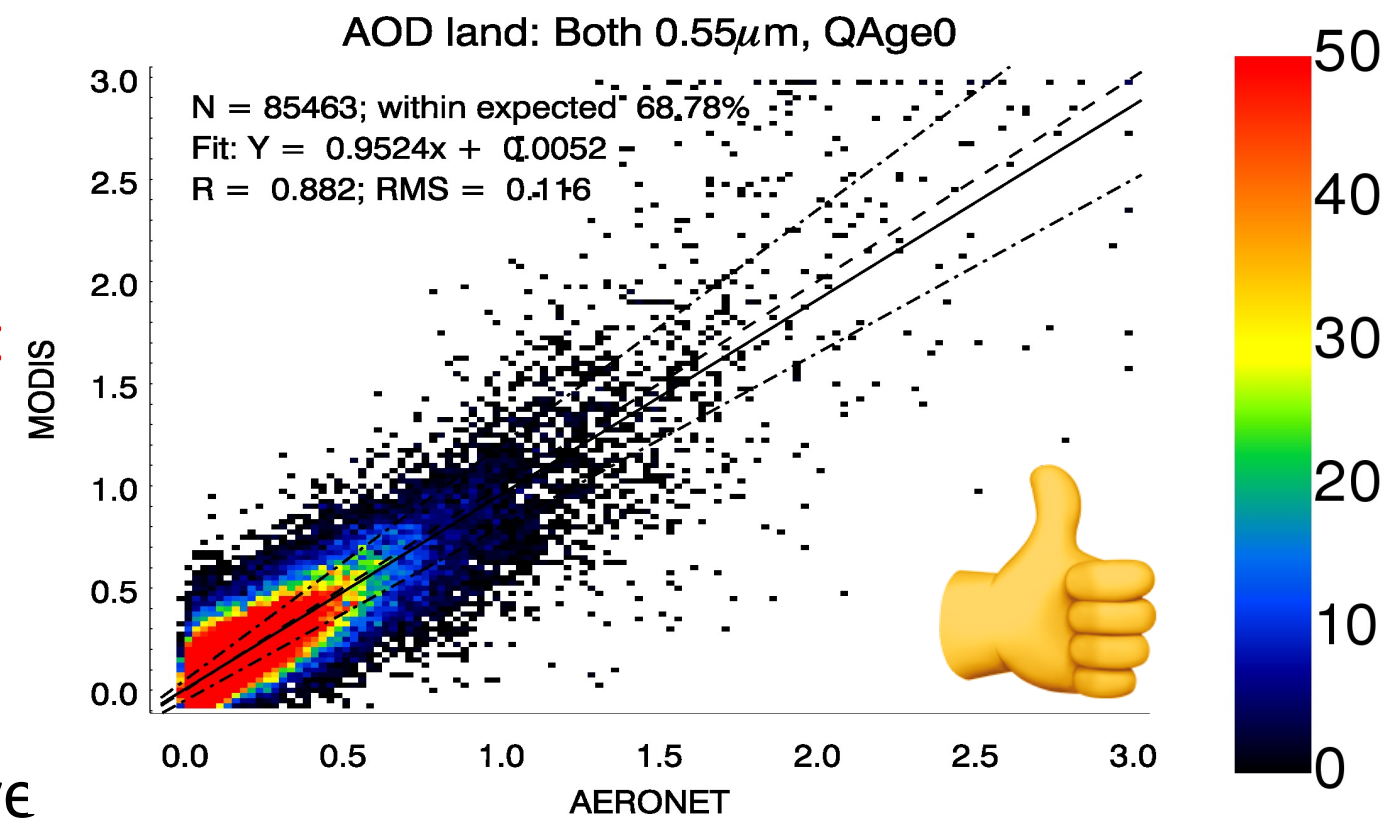
Remote sensing = Blind Men and Elephant



https://medium.com/betterism/the-blind-men-and-the-elephant-596ec8a72a7d

Background (There are many validated algorithms)

- At NASA Goddard, we run many algorithms developed for many sensor/platform combinations
- To stay in business, each of us must claim that we get the right answer on average.
- How is this possible?
- Each algorithm makes ‘assumptions’ about the dust properties (size, shape, refractive index)



Background (Why is this a problem)

- Global and regional models used in AeroCom all make their own assumptions for dust and they are NOT the same as used by retrieval algorithms
- Future remote sensing capabilities (e.g. PACE, AOS) will be joining multiple capabilities into one sensor/platform.
- We run the risk of well-validated assumptions for algorithm/sensor/platform #x being inconsistent for #y.

Dust models

- An ***aerosol model*** is a set of assumptions about size distribution, shape distribution, and spectral refractive index of a particular “type” of aerosol. Each algorithm has aerosol models which are intended to represent dust.
- How similar / different are the ***dust models*** in the different algorithms?
  - For example, MODIS wants dust to ”fit” into VIS/SWIR space whereas OMI wants to “fit” in UV space.
- For each algorithm, I explored the literature and/or asked the developers for information.
- My goal is to put all parameters of dust models on the same scale.

Motivation

This work was motivated by

- a larger Goddard-funded “Science Task Group” (STG) on dust properties in models versus observations. This Dust STG is led by Patricia Castellanos
- Need for a “unified” algorithm for PACE Ocean Color Imager (OCI) led by Lorraine Remer.
- My own curiosity about dark-target models I had derived 15 years ago.

What did I ask for?

For every algorithm, I asked for properties of:

- Size distribution (dV/dlnr)
  - Whether assumed lognormals or not, and how many modes (1 or 2 or more?)
  - If lognormals,
    - then mean and stddev radius of number or volume for each mode (r_g, r_v, σ)
  - If not lognormals, then other properties of the moments.
  - Is the size distribution "dynamic" (e.g. function of loading or AOD?)
- Shape distribution
  - Spheres? Spheroids? Something else?
  - Many teams have assumed collections of spheroids with aspect ratios – often the Dubovik et al (2006) distribution used for AERONET retrieval
- Refractive indices
  - Complex (real + imaginary) for wavelengths or wavelength bands used in a retrieval
  - Whether "dynamic" (function of AOD)
- Anything else?
  - For example, some teams used scattering codes with limits on size parameter ($x = 2\pi r/\lambda$)

First example: AERONET retrieval

- Let's look at one case: Capo Verde from March 9, 2006 @ 10:24 UTC (same case as used in J. Lee's (2017) paper.)

Properties of downloaded AERONET retrieval

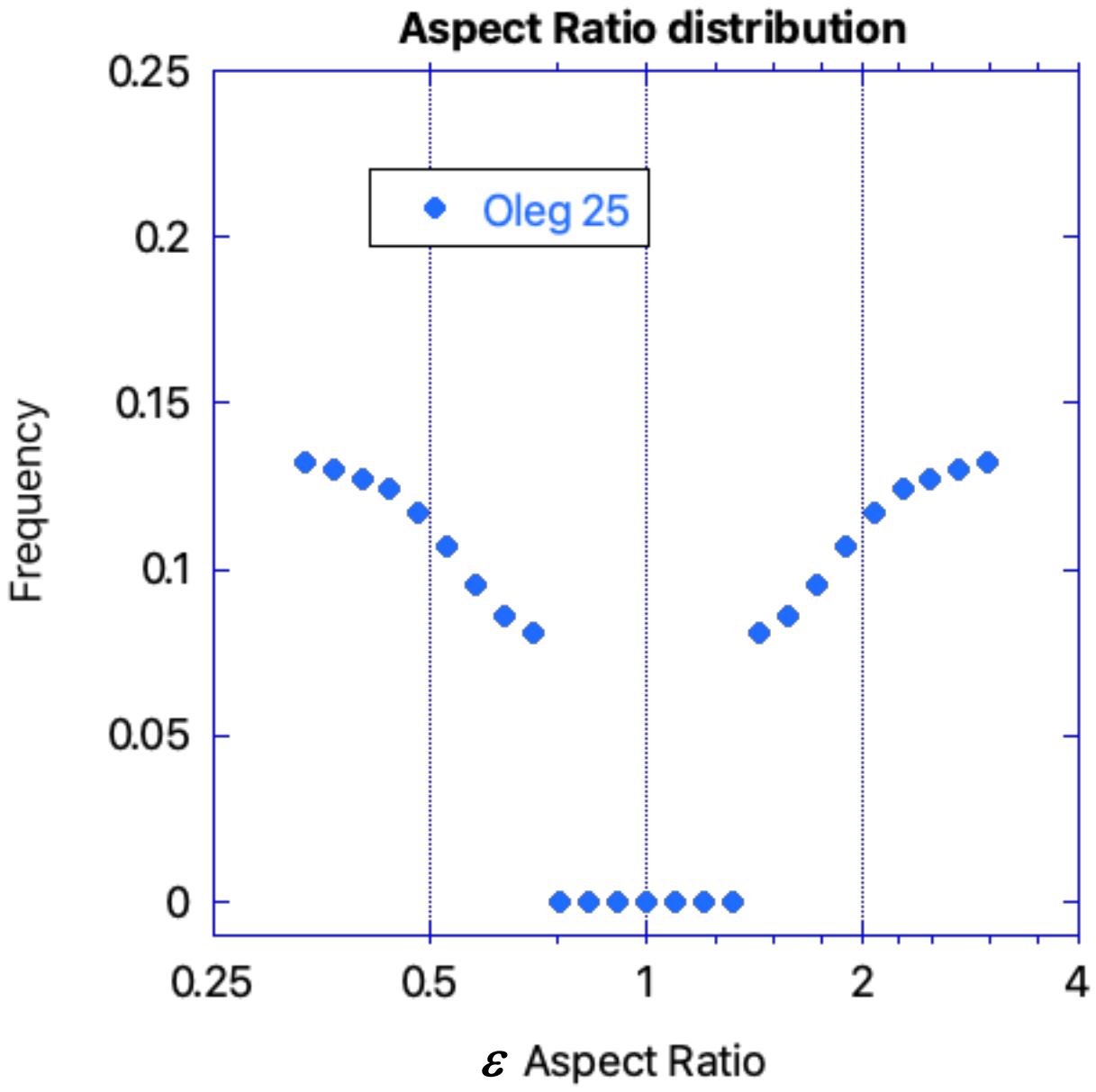
SizeParameter / Mode	Fine	Coarse		Parameter / Wavelength	440	675	870	1020
VolConc (C_v)	0.094	1.593		Sun-mode AOD	2.793	2.748	2.617	2.500
Reff (r_{eff})	0.248	1.551		**Refr_Real (n)**	**1.4749**	**1.4469**	**1.4379**	**1.419**
VolMeanR (r_v)	0.291	1.797		**Refr_Img (k)**	**0.00377**	**0.00055**	**0.00059**	**0.0005**
StdDev (s)	0.481	0.534		Extinction (k_{ext})	2.826	2.766	2.628	2.512
Inflection (r_{inf})	0.439			SSA (w_0)	0.913	0.989	0.990	0.993
Sphere Fraction (f)	0.0			Asymmetry (g)	0.819	0.773	0.761	0.765
				Lidar Ratio (k)	70.025	54.469	55.045	60.559
				Lidar Depol (d)	0.296	0.314	0.323	0.332
				Extinct. FMF (h)	0.274	0.171	0.112	0.079

Thank you Dave Giles for making sure I understood this

AERONET “re-retrieval” (1)

- Assume distribution of spheroid aspect ratios “oleg 25” which is same as used by AERONET inversion(Dubovik et al., 2006). Used for current (V3) of AERONET inversions.

- Note there are no spheres $f(\varepsilon = 1) = 0.0$.



AERONET “re-retrieval” (2)

Use Dubovik, Sinyuk, Lapyonik (DSL) Code used for AERONET and GRASP

SizeParameter / Mode	Fine	Coarse
VolConc (C_v)	0.094	1.593
Reff (r_{eff})	0.248	1.551
VolMeanR (r_v)	0.291	1.797
StdDev (s)	0.481	0.534
Inflection (r_{inf})	0.439	
Sphere Fraction (f)	0.0	

Parameter / Wavelength	440	675	870	1020
Sun-mode AOD	2.793	2.748	2.617	2.500
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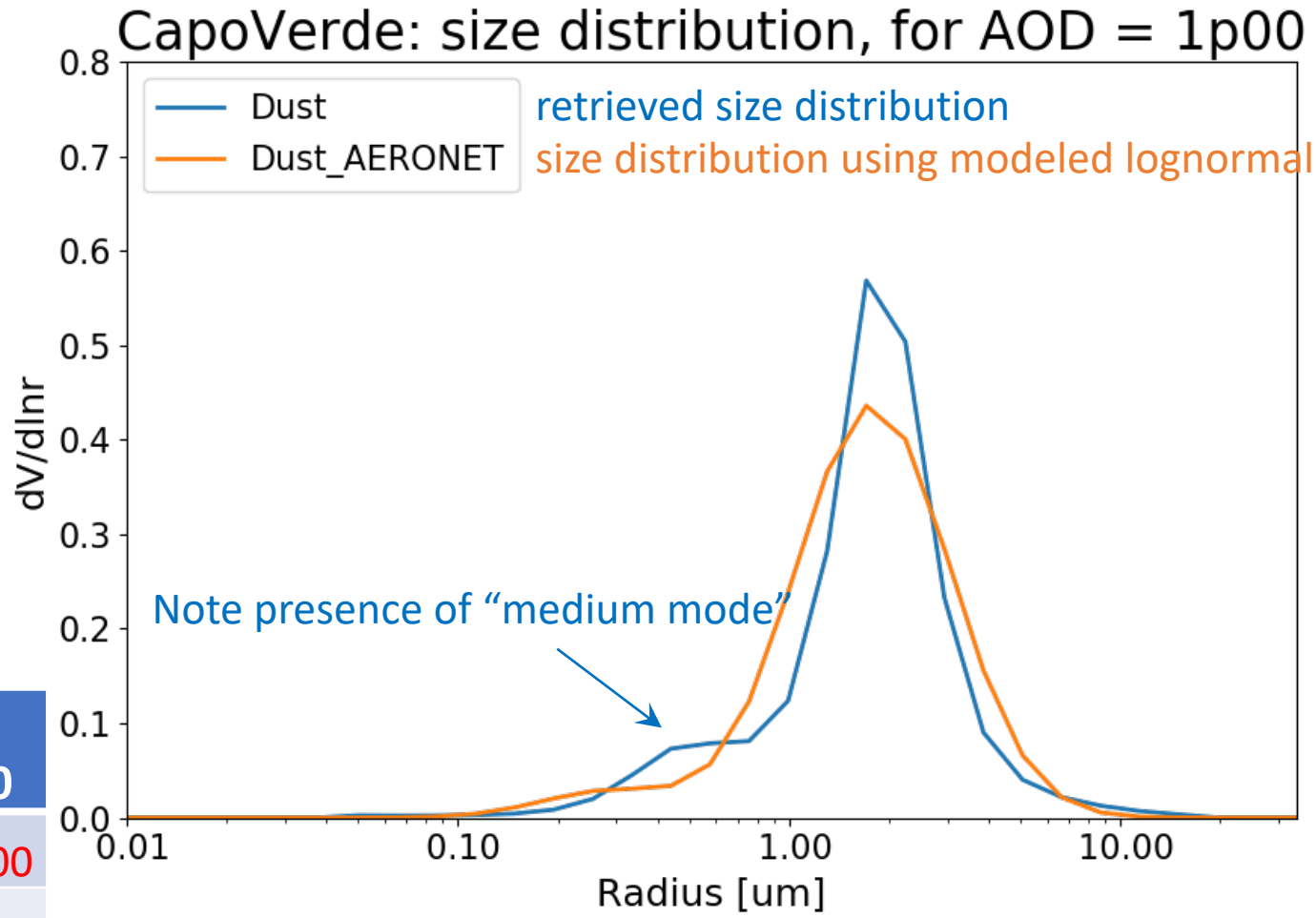
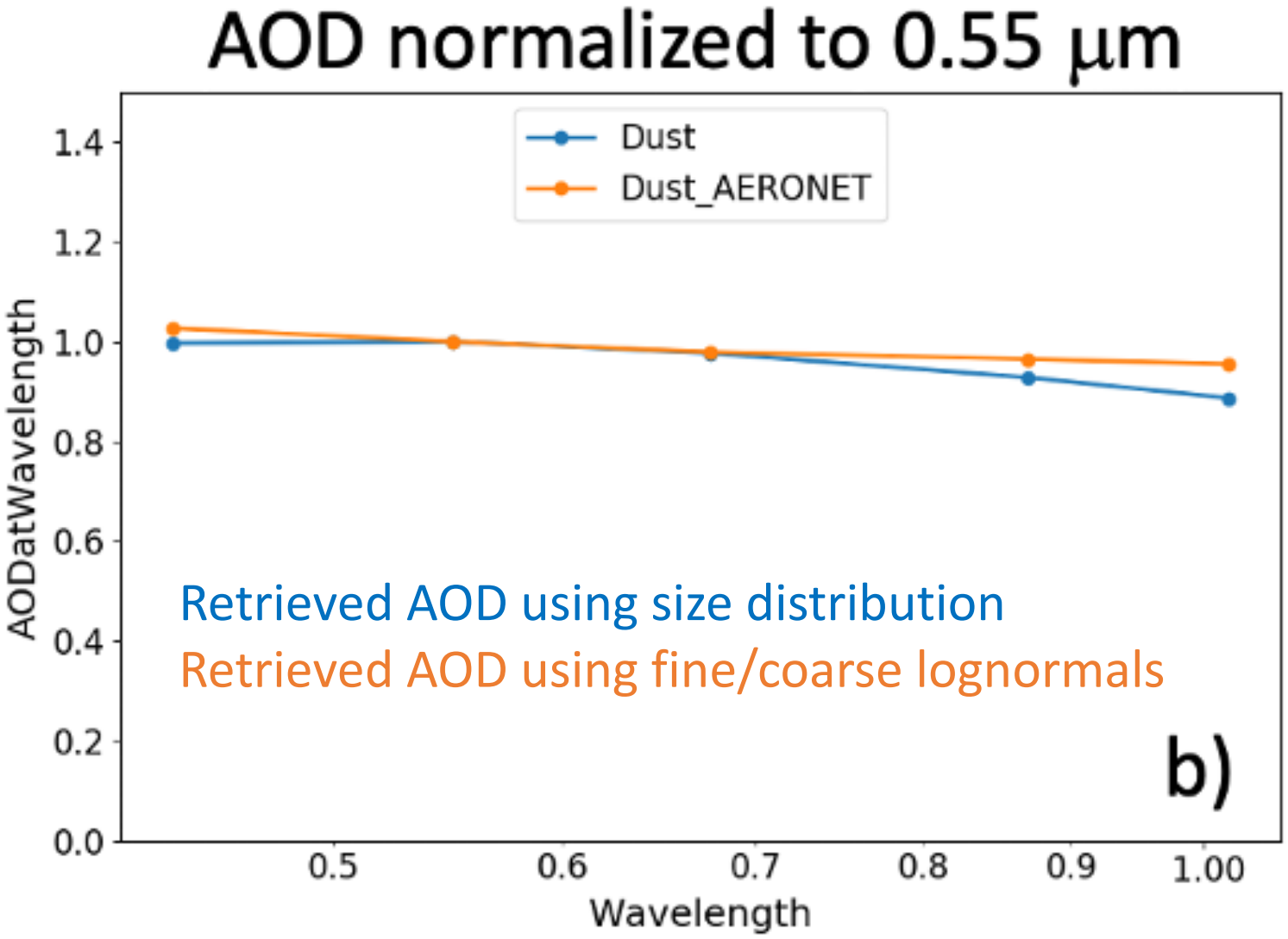


(Yes, Ralph, the medium mode is here)

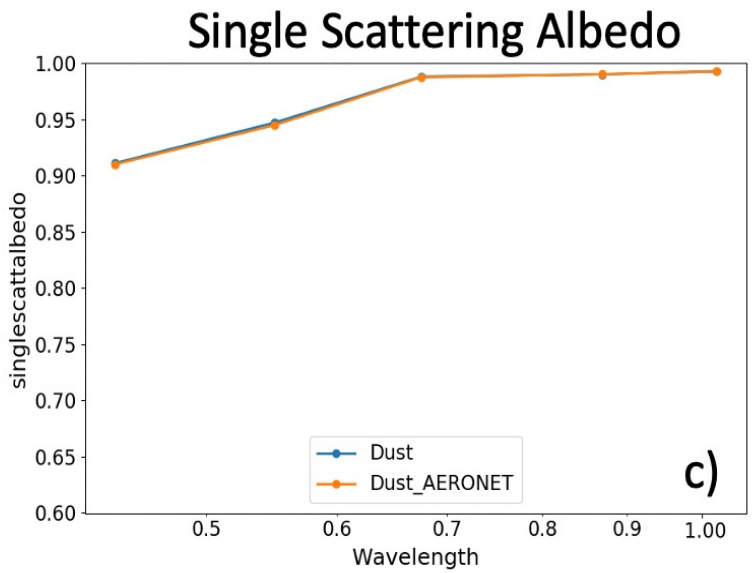
AERONET “re-retrieval” (results 1)

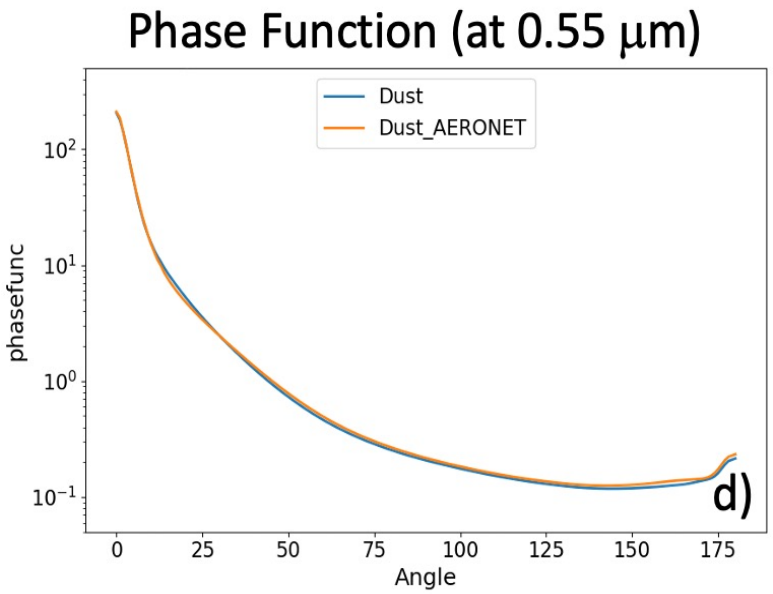
- Used AE fitting to derive AOD at 0.55 μm.
- The point is that spectral dependence of AOD (Angstrom Exponent) is different!
- Note that using original size distribution in fact gives much closer results to original retrieval (and sun AOD) than lognormals.

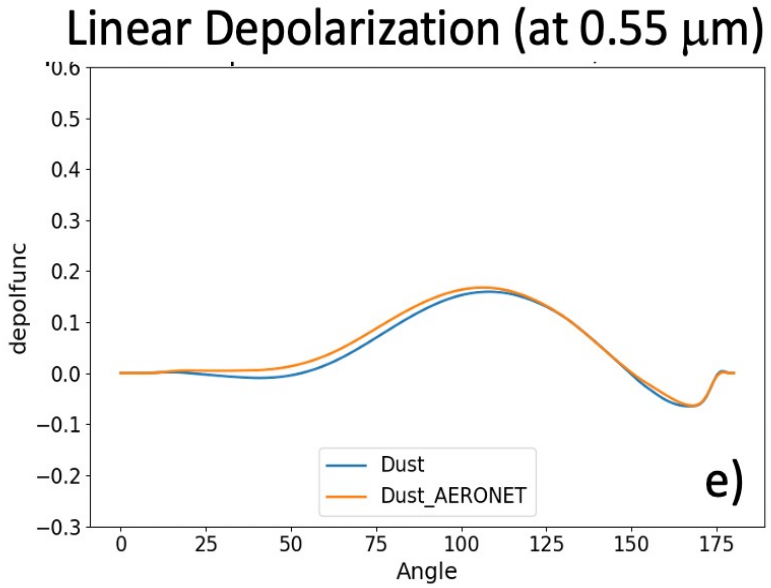


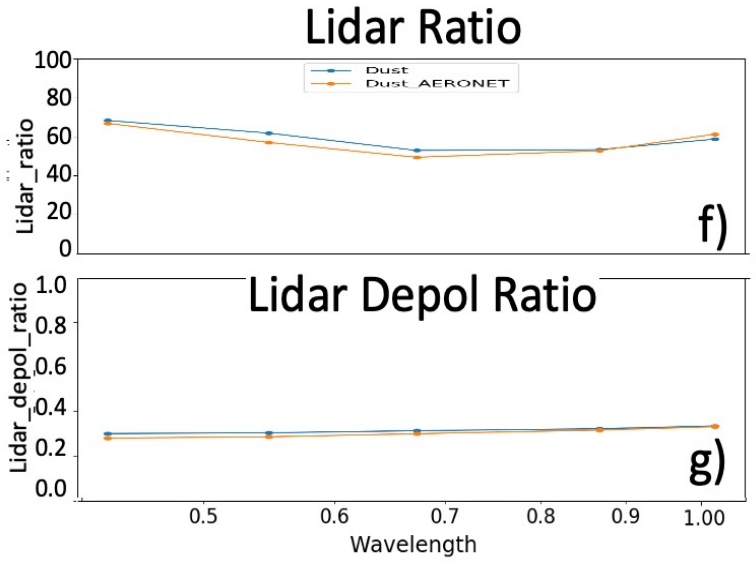
AERONET “re-retrieval” (results 2)

- In addition to AOD dependence, we can calculate all other parameters derived by AERONET for these conditions.
- In turns out that ***except*** for AOD spectral dependence, most other parameters compare pretty well.



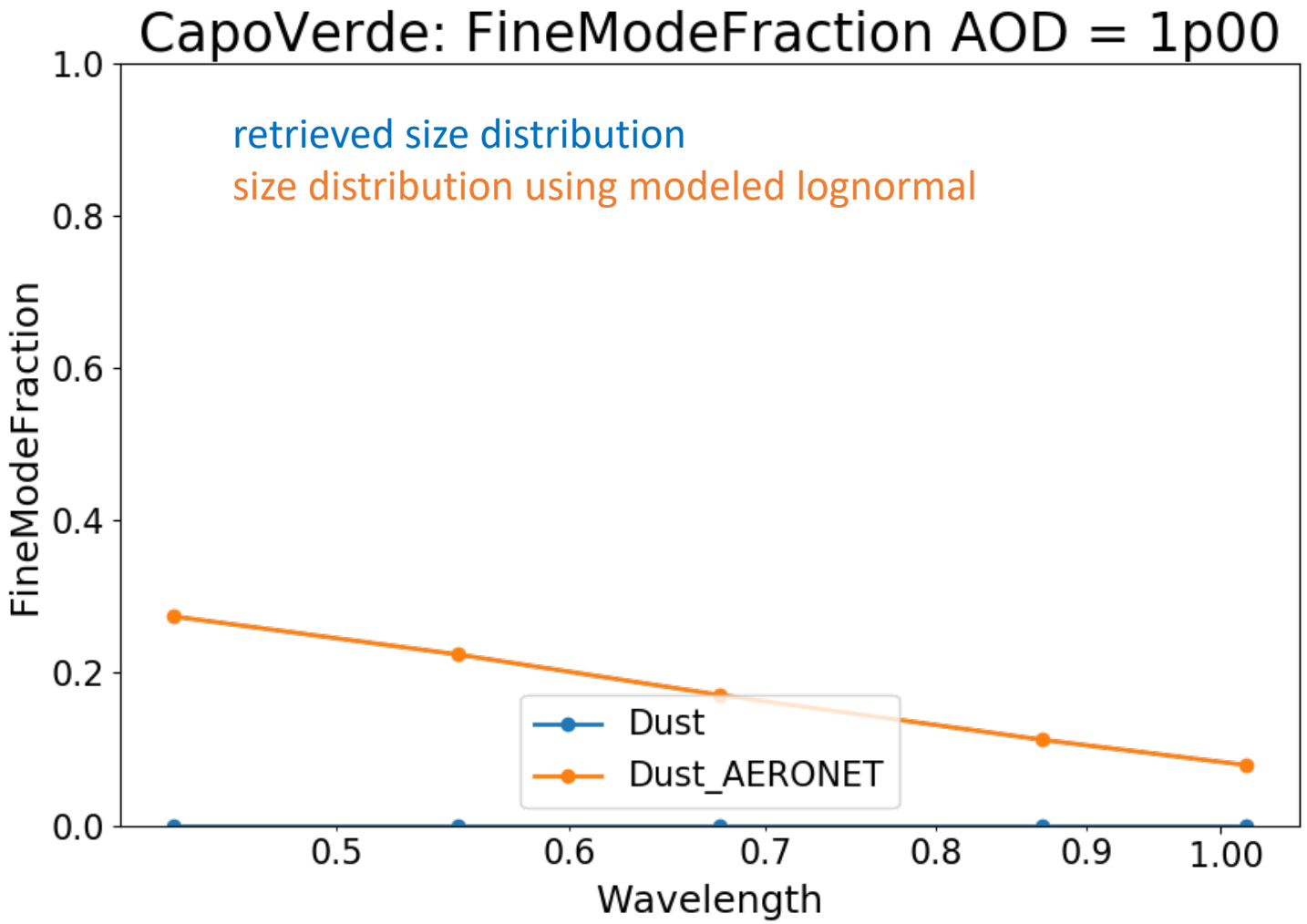






Fine Mode Fraction

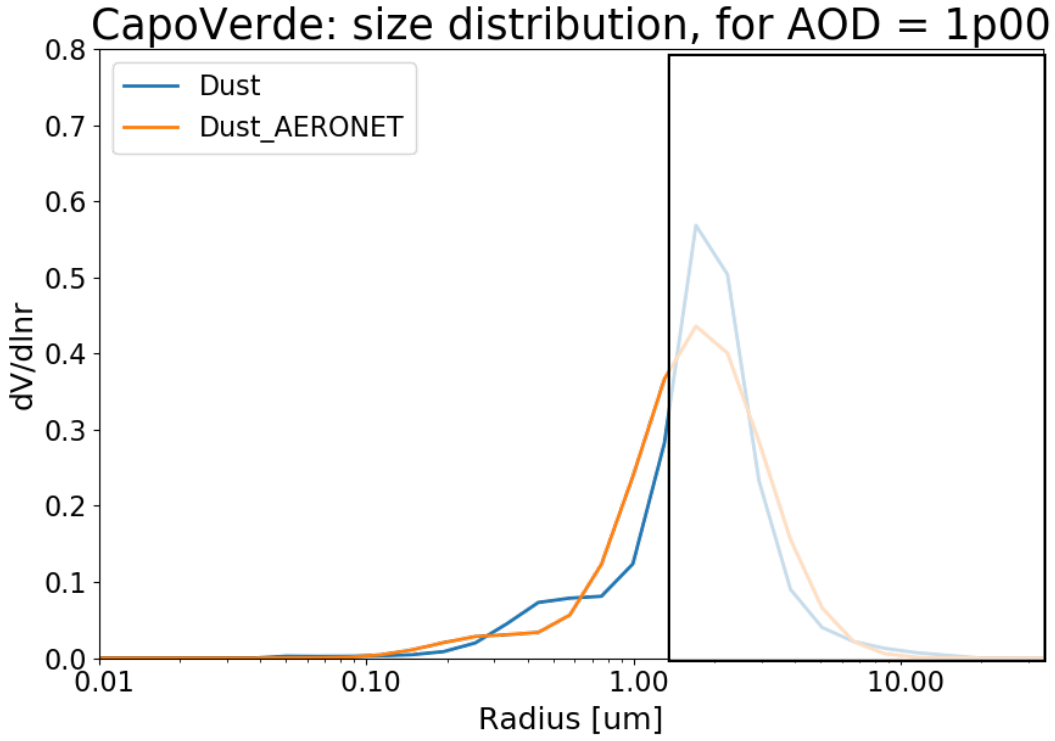
- If we assume the bi-lognormal model
- **Dust is "coarse dominated"**
- We calculate the "Fine Mode Fraction" (η) in terms of AOD
- FMF (η) ~ 0.2 at 0.55 μm for the dust
- FMF shown for AOD=1.0
- Note that FMF is undefined for the retrieved size

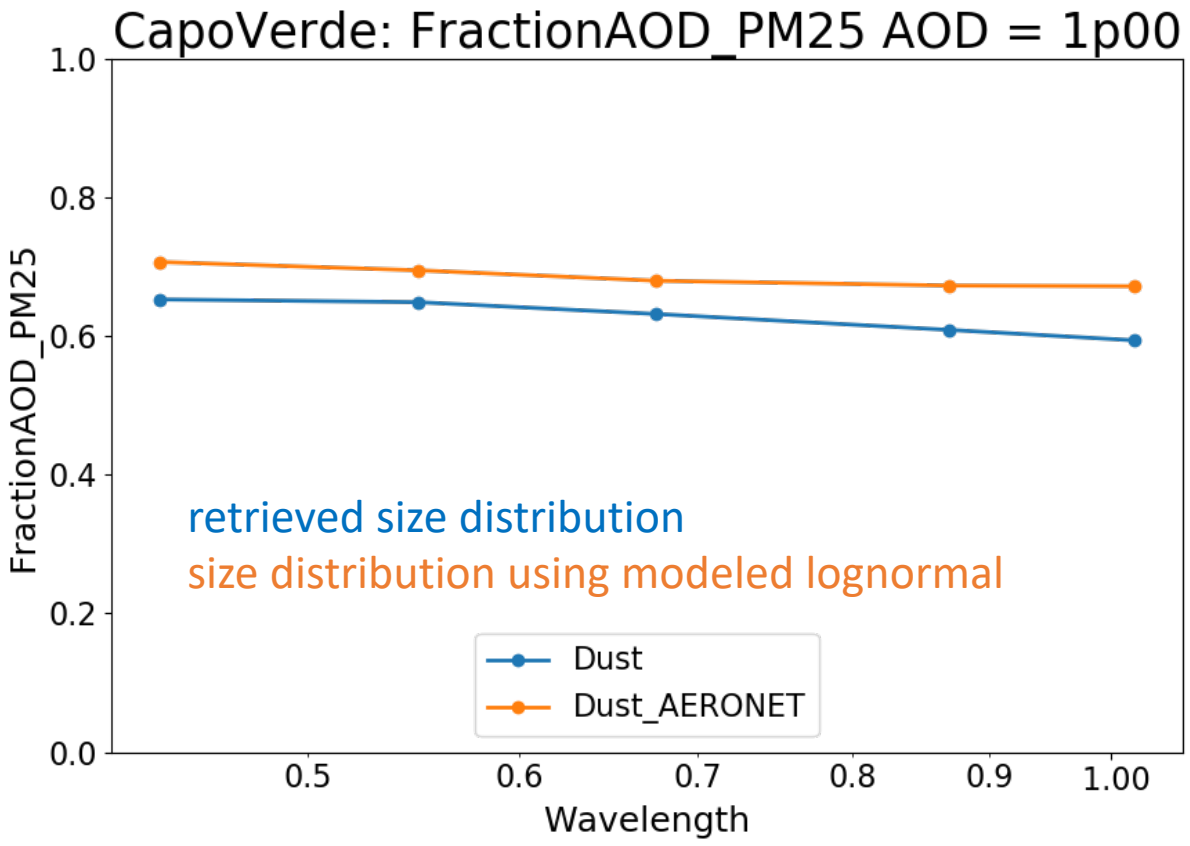


Fraction AOD for PM2.5.

- FMF is fraction of Mode A vs Mode B, assuming that Mode A is ‘smaller’ than Mode B.
- As we know, there are often ***multiple modes, leaving FMF undefined.***

Let’s use the scattering code to quantify the fraction of the extinction (and thus AOD) that would be arising from particles with D<2.5 μm, or r<1.25 μm (***mask out r>1.25***).

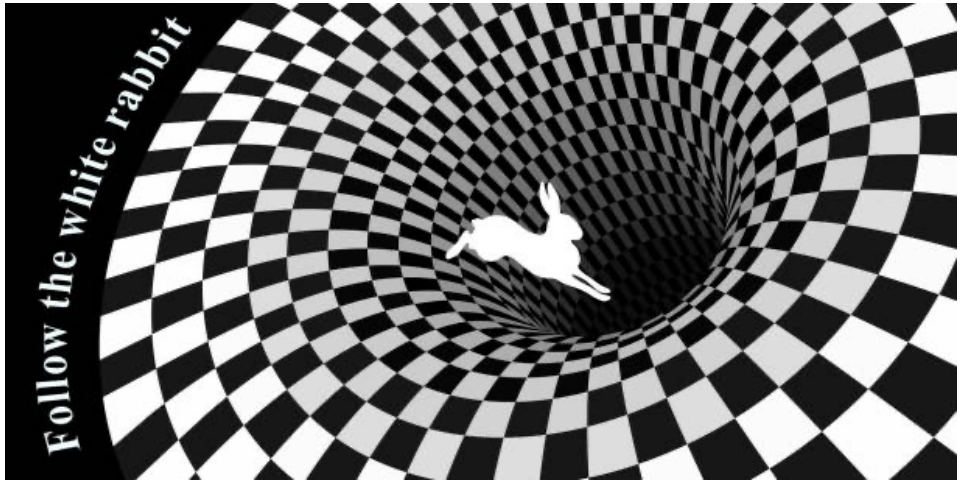




Dust models from satellite algorithms

- Yes, of course, there is a variety of dusts around the world, and even a variety of dust retrieved at Capo Verde.
- **How do our assumptions in retrievals compare with this dust case and each other?**
- Wherever possible I take what folks give me and run DSL code
- In all cases, I am calculating for a ‘fixed AOD’ at a ‘reference wavelength’.

- I went down many rabbit holes, especially in making sure I understood stuff I thought I had understood 20 years ago.
- Relationships between r_g and r_v, extinction efficiencies and coefficients, normalizations for size distributions, etc.



MODIS & VIIRS algorithms

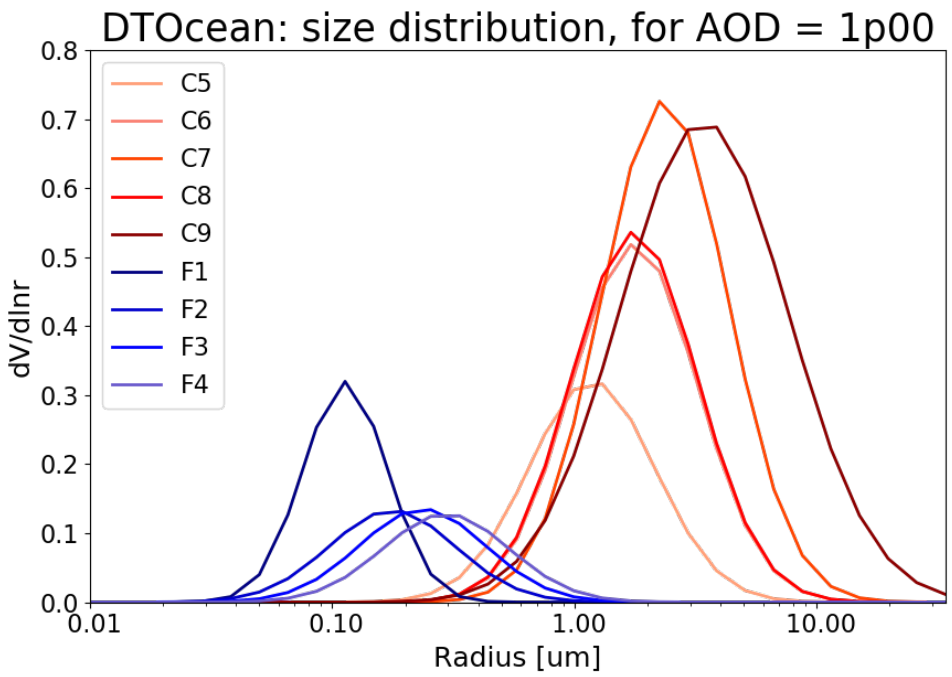
- Since AERONET retrieves at 440, 675, 870, and 1020 nm, *all satellite algorithms have assumed that properties can be interpolated to relevant wavelengths.*

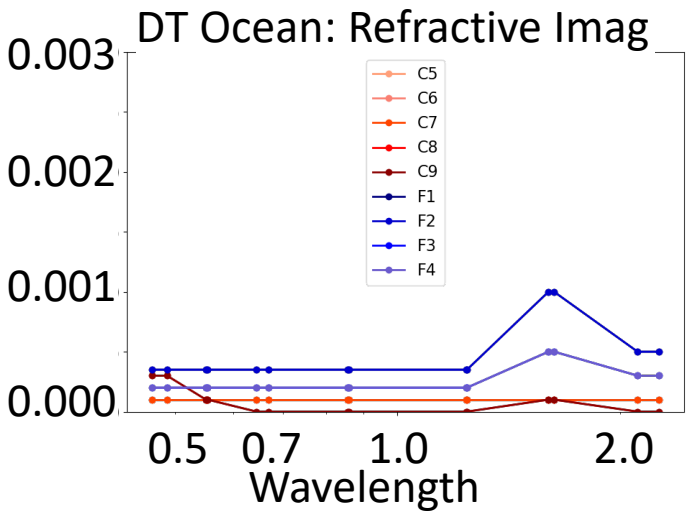
- Some algorithms use some bands, others use others.
- Reference wavelength for Dark Target and Deep Blue is Green for MAIAC it is Blue.

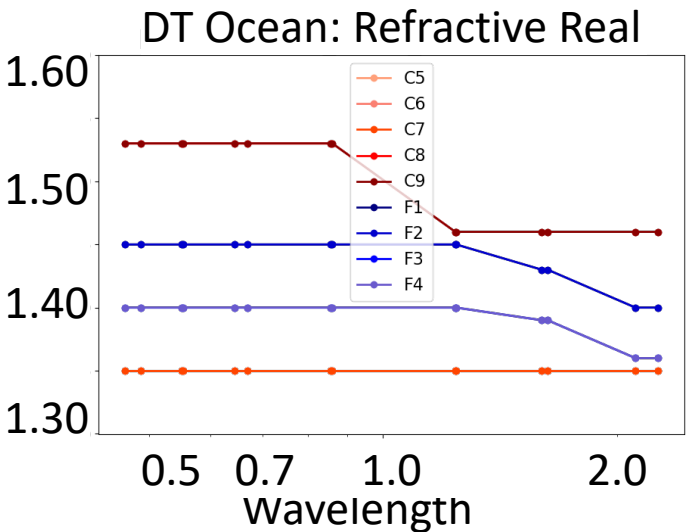
Sensor	MODIS		VIIRS	
Satellite(s)	Terra & Aqua		SNPP & NOAA20	
	Band	Wave	Band	Wave
Deep Blue	B8	0.41	M1	0.41
Dark Blue	B9	0.44	M2	0.44
Blue	B3	0.47	M3	0.49
Green	B4	0.55	M4	0.55
Red	B1	0.65	M5	0.67
NIR	B2	0.86	M6	0.86
SWIR1	B5	1.24	M8	1.24
SWIR2	B6	1.63	M10	1.60
SWIR3	B7	2.11	M11	2.26

Dark Target Ocean (Assumptions)

- Spherical
- Bi-lognormal
  - Choice 4 fine Fx modes
  - Choice 5 coarse Cy modes
- Fixed (non-dynamic) refractive indices and size distributions for each model
- *In theory, coarse modes C8 and C9 are representative of "dust"*
- During retrieval, Fx and Cy are mixed. So we might expect solution that includes C8 or C9.

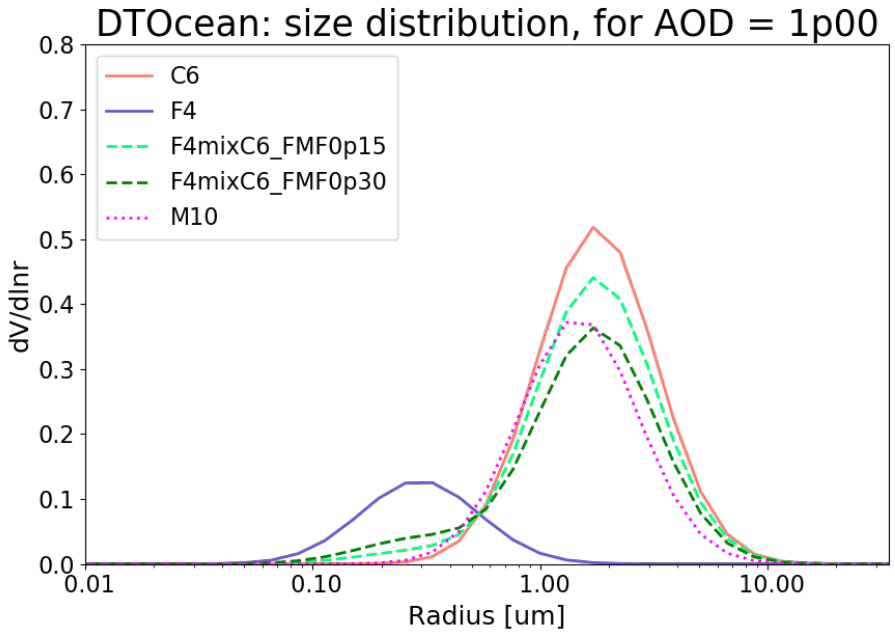


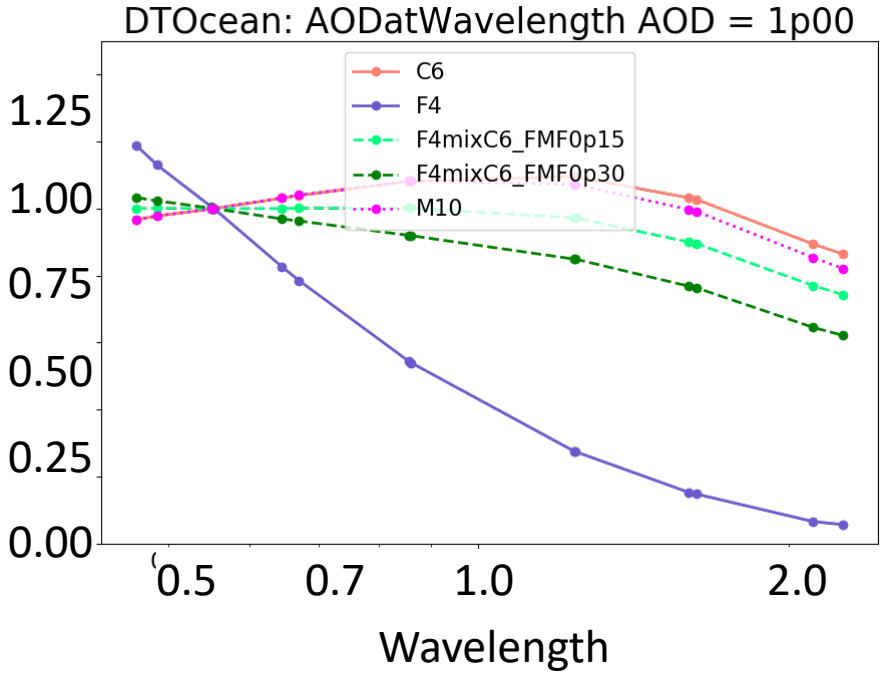




Dark Target Ocean (Results)

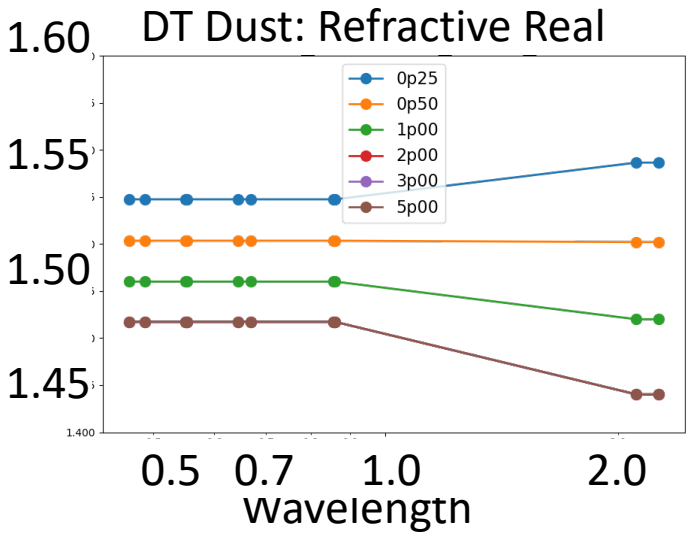
- However, although C8 and C9 are 'coarse' the retrieval doesn't pick them (probably because they are spherical)
- Instead chooses combo of F4 and C6 with AOD Fraction of 0.15 or 0.30
- Yaping Zhou et al., have developed model "M10" that is similar to C8 but uses Oleg25 spheroids

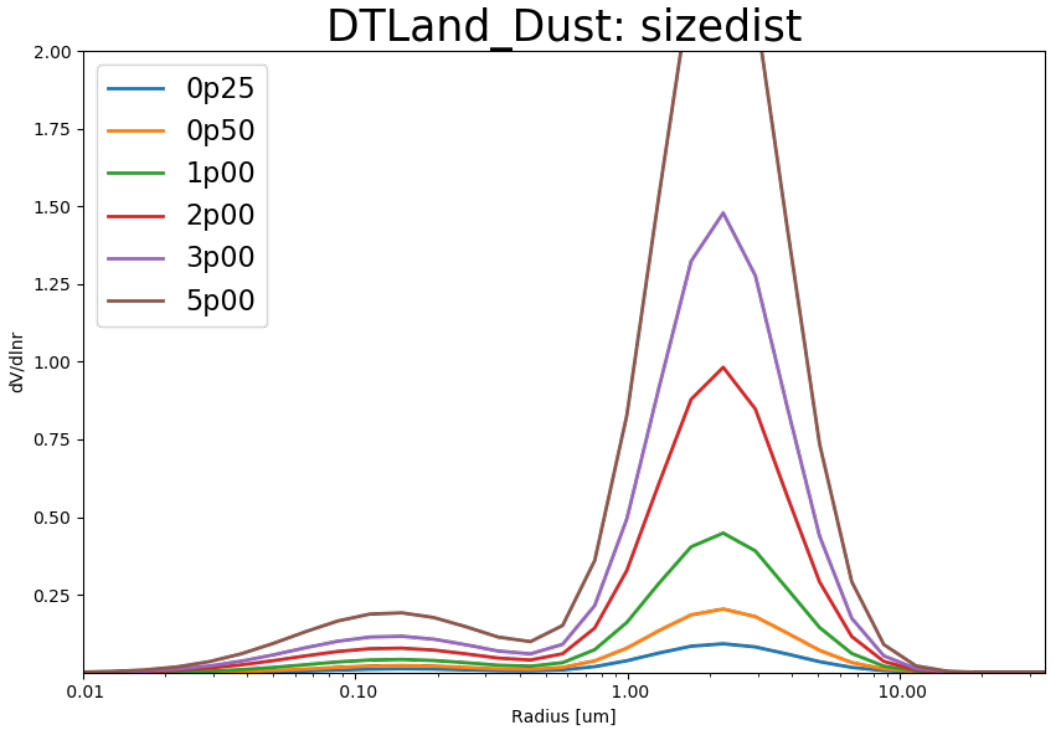




Dark Target Land (Assumptions)

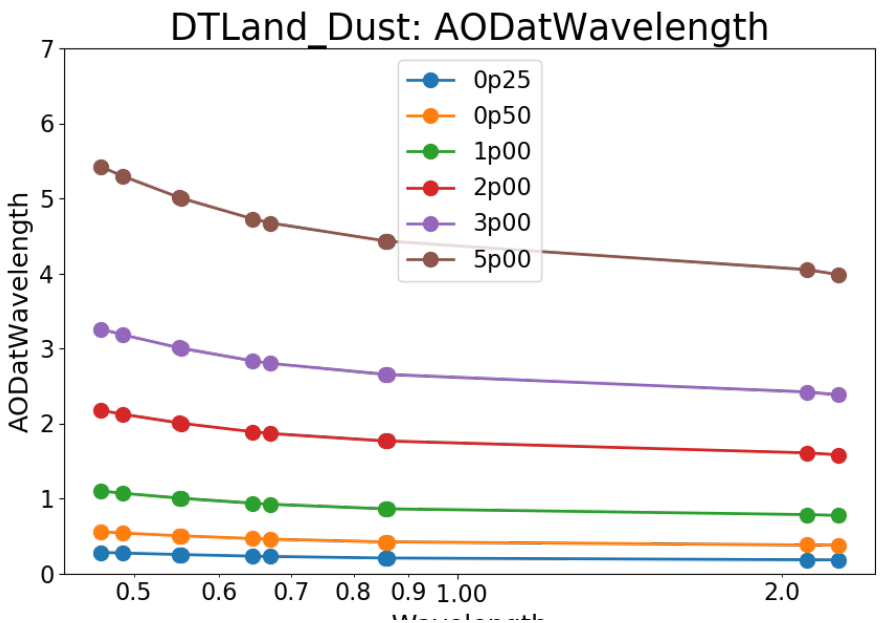
- Multi-lognormal
- Urban, Generic, and Smoke models are:
  - Are bi-lognormal and fine-dominated.
  - Spherical
- Dust model
  - is bi-lognormal and coarse-dominated
  - Non-spherical (uses spheroid aspect ratios
- Dynamic (function of AOD) refractive indices and size distributions for each model. Plotted for AOD = 1.0, and other values of AOD.

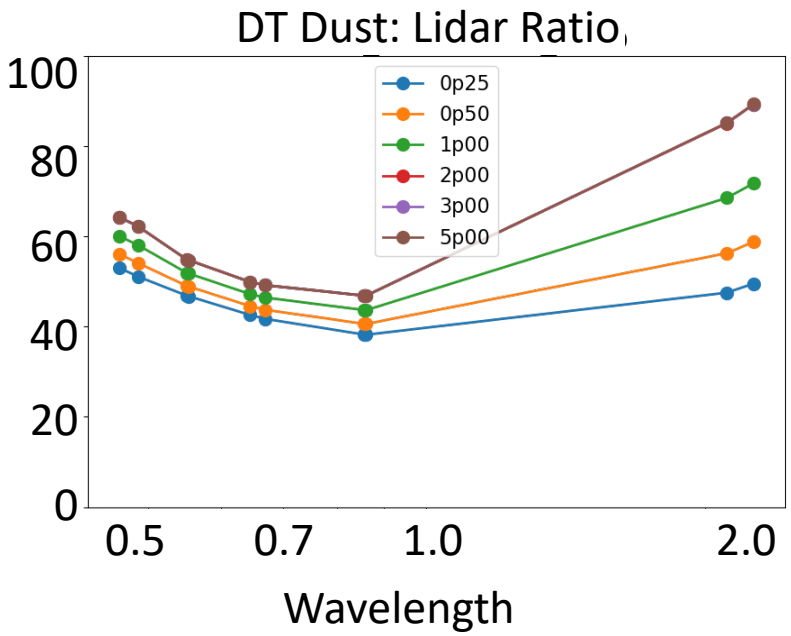


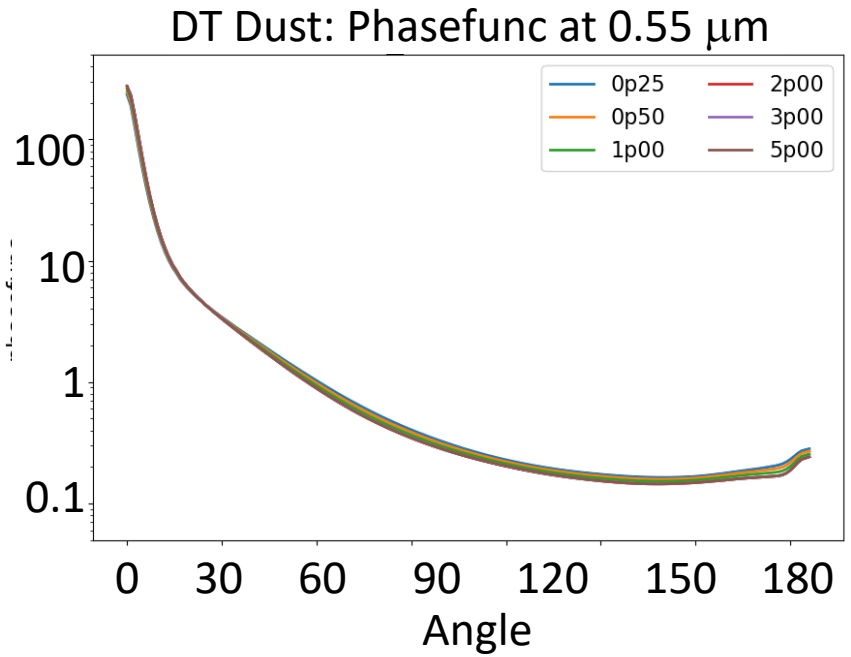


DT Land: Results (1)

- Dust Model:
  Note that calculated properties vary by index AOD.
  AOD = 1.0

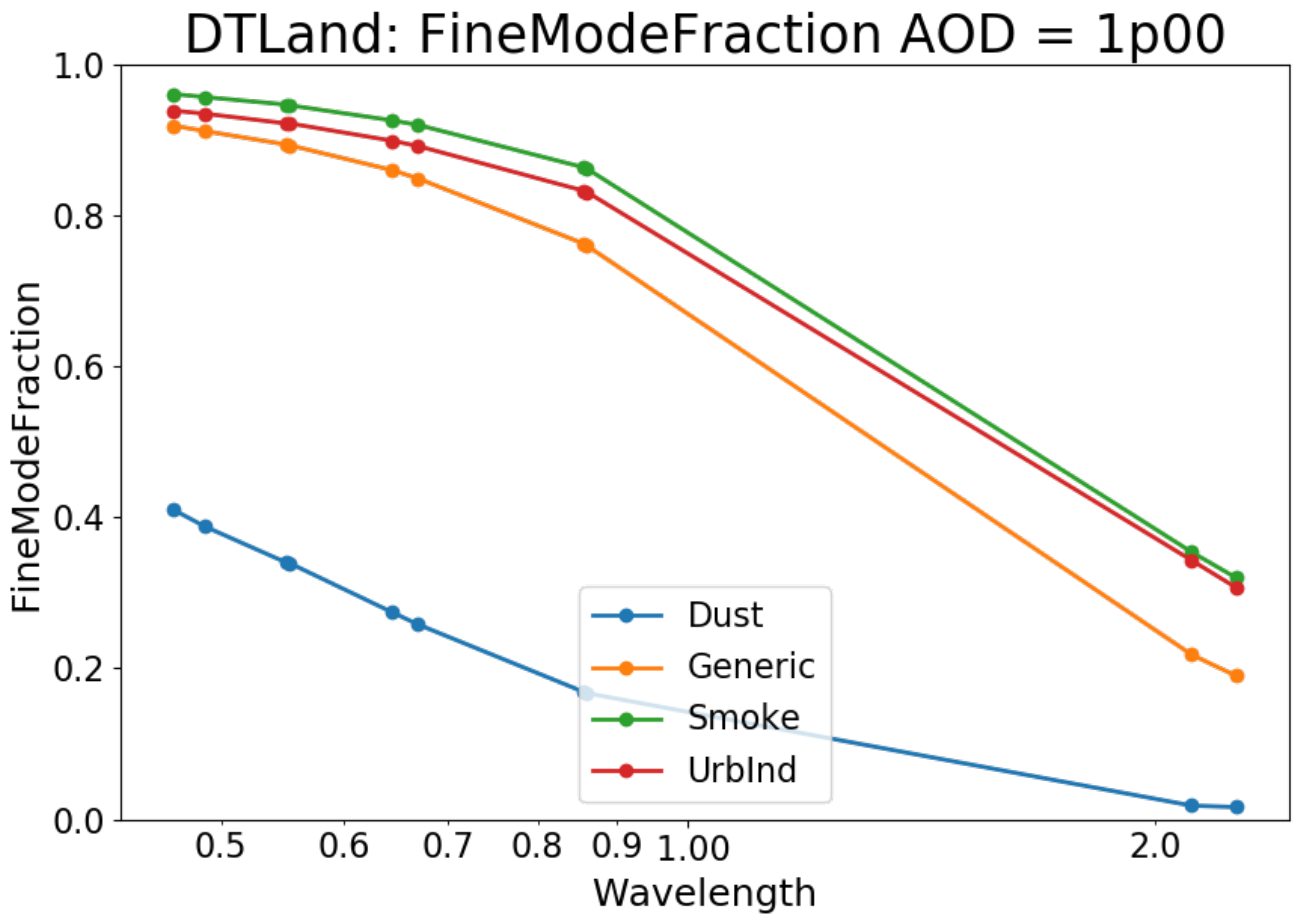






DT Land: Fine Mode Fraction

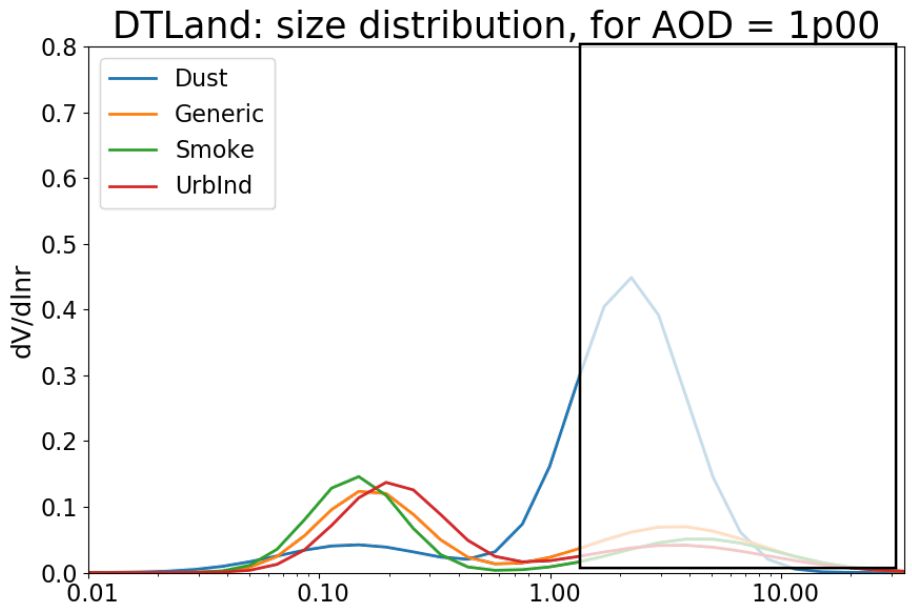
- Remember that size distribution for all DT-Land models are already 'bi-lognormal'.
- **Dust is "coarse dominated"**
- We cn calculate the "Fine Mode Fraction" (η) in terms of AOD?
- FMF (η) ~ 0.3-0.4 at 0.55 μm for the dust
- FMF shown for AOD=1.0

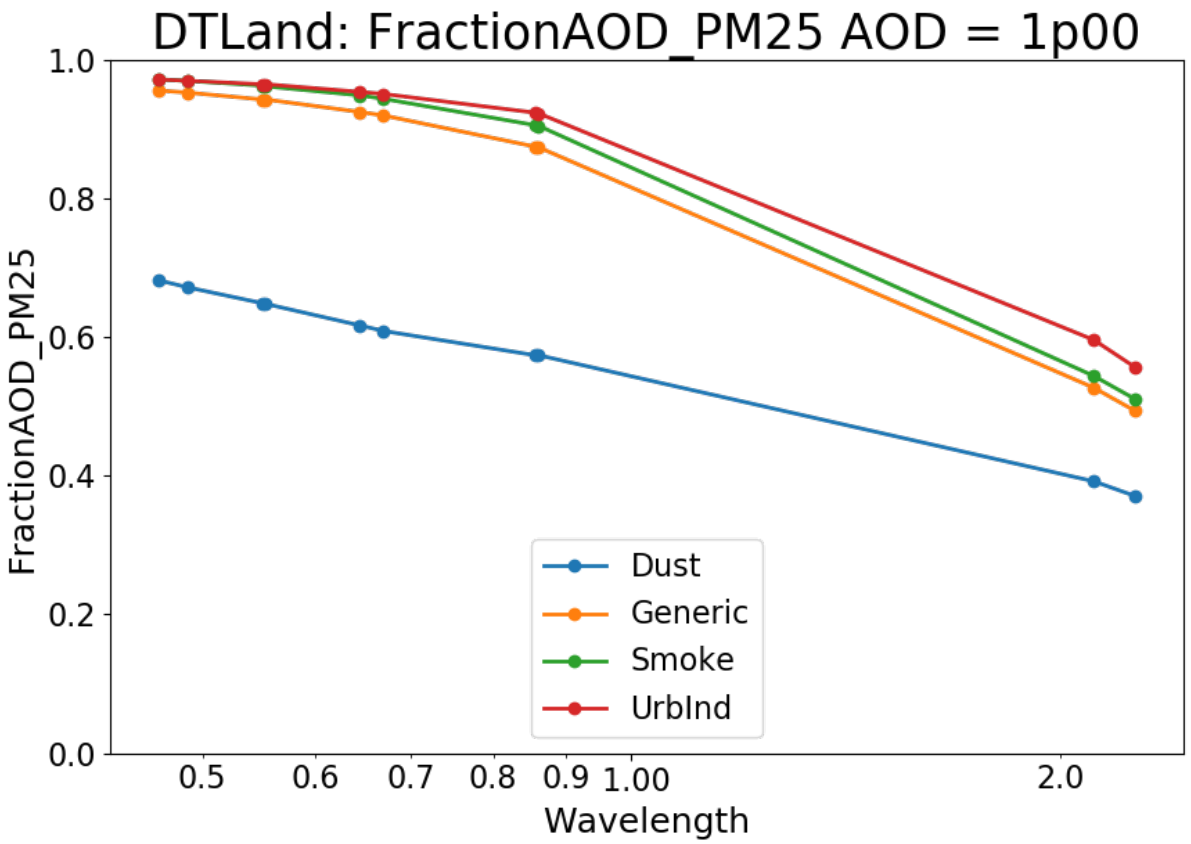


Fraction AOD for PM2.5.

- FMF is fraction of Mode A vs Mode B, assuming that Mode A is ‘smaller’ than Mode B.
- As we know, there are often ***multiple modes, leaving FMF undefined.***

Let’s use the scattering code to quantify the fraction of the extinction (and thus AOD) that would be arising from particles with D<2.5 μm, or r<1.25 μm (<u>mask out r>1.25</u>).

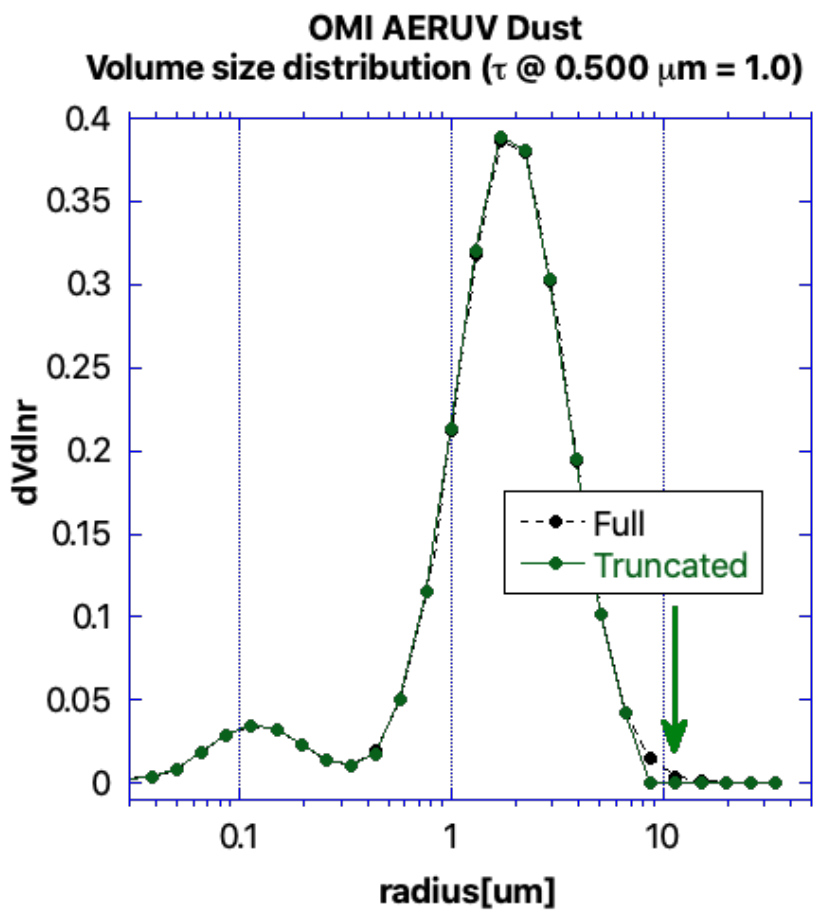




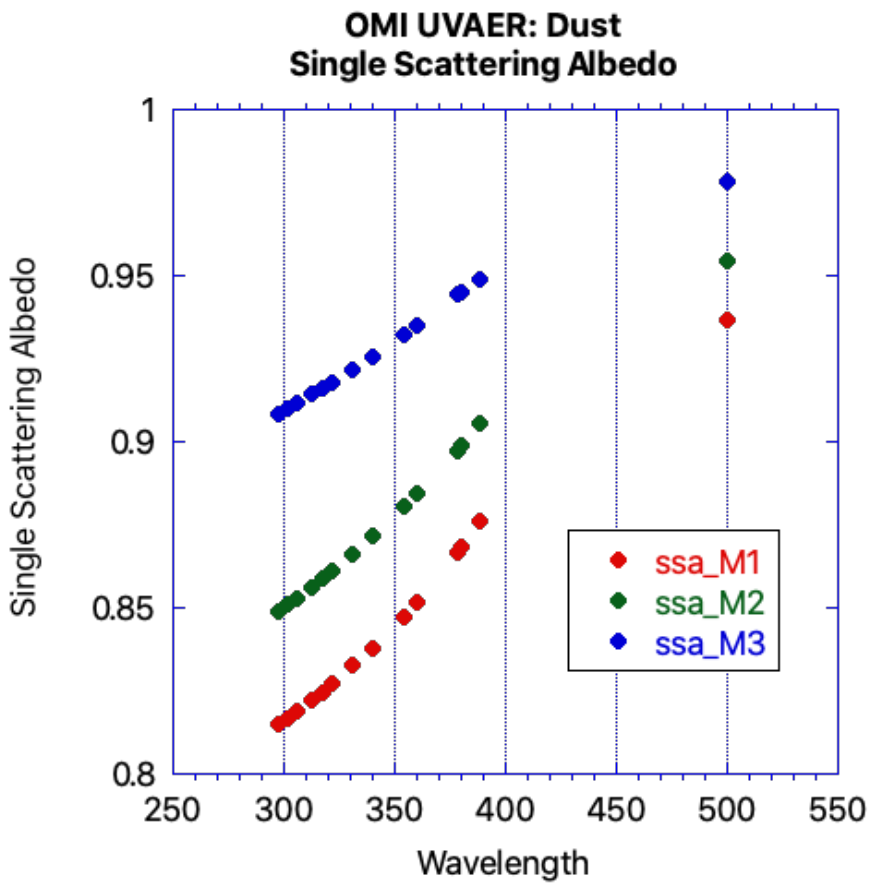
OMI AERUV: (2 modes, spheroids)

Note mode fractions defined by number

	Min Radius[µm]		Max Radius[µm]		r_g [µm]		sigma [µm]		N_{conc} [/cm²]	
Aerosol Type	Fine	Coarse	Fine	Coarse	Fine	Coarse	Fine	Coarse	Fine	Coarse
Mineral Dust	0.00627	0.06298	0.43125	7.12764	0.052	0.67	1.697	1.806	13.531	0.0588



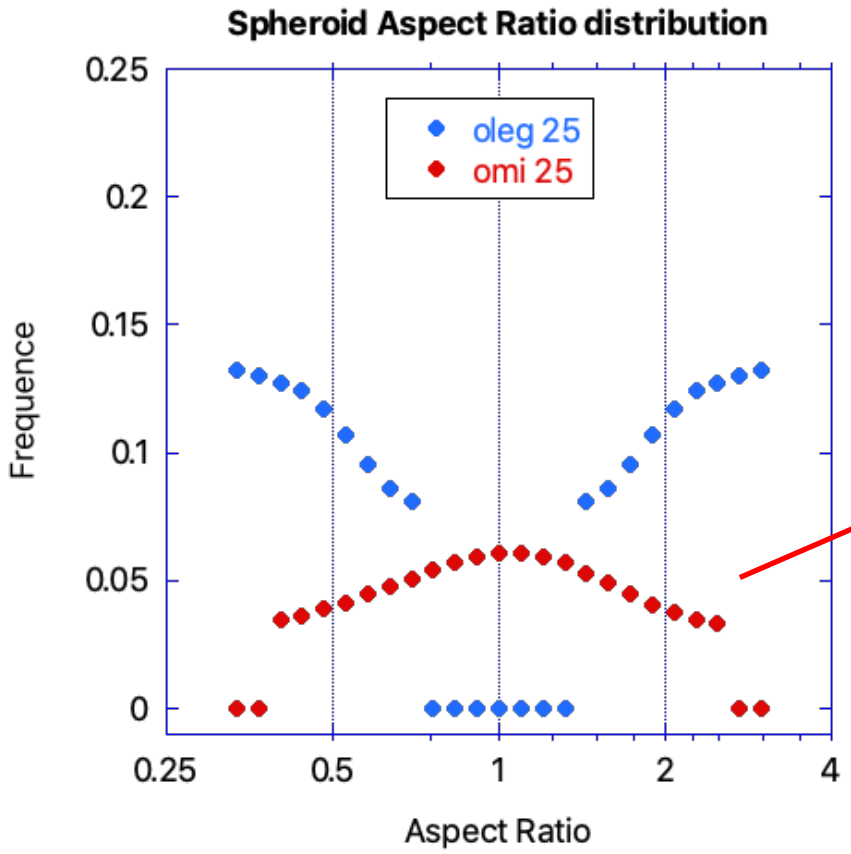
Variety of imaginary refractive indices leading to variety of SSA

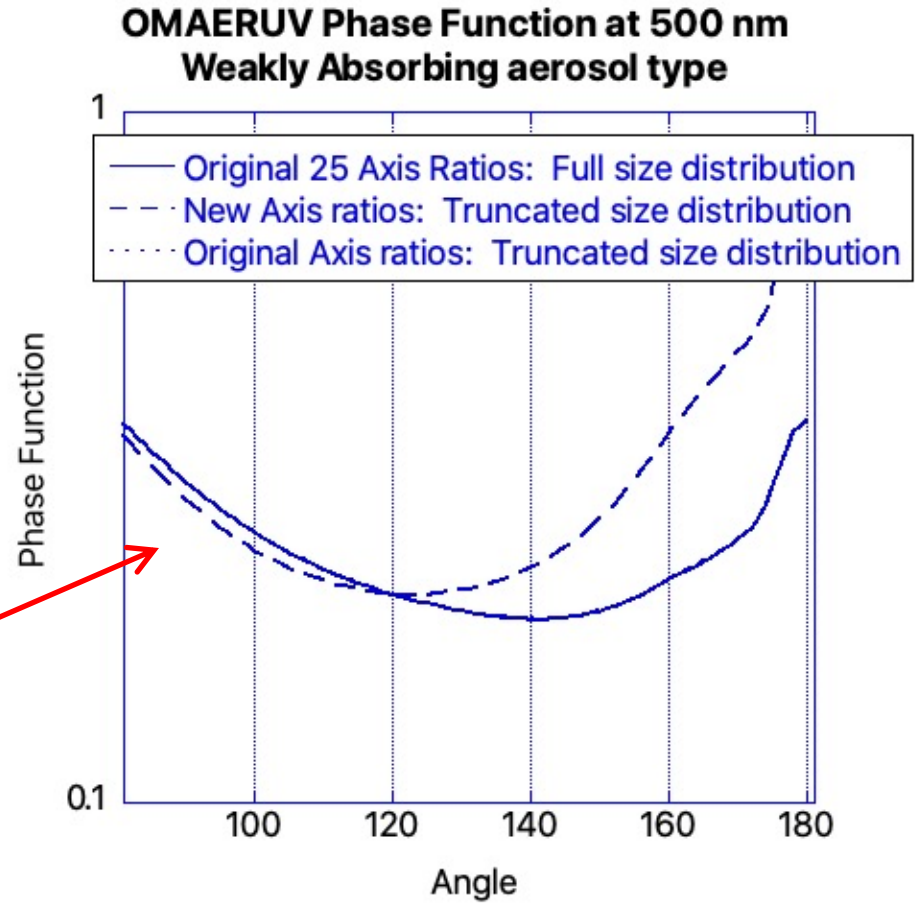


Note shorter wavelengths (in short VIS and near UV)

OMI AERUV: testing 3 models (2 modes each)

- OMI (over ocean) assumes a different set of of 25 aspect rations ("omi 25") which includes some spheres





- "truncation" of size distribution makes very little difference for phase function
- But omi 25 vs oleg 25 matters!

Unfortunately, I don't have time, so let me get to the point (1)

- Every GSFC algorithm has models defined a bit differently
- If possible, I used DSL scattering code to calculate similar outputs
  - Deep Blue / SOAR (for MODIS & VIIRS wavelengths, normalized to 0.551 μm)
  - MAIAC: (for MODIS wavelengths, normalized to 0.466 μm)
  - MISR standard: (for MISR wavelengths, normalized to 0.558 μm)
  - OMIAERUV: (for OMI wavelengths, normalized to 0.500 μm)

- I also calculated for a standard "Mars" model
  - Normalized to 0.550 μm.
  - This model assumed a 'modified gaussian' rather than multi-lognormal.

Unfortunately, I don’t have time, so let me get to the point (2)

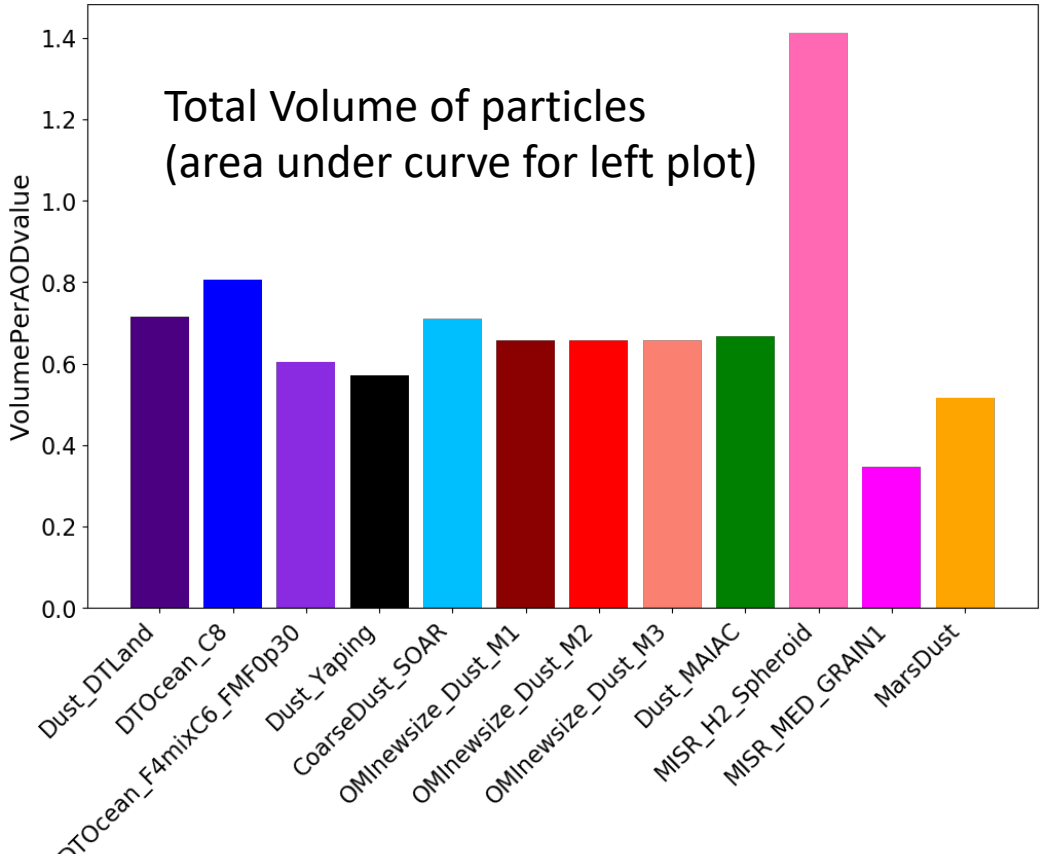
- If my calculations using DSL code don’t match what the algorithm team has given me, I used their numbers.
  - For example, for a MISR super coarse mode, DDA calculations were too intensive to simulate particles >15 μm, so lognormal tails were truncated.
  - Also for MISR, one of their medium modes assumes “grains”, which cannot be simulated using DSL code.
  - For Mars Dust, I cannot reproduce T-matrix calculations for “Cylinder” shape.

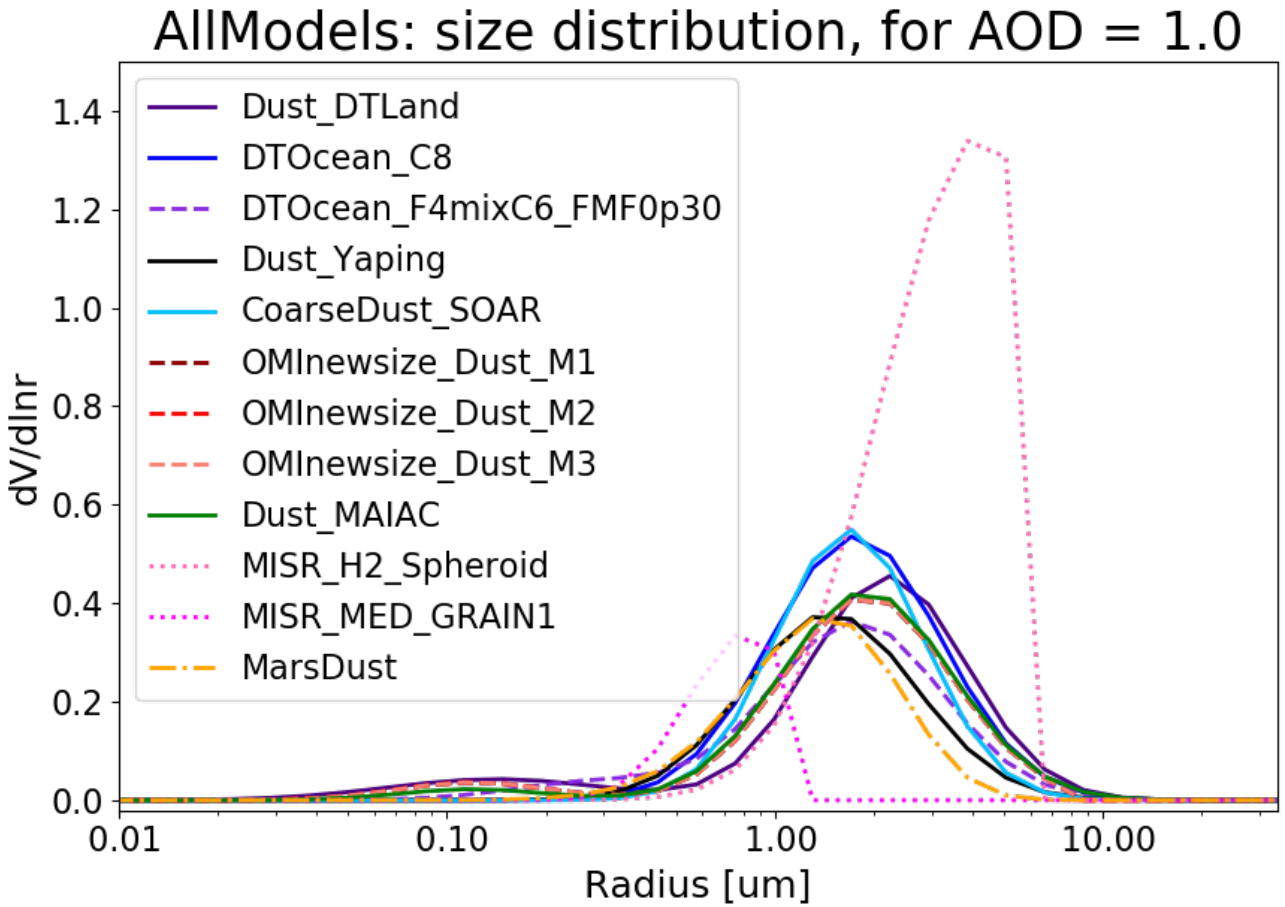
- Anyway, let’s see what happens.

Size Distribution

Volume required to derive: AOD = 1.0 at reference wavelen

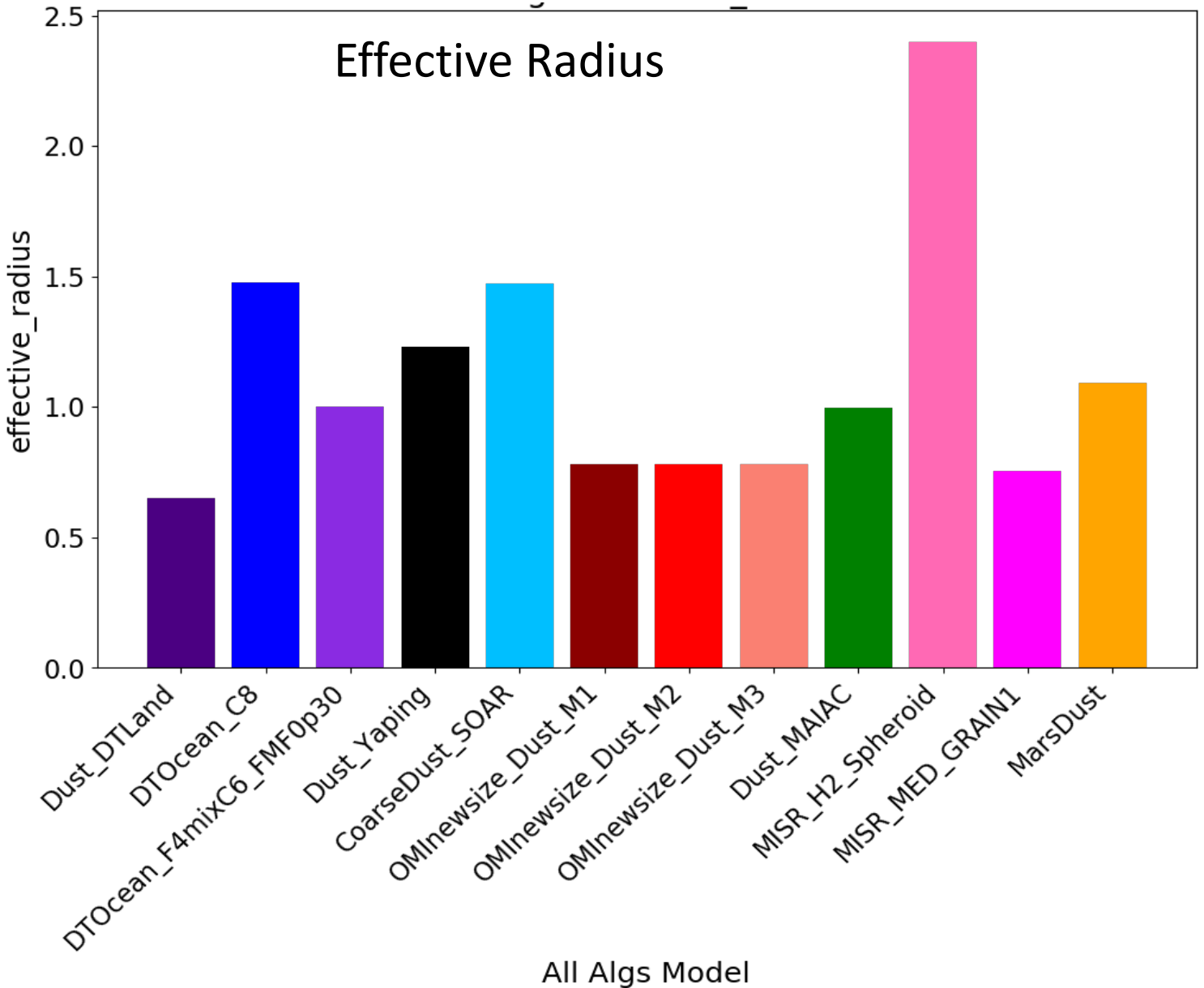
Dark-Target: 0.554 μm
SOAR: 0.551 μm
OMI: 0.500 μm
MAIAC: 0.466 μm
MISR: 0.558 μm.
MarsDust: 0.550 μm

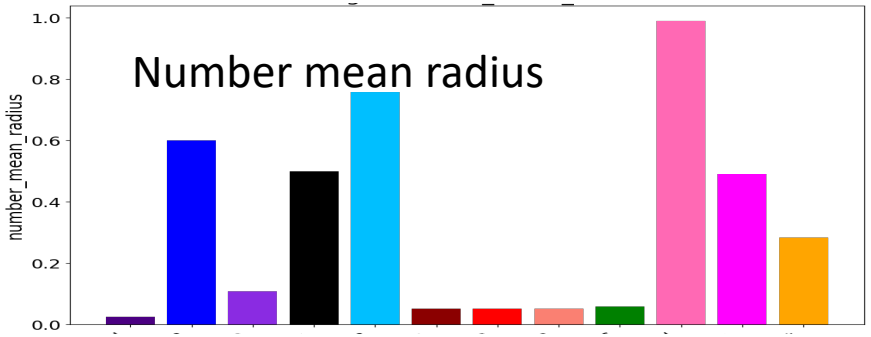


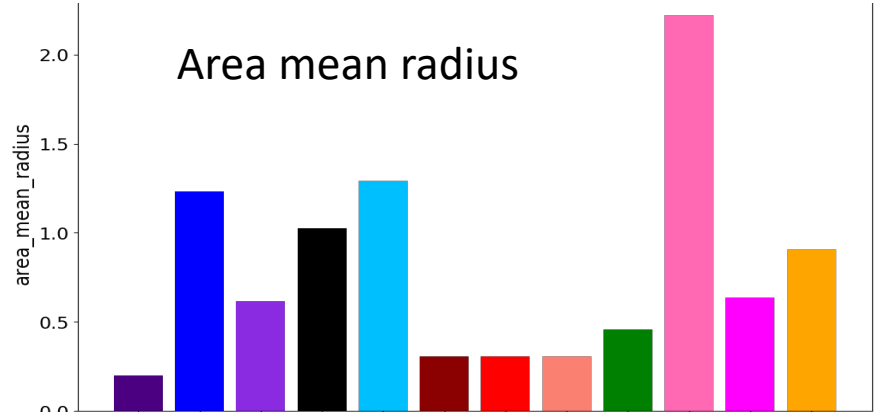


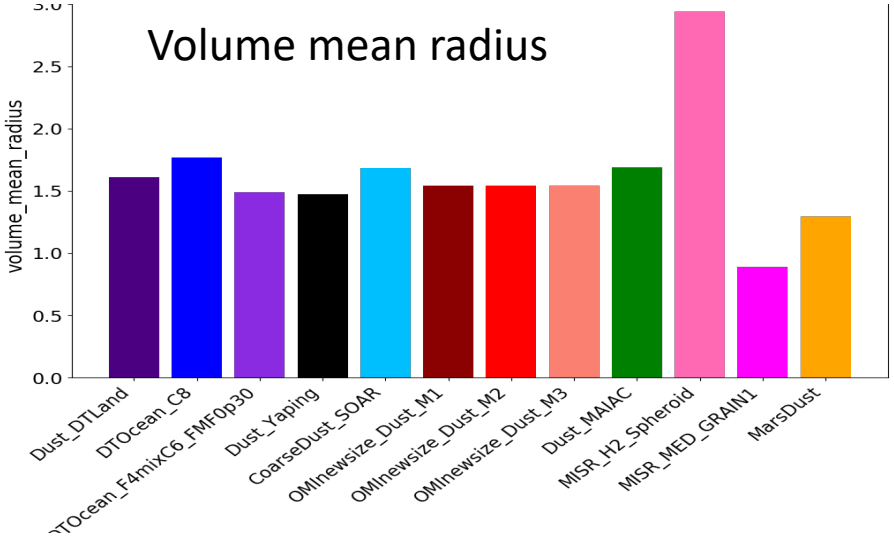
Noting MISR is only algorithm that has choice of “medium” modes

Characteristic radius parameters



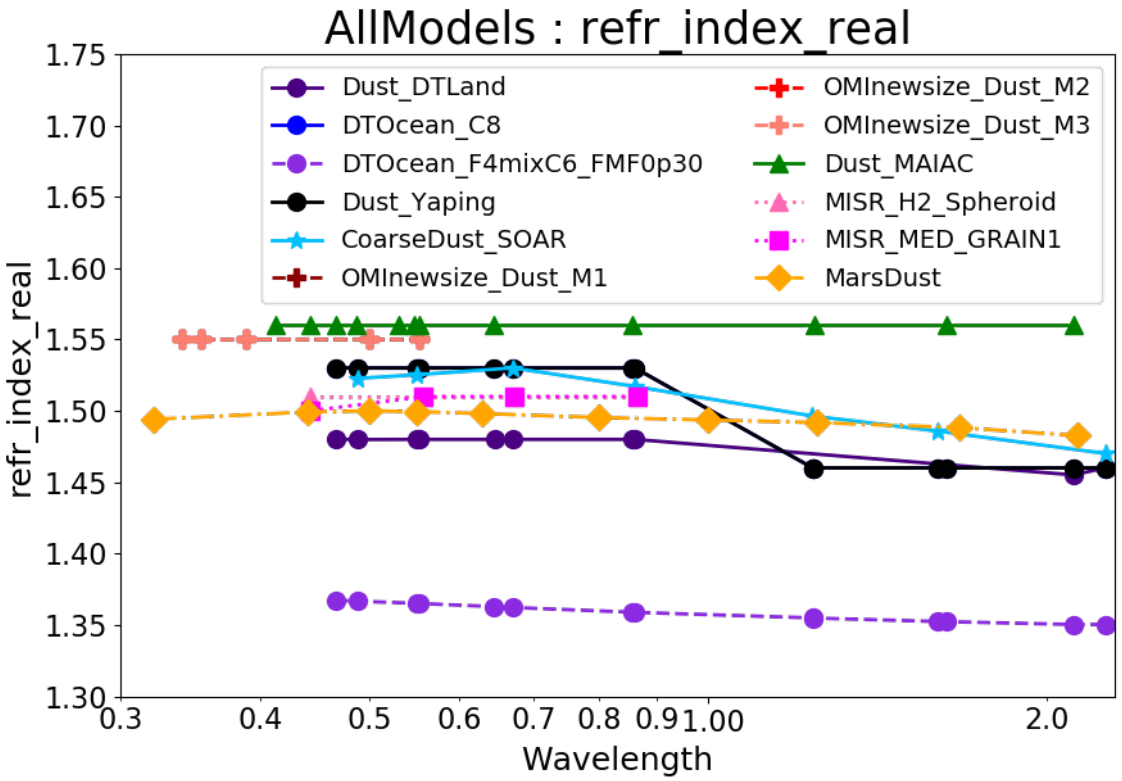


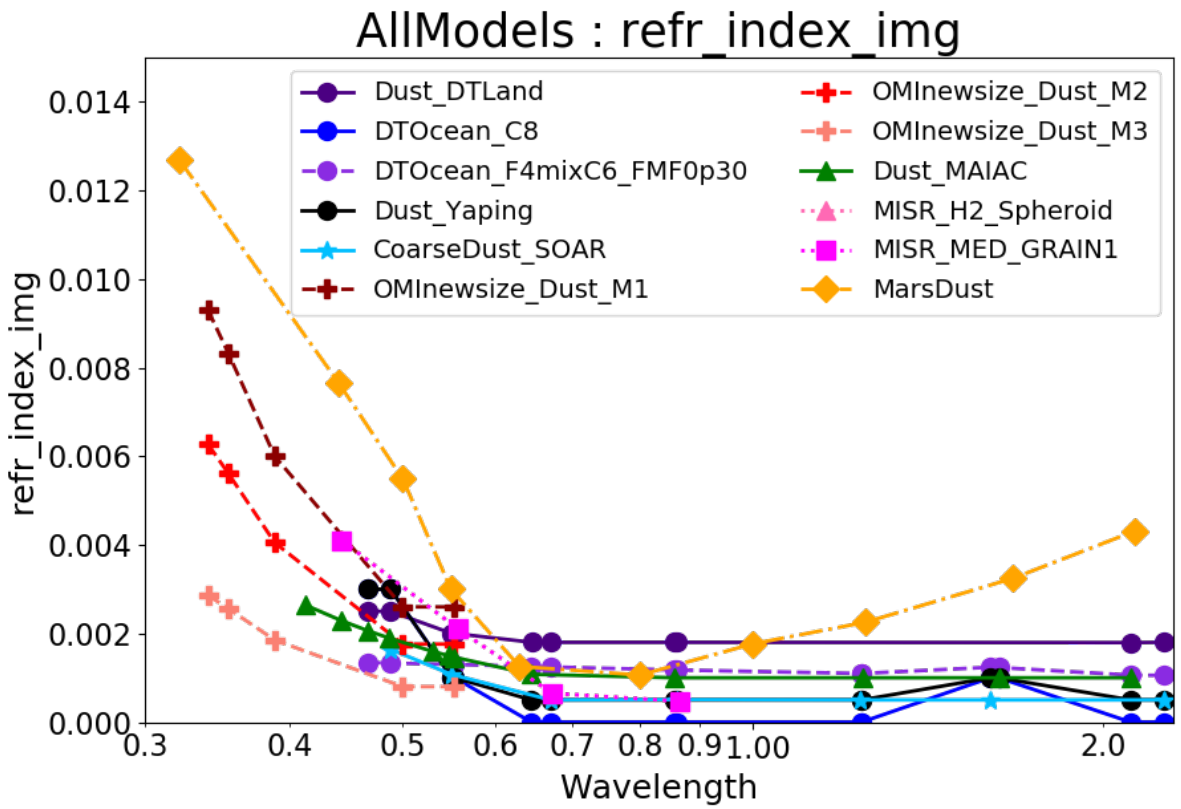




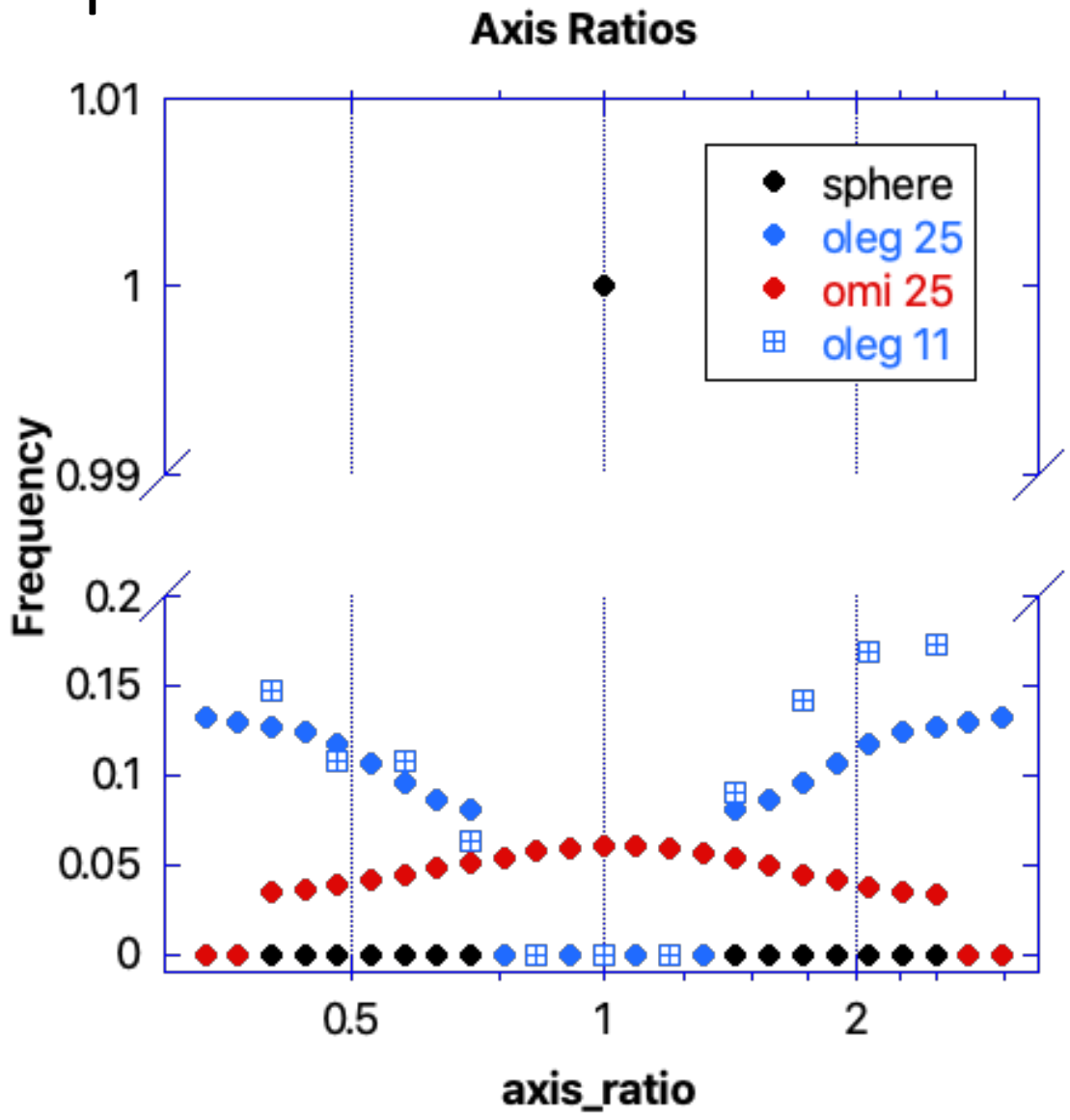
Refractive Index

- For some dust models, refractive indices are different for fine and coarse modes. Here we plot extinction weighted refractive indices
- Some models are dynamic, so plotted are for AOD = 1.0





Aspect ratios



Different dust models are different shapes

Sphere: Dark-Target ocean (current)

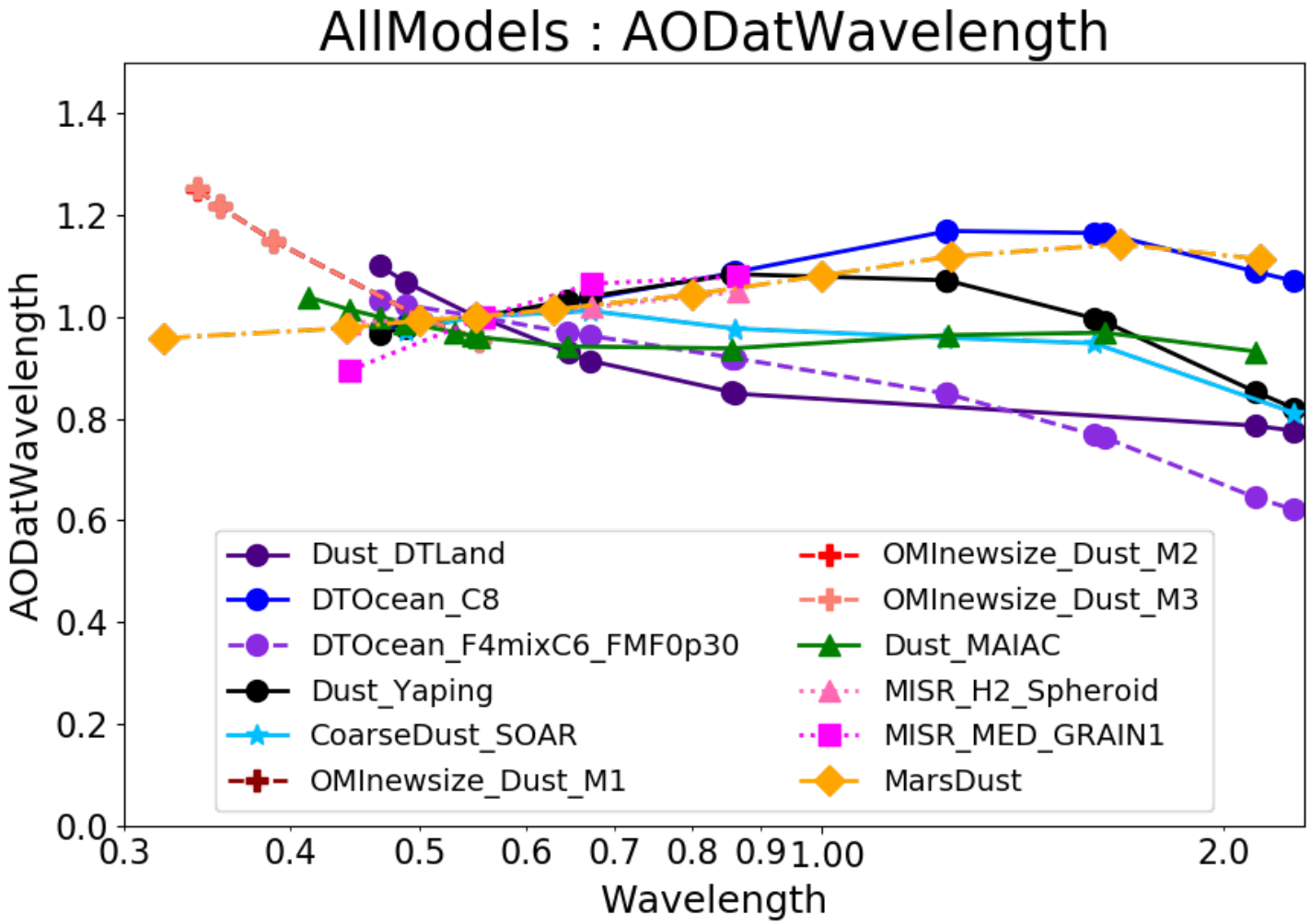
Spheroids:

- Oleg11: Dark-Target land
- Oleg25: SOAR, OMI-land, MAIAC, DT M10
- OMI25: OMI-ocean
- MISR Spheroid: Don't know shape

Other

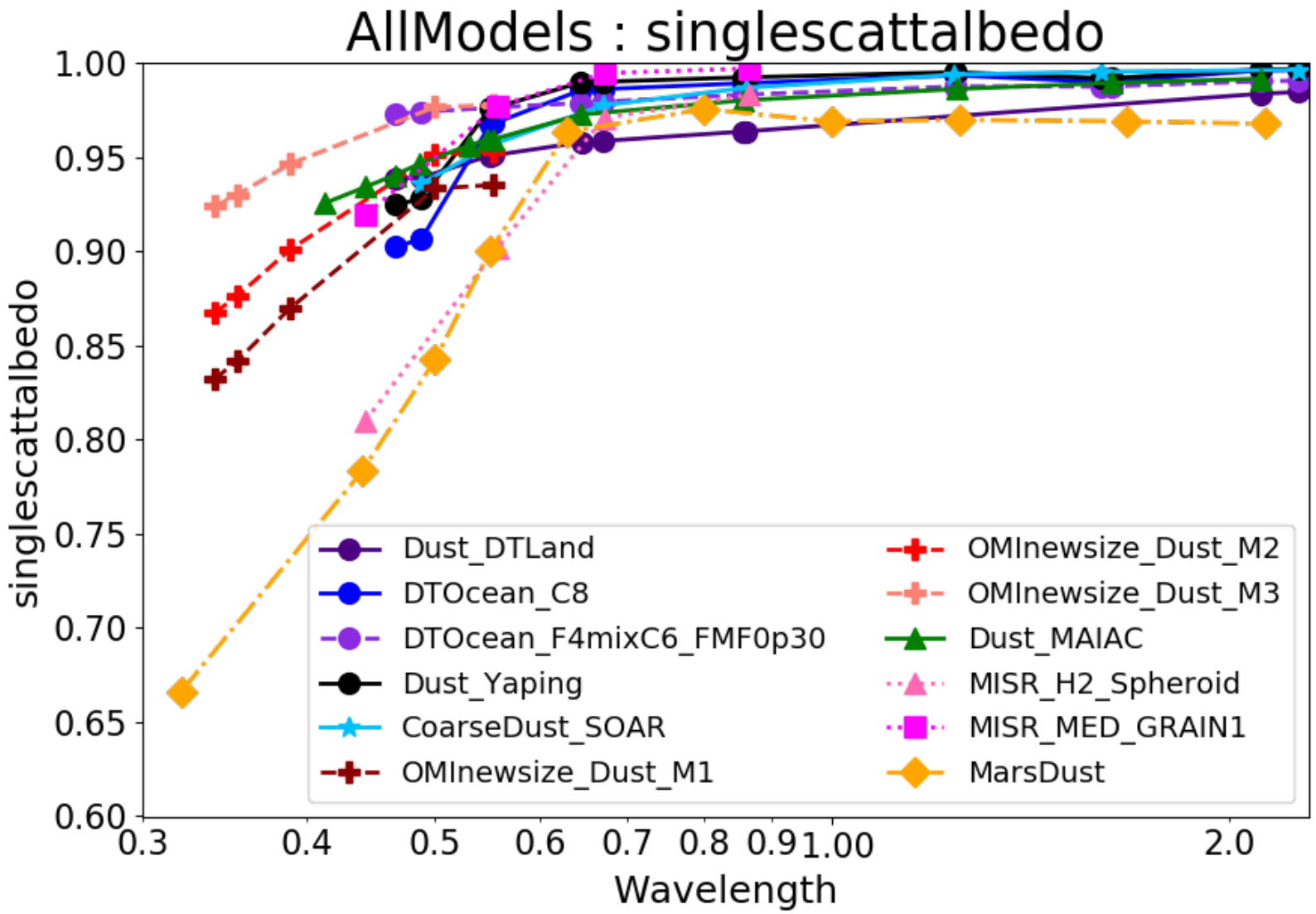
- "Grains": MISR Medium
- "Cylinders": MarsDust

Spectral AOD

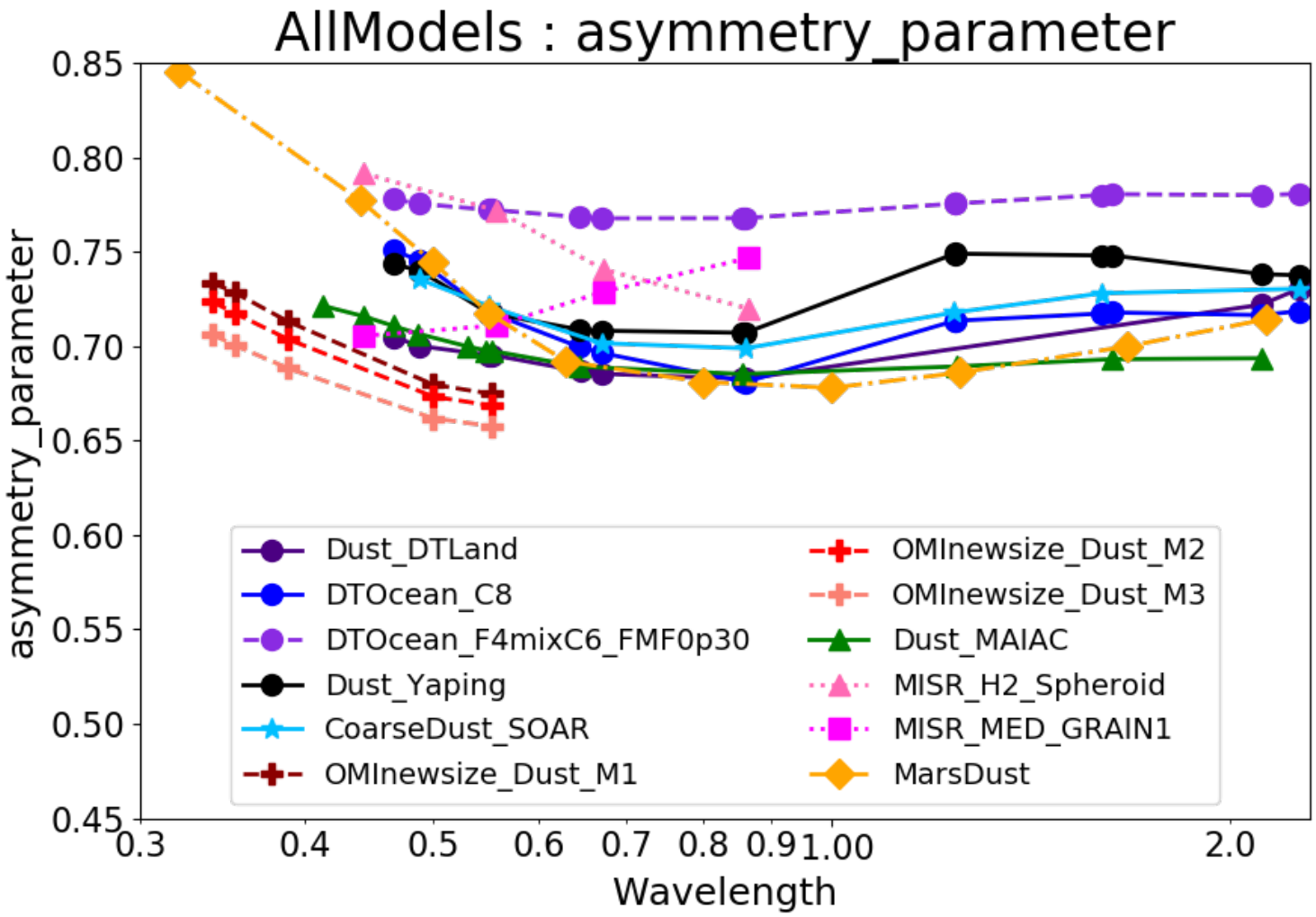


Dark-Target: Defined at 0.554 μm
SOAR: defined at 0.551 μm
OMI: defined at 0.500 μm
MAIAC: defined at 0.466 μm
MISR: defined at 0.558 μm.
MarsDust: defined at 0.550 μm

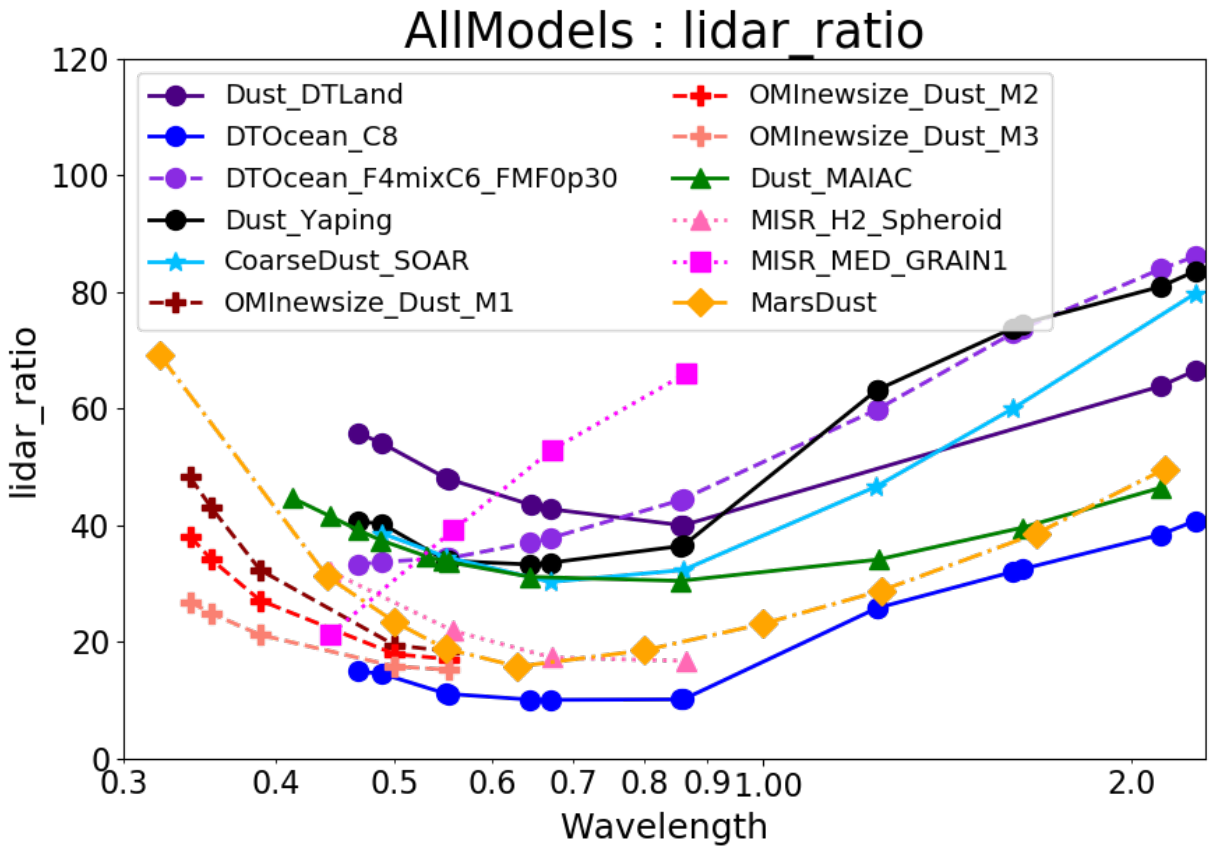
Spectral SSA

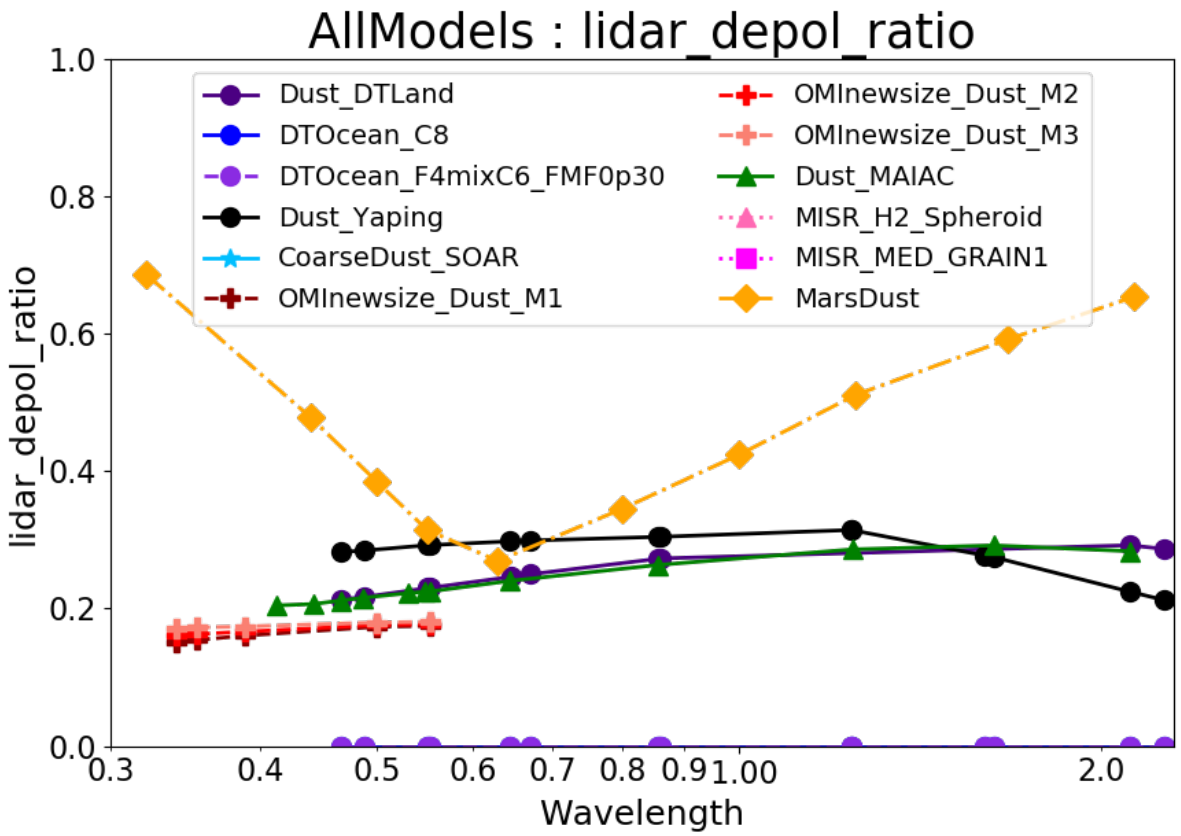


Asymmetry parameter

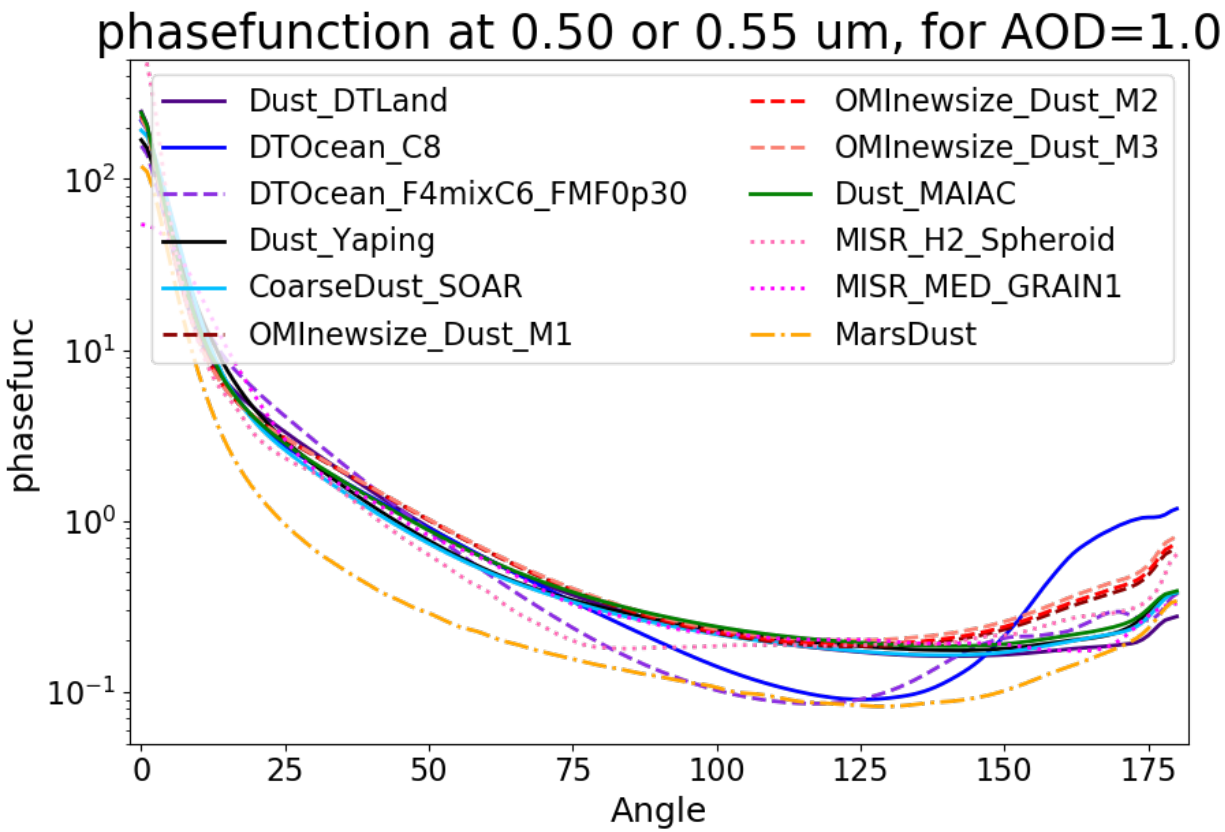


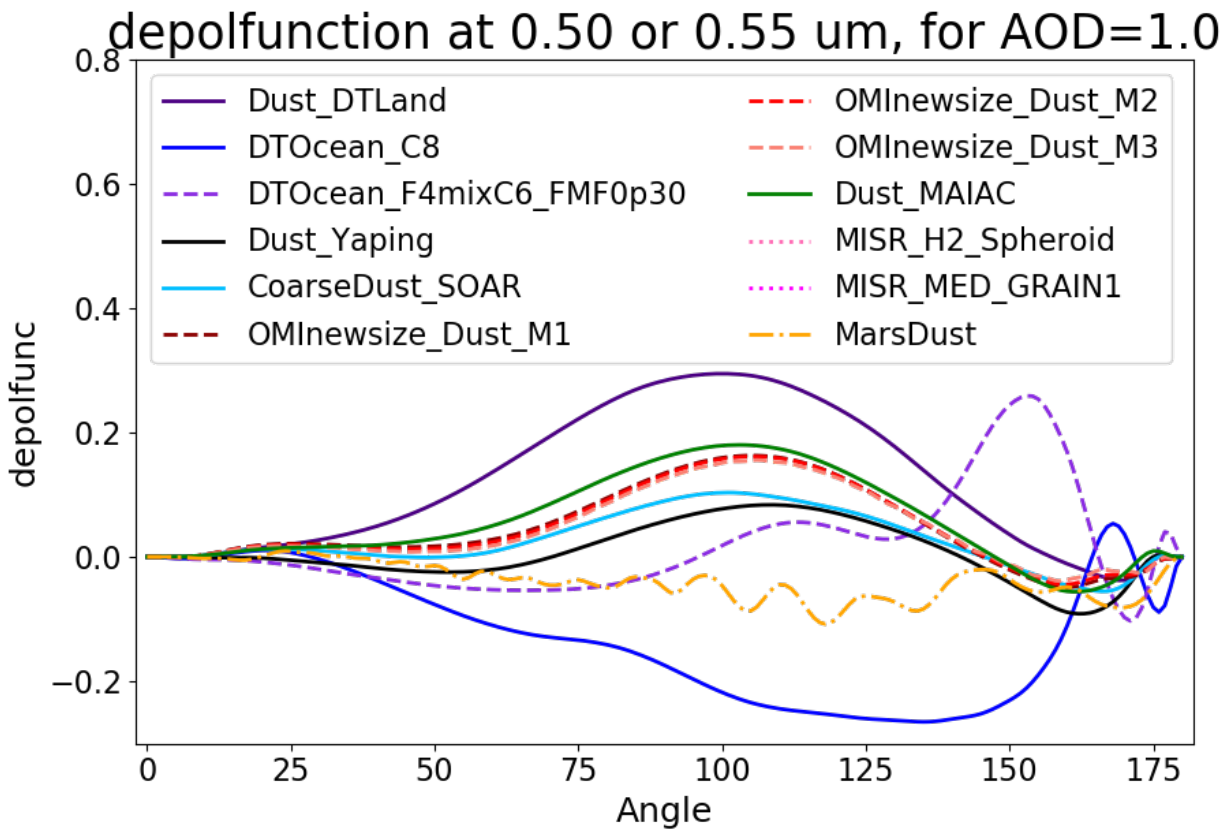
Lidar Ratio and Lidar Depolarization Ratio





Phase Function and Depolarization





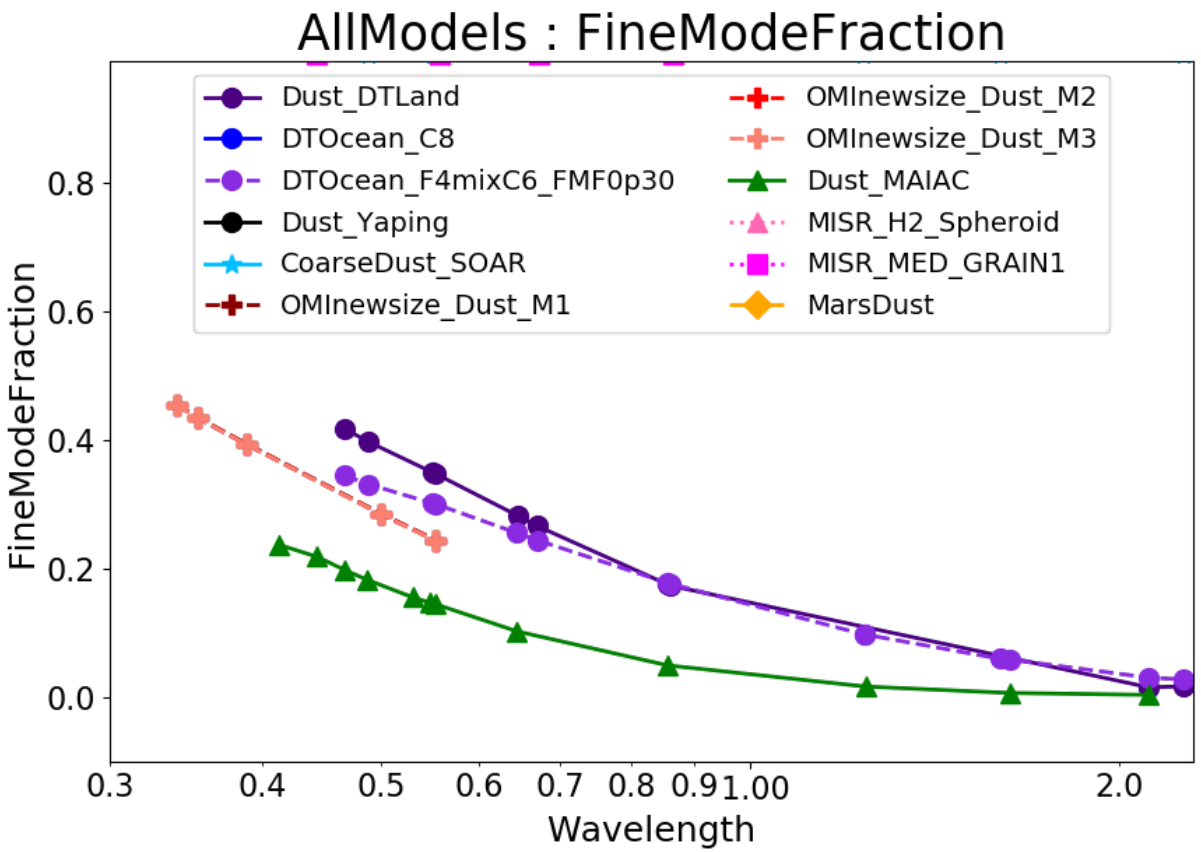
Calculated by:

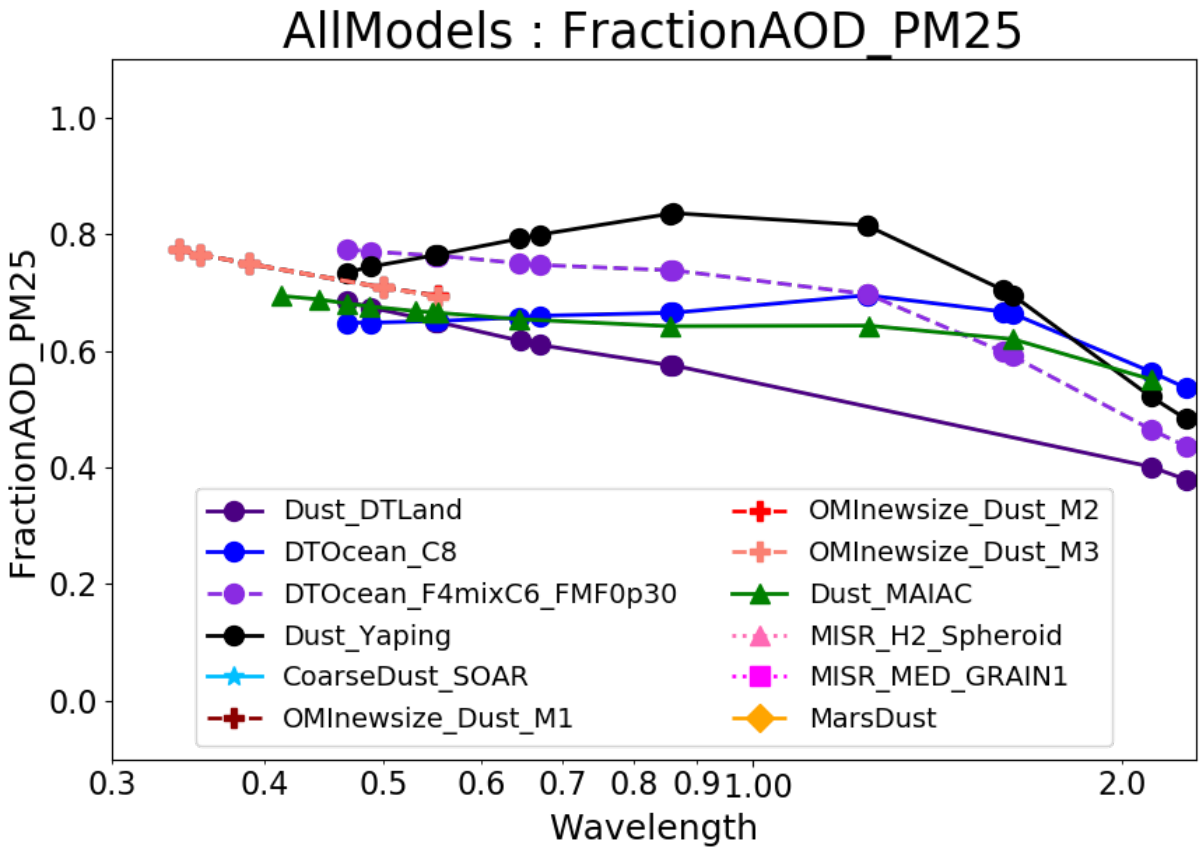
Mie code: DTOcean
DSL code: Dust_DTLand, Dust_Yaping, OMI, MAIAC*
Meng Database: SOAR
MISR team / DDA: MISR
T-Matrix: MarsDust

Depolfunc = -p12/p11

Note that MISR p12 not supplied

AOD Fine mode fraction and PM25 fraction





Fine mode fraction ***undefined*** for <2 or >2 modes

- fPM always defined!
- Remember Capo Verde had fPM = 0.7
- But can't compute from MISR or MarsDust (because I don't have the code).

Summary (1)

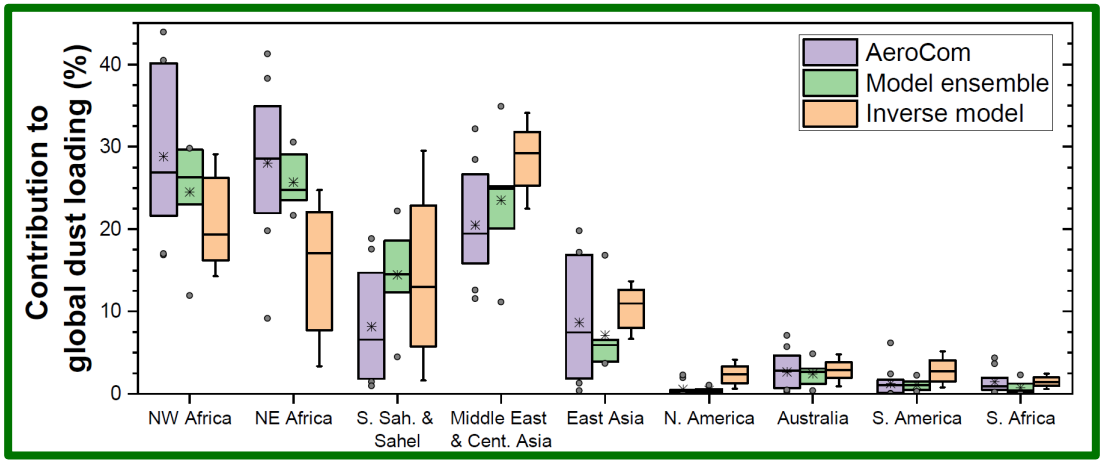
- All of our Goddard retrieval algorithms validate well
  - (and deserve more funding!)
- Yet, our assumptions within algorithms are dependent on the results we are trying to achieve
- This results in different assumptions for common aerosol types including "dust models".
- My goal was to try and find a way to visualize the differences between the dust models in different algorithms.
- Some questions to ask:
  - How much difference do these models make when it comes to doing aerosol retrieval?
  - How do these assumptions in our retrievals jibe with assumptions made in models?
  - Is there "one" model that is suitable for dust retrieval from all platforms?

Contribution of the world's main dust source regions to the global cycle of desert dust

(with application to regional constraints on dust absorption)

Jasper F. Kok

University of California – Los Angeles (UCLA), jfkok@ucla.edu



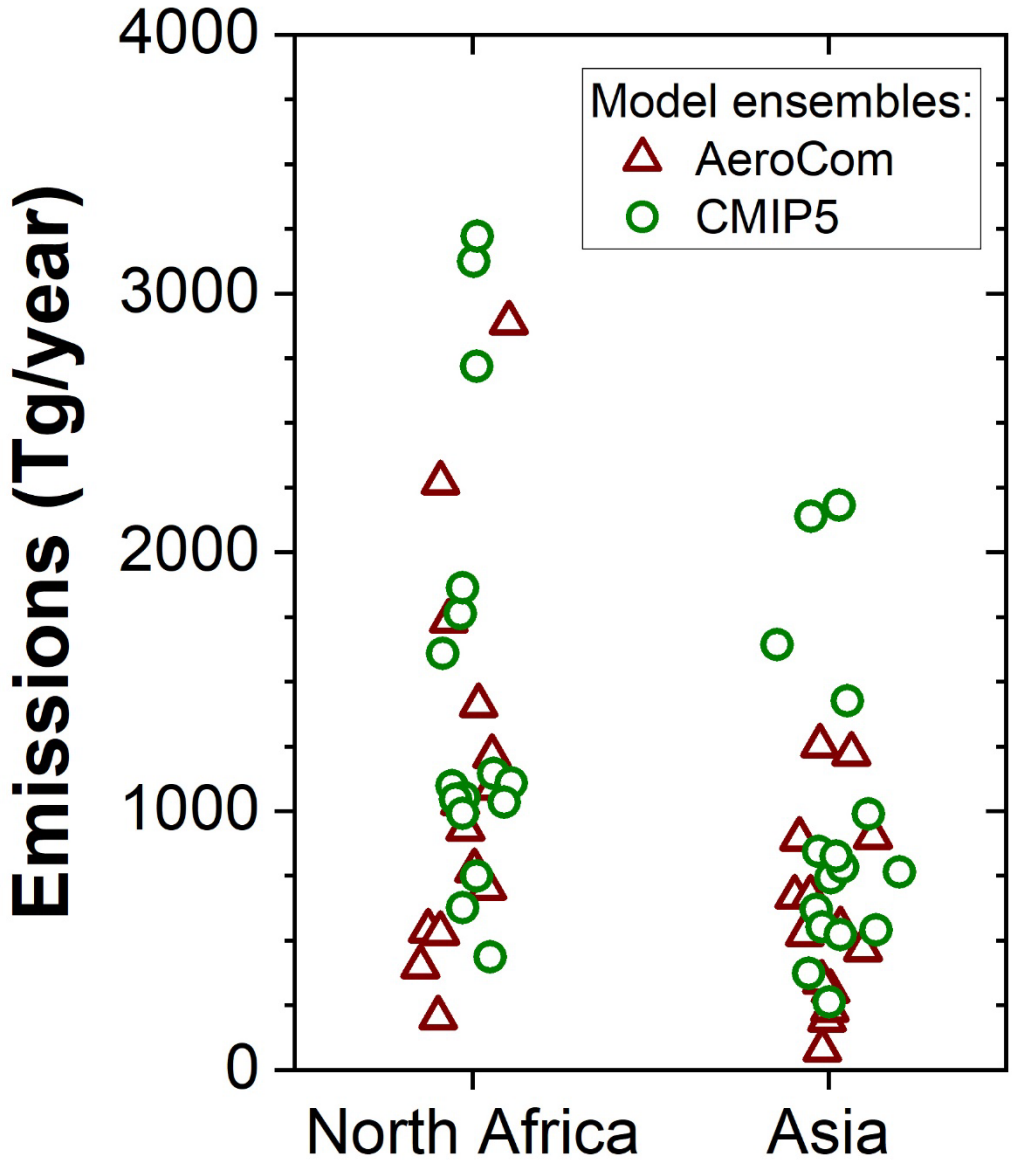
Main take-home points:

- More accurate representation of global dust cycle from integrating model ensemble with observational constraints on dust properties and abundance
- Dust origin: 50% North Africa, 40% Asia, 10% other source regions
- Models overestimate African dust and underestimate Asian dust
- North African dust is less absorbing than modeled

Collaborators: Adeyemi Adebiyi, Samuel Albani, Yves Balkanski, Ramiro Checa-Garcia, Mian Chin, Peter Colarco, Douglas Hamilton, Yue Huang, Akinori Ito, Martina Klose, Danny Leung, Longlei Li, Natalie Mahowald, Ron Miller, Vincenzo Obiso, Carlos Pérez García-Pando, Adriana Rocha-Lima, Bjørn Samset, Jessica Wan, Chloe Whicker

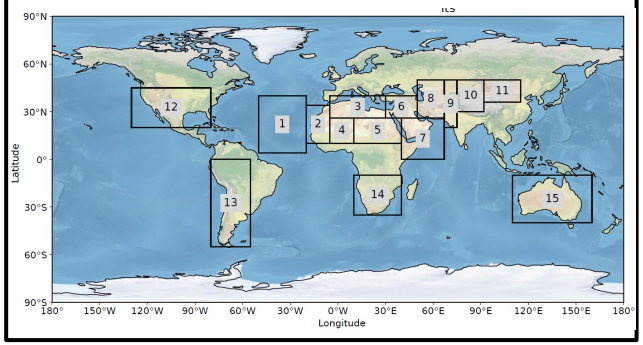
Models cannot accurately predict contribution of different source regions

- Dust source region **determines mineralogy** and thus impacts on radiation, clouds, biogeochemistry
- **~ x10 times** spread in current models (also see Dongchul's talk yesterday)
- Better (?) approach: **integrate constraints** on dust properties and regional dust AOD **with model ensemble results**



DustCOMM data set of 3D global dust cycle resolved by source region

Ridley et al. (2016) constraints on dust AOD for 15 regions



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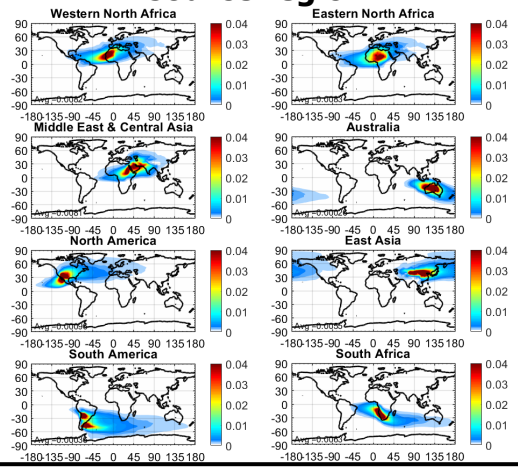
Dust AOD produced by unit dust loading from different source regions

Ensemble of simulations of unit loading of each size from each source region



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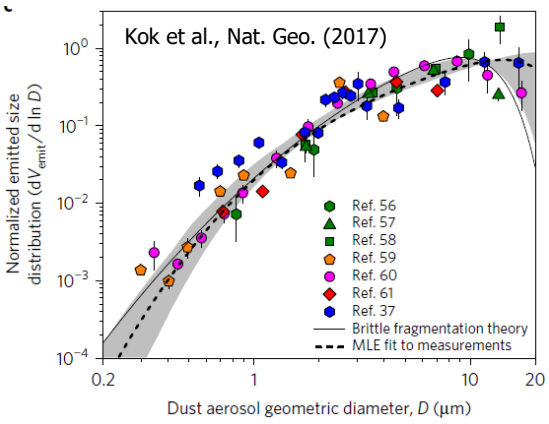
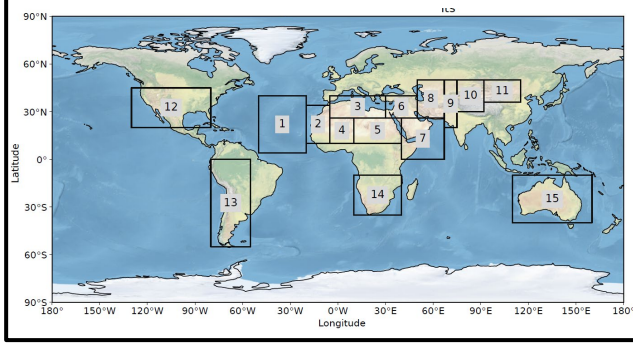
Observational constraints on dust size distribution (D ≤ 20 um) and mass extinction efficiency



Kok et al., ACP (2021a, 2021b)

DustCOMM data set of 3D global dust cycle resolved by source region

Ridley et al. (2016) constraints on dust AOD for 15 regions



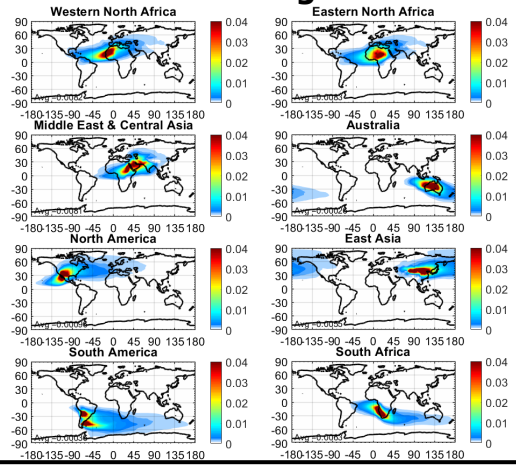
Add up units of dust loading from each source region in way that minimizes error against dust AOD constraints

3D dust cycle resolved in
- Time (season)
- Particle size
- Source region
- With realistic uncertainties

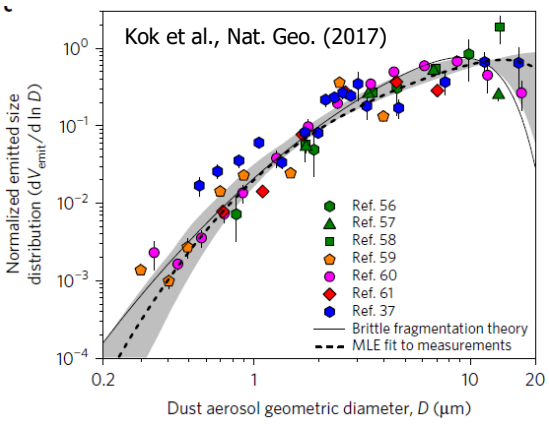
Data available at dustcomm.atmos.ucla.edu

Dust AOD produced by unit dust loading from different source regions

Ensemble of simulations of unit loading of each size from each source region



Observational constraints on dust size distribution (D ≤ 20 um) and mass extinction efficiency



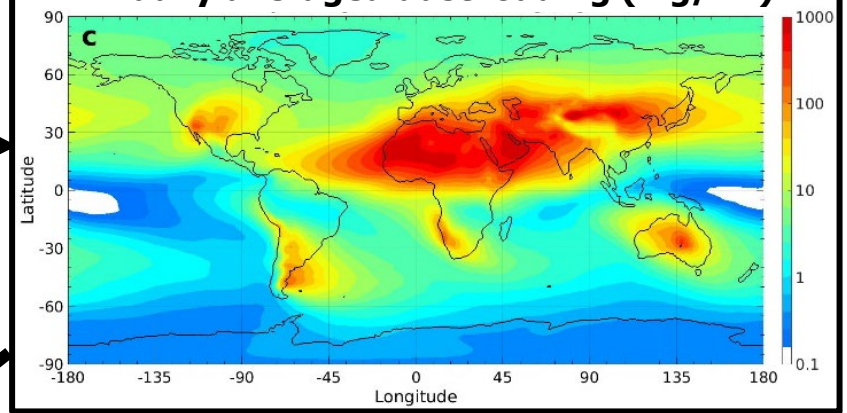
Kok et al., ACP (2021a, 2021b)

Integrating observational constraints with model ensemble produces improved representation of global dust cycle

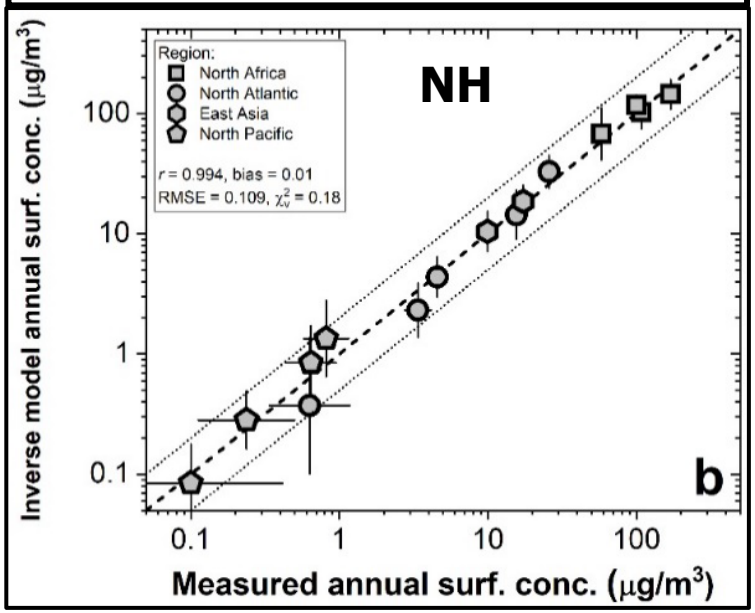
3D dust cycle resolved in
- Time (season)
- Particle size
- Source region
- With realistic uncertainties

Data available at
https://dustcomm.atmos.ucla.edu/

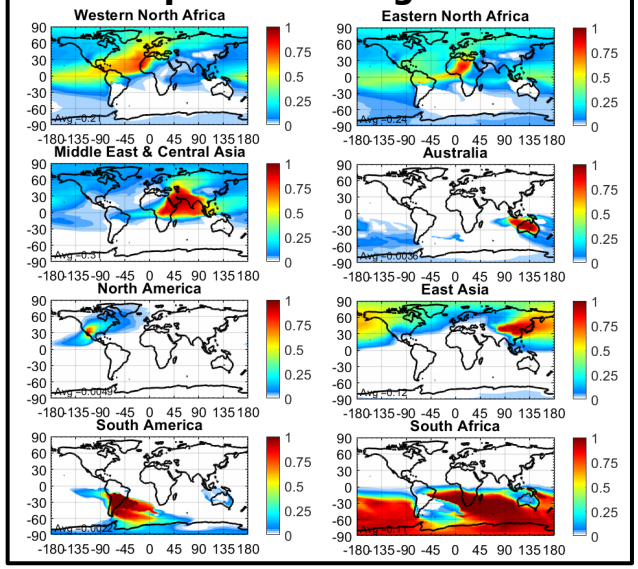
Annually averaged dust loading (mg/m²)



Improved agreement against independent data sets



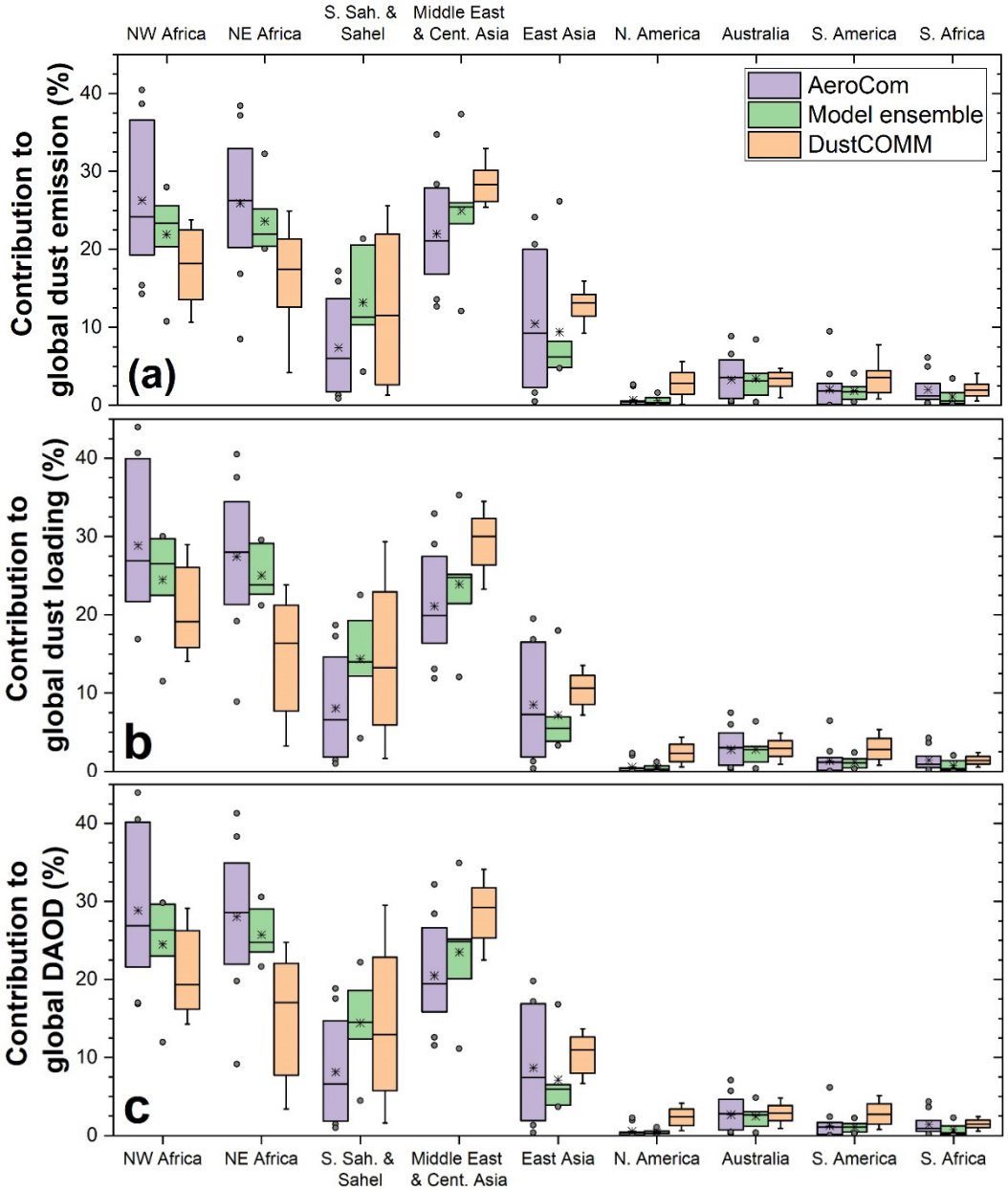
Fractionation of dust loading per source region



Kok et al., ACP (2021a, 2021b)

Models overestimate African dust, underestimate Asian dust

- Our results:
  - African dust ~50%
  - Asian dust ~40%
  - Minor source regions ~10%
- AeroCom and current models:
  - African dust ~65%
  - Asian dust ~30%
  - Minor source regions ~5%

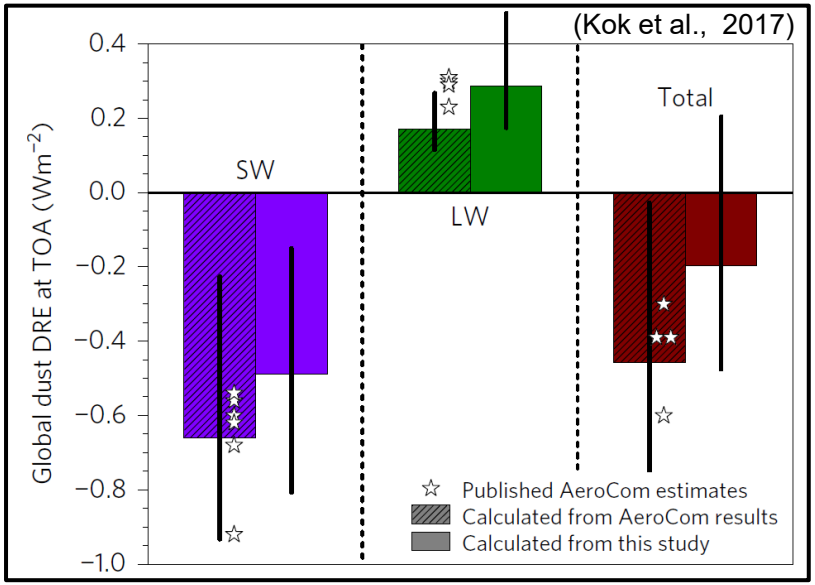


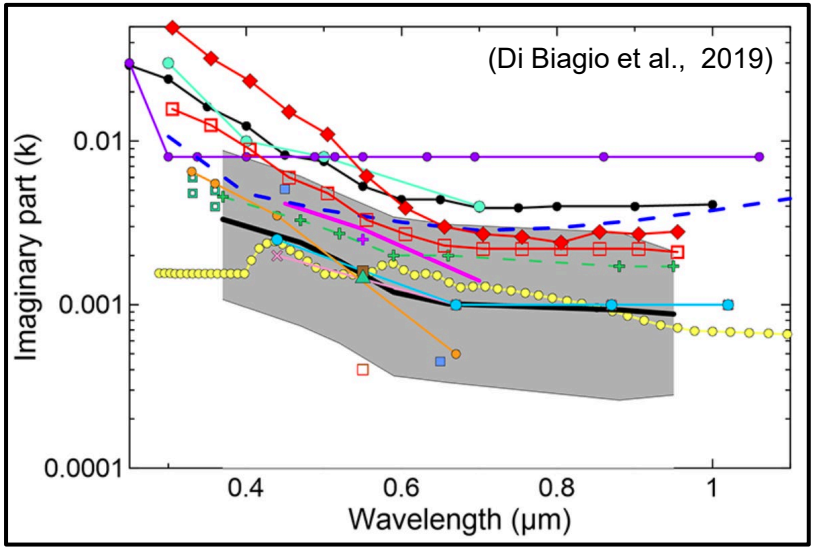
Kok et al., ACP (2021a, 2021b)

Application of source-resolved dust data set: constrain dust absorption

- Uncertainty in warming from **dust absorption dominates uncertainty in dust DRE**
  - Do not have good observational constraints on aerosol absorption (dust ~30% of AAOD; Sand '21)
  - EMIT mission can partially address this

- Constrain dust absorption over North Africa using
  - DustCOMM size-resolved loading per source region
  - In situ SSA measurements



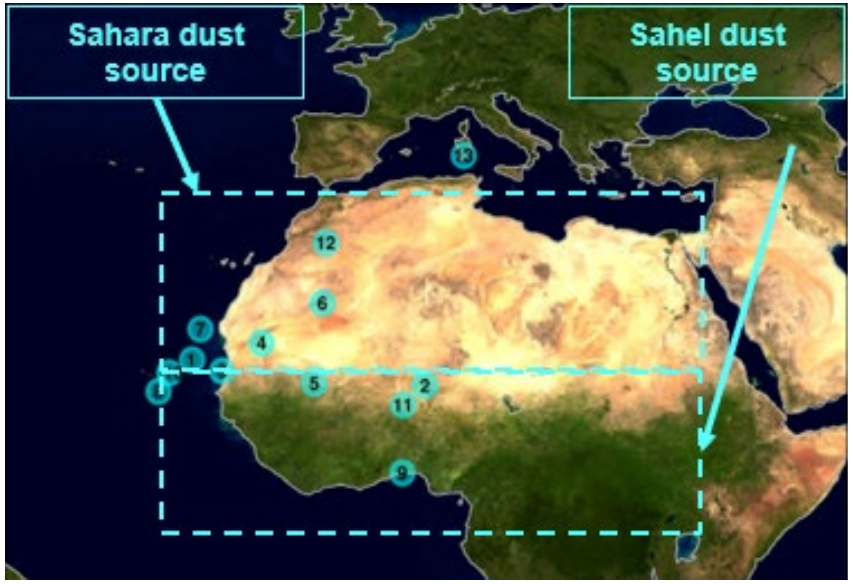


Using DustCOMM source-resolved constraints to determine absorption by North African dust

Over a dozen **in situ measurements** of dust single scattering albedo

+

Constraint on **size-resolved loading per source region** from DustCOMM



Obtain the **dust index of refraction per source region** that maximizes agreement with SSA measurements

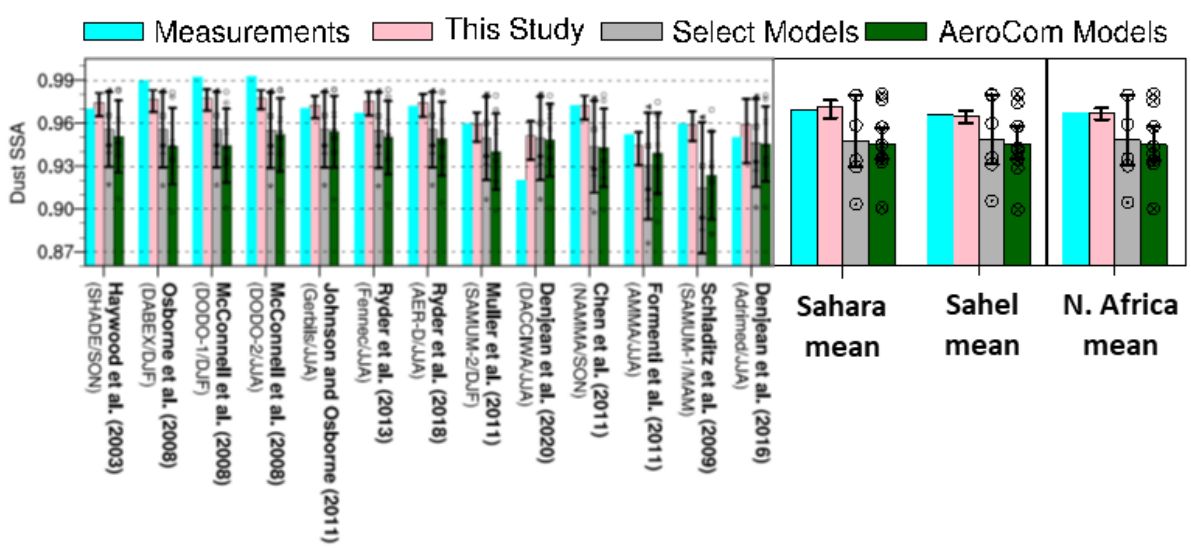
Constraint on absorption (AAOD) due to North African dust

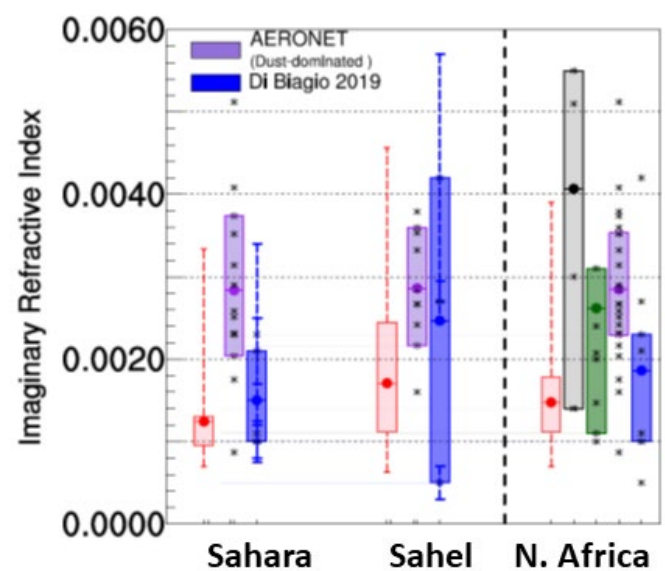
Kok et al., ACP (2021a, 2021b)

Most global models overestimate absorptivity of North African dust

- **SSA too low** for most models
  - In **AeroCom phase 3** – CAM5-Atras, ECHAM6.3-HAM2.3, ECHAM6.3-SALSA2.0, GEOS-i33p2, GISS-ModelE2, INCA, NorESM2, OsloCTM3 (Sand et al., 2021)
  - In **our ensemble** - CESM, Arpege, IMPACT, GISS ModelE, WRF-Chem, GEOS-Chem

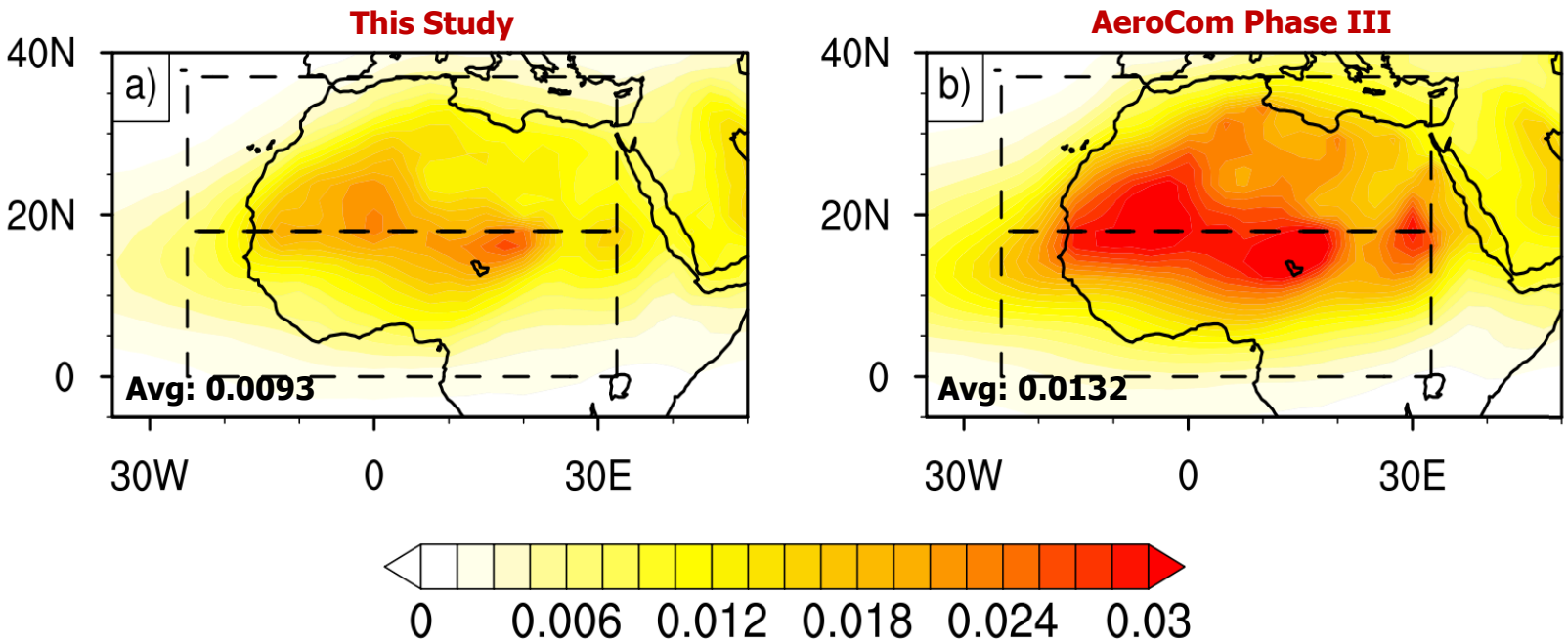
- Dust **imaginary refractive index is ~half** of that used in models
  - **AERONET also overestimates** imaginary refractive index
  - Our estimates are **consistent with recent lab-based measurements** (Di Biagio et al., 2019)





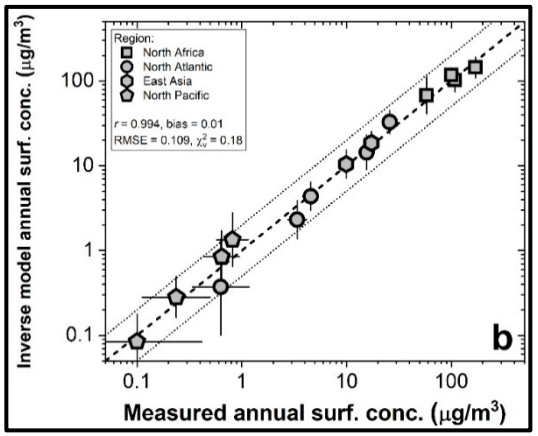
Model overestimation of dust absorption (DAAOD) is reduced by missing coarse dust

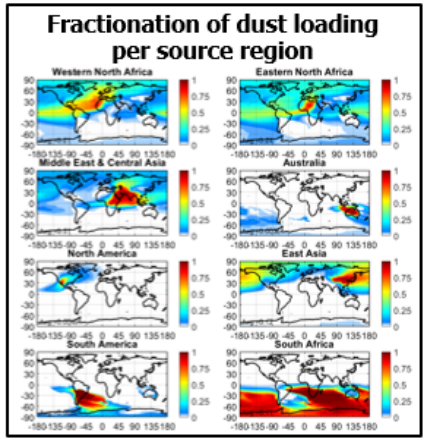
- Previous work has shown that models **underestimate coarse dust** (D > 5 um) (e.g., Ryder et al., 2019; Adebiyi and Kok, 2020)
- Dust SSA decreases with particle size
  - → Model **biases partially cancel each other**
  - → Results in net **overestimation of dust absorption (DAAOD) of 'only' ~40%**
- By itself, would cause **underestimate of dust SW cooling**

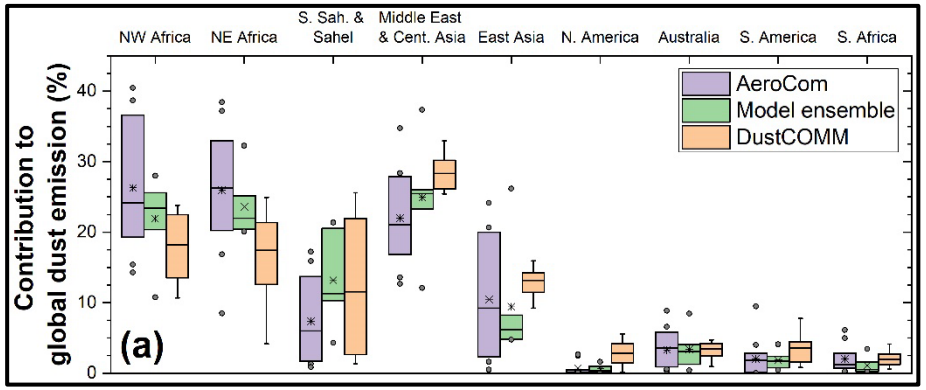


Summary & Conclusions

- New approach: integrating model ensemble with observational constraints on dust properties and abundance
- DustCOMM data set yields:
  - Improved agreement against independent data
  - Dust cycle (emission, loading, deposition, etc) resolved by season, particle size, **source region**
  - Data freely available from dustcomm.atmos.ucla.edu
- Dust origin:
  - 50% North Africa
  - 40% Asia
  - 10% other source regions
- Models **overestimate African dust** and **underestimate Asian dust**

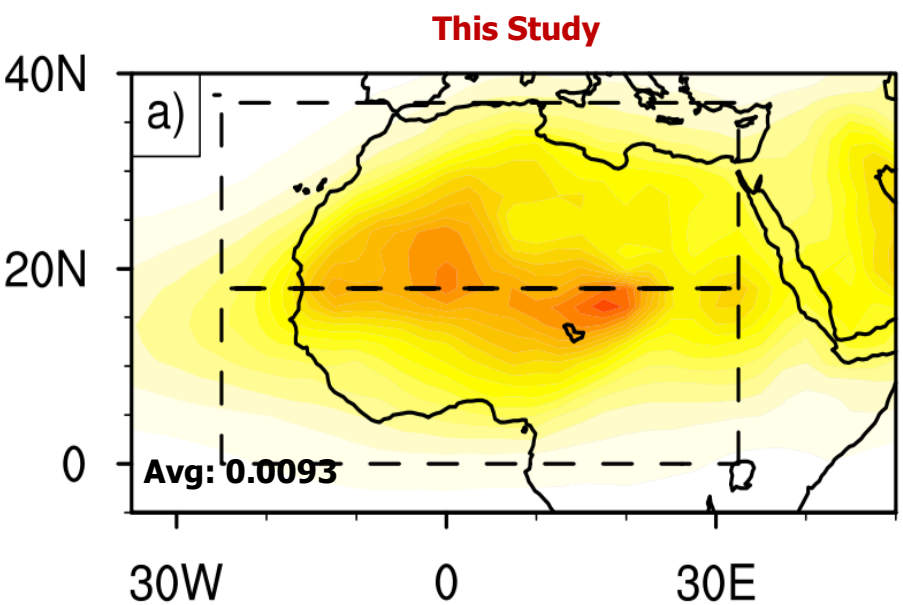


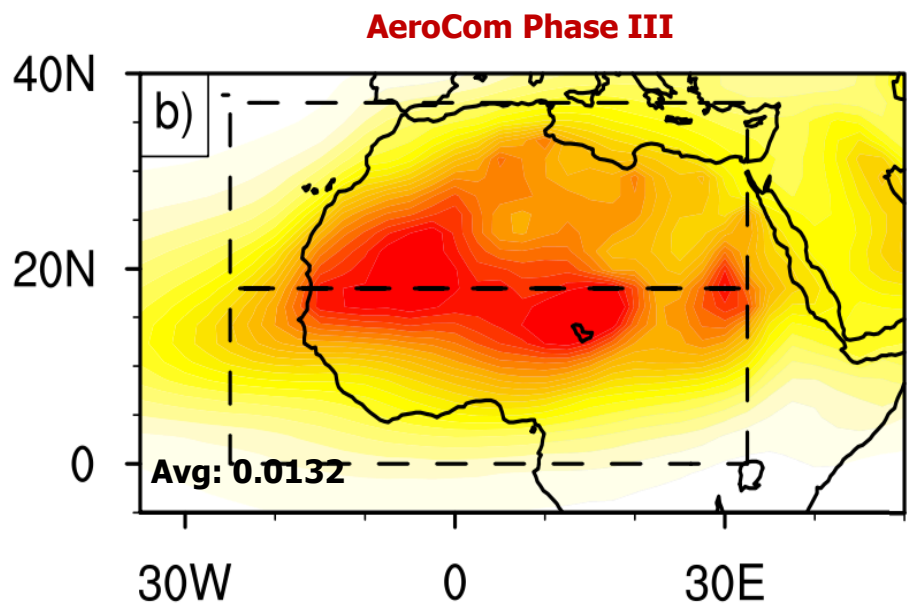




Summary & Conclusions cont'd

- **Models overestimate dust absorption** compared to in situ measurements
  - Due to overestimation of imaginary index of refraction
- Causes **overestimation of dust AAOD** of ~40%
  - Fine size bias in models reduces overestimate of absorption





Thank you!

Thoughts? Comments? → jfkok@ucla.edu

The presented work was from the following references:

Kok, J. F., et al. (2021), Contribution of the world's main dust source regions to the global cycle of desert dust, Atmospheric Chemistry and Physics, 21, 8169-93.

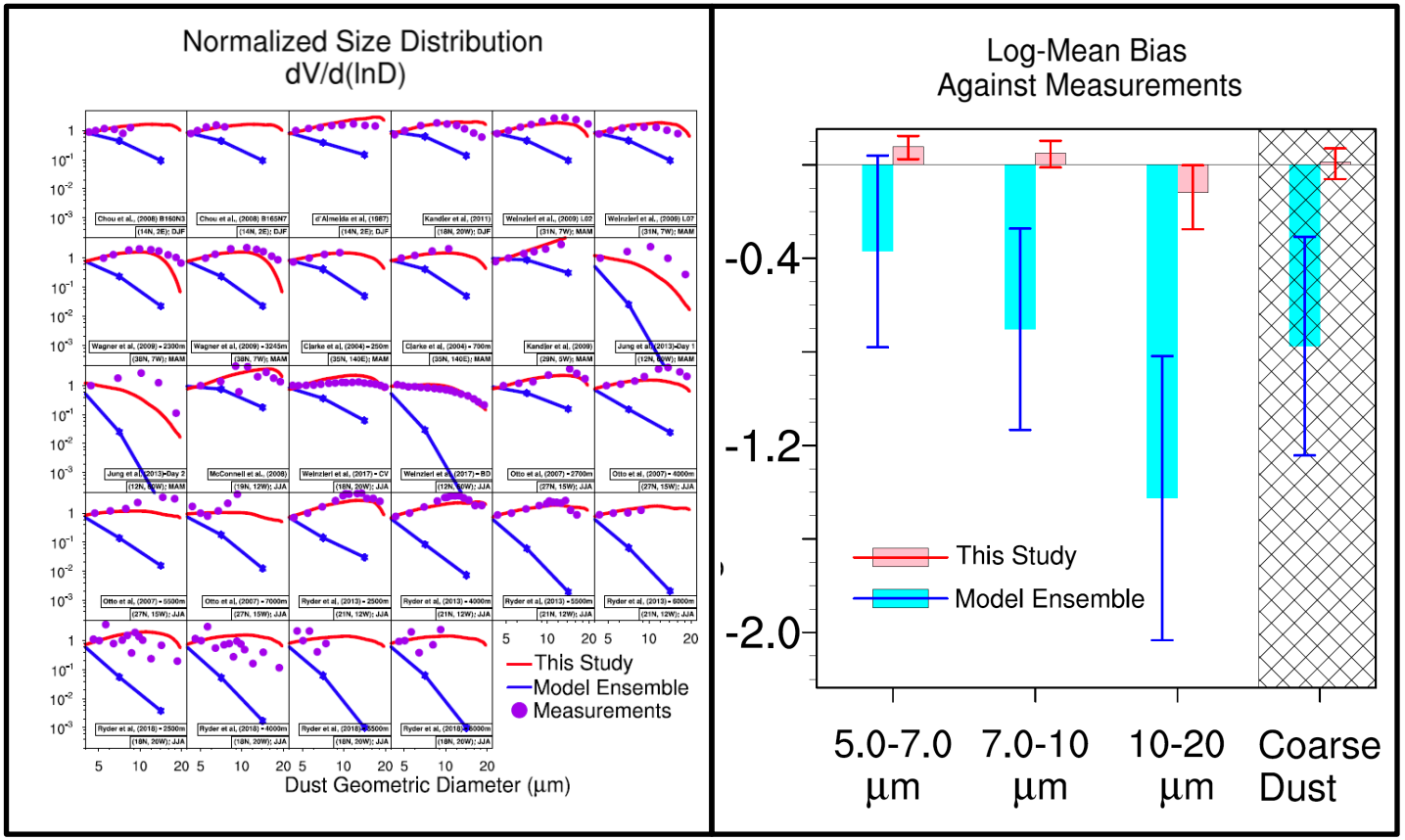
Kok, J. F., et al. (2021), Improved representation of the global dust cycle using observational constraints on dust properties and abundance, Atmospheric Chemistry and Physics, 21, 8127-67.

Adebiyi, A. A., Y. Huang, B. H. Samset, and J. F. Kok (in preparation), Climate models and remote-sensing retrievals overestimate the absorption of solar radiation by North African dust

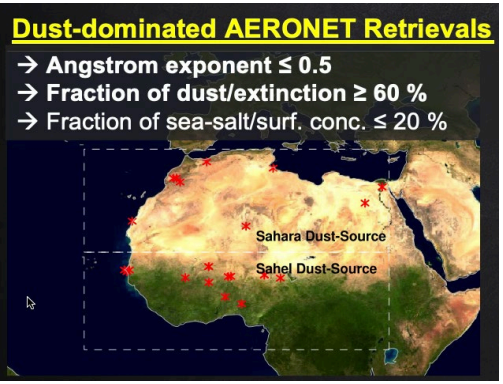
Main take-home points:

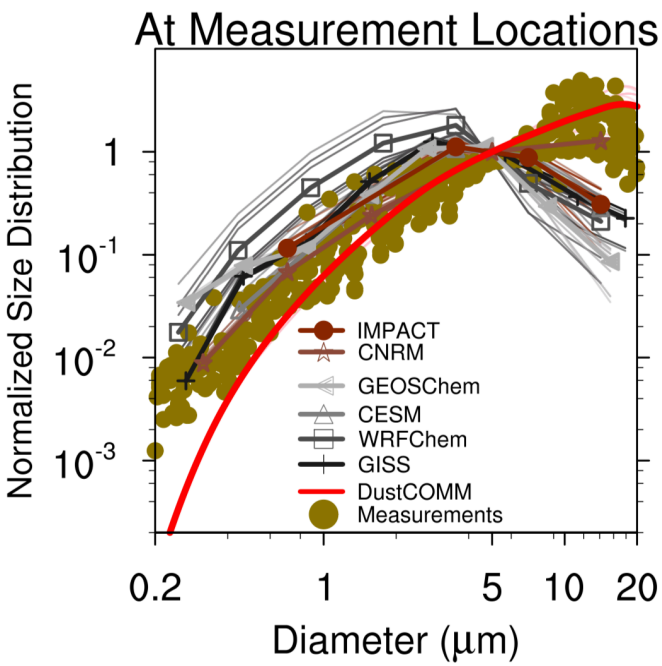
- More accurate representation of global dust cycle from integrating model ensemble with observational constraints on dust properties and abundance
- Dust origin: 50% North Africa, 40% Asia, 10% other source regions
- Models overestimate African dust and underestimate Asian dust
- North African dust is less absorbing than modeled

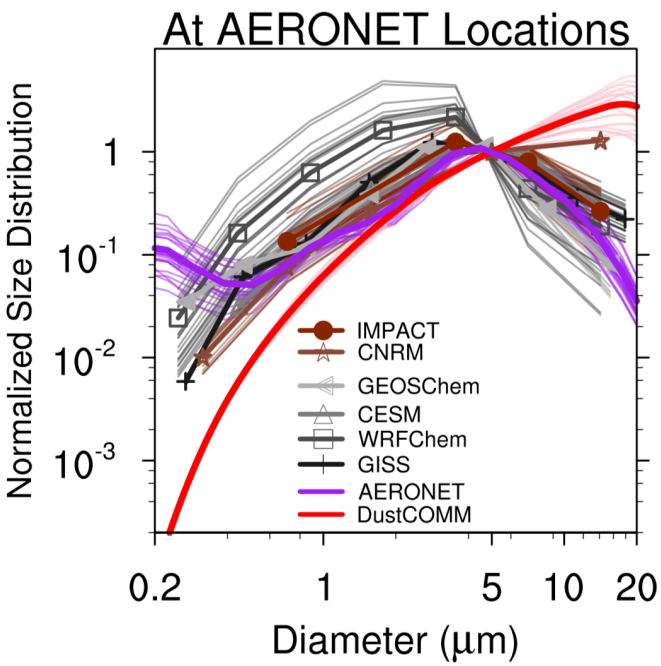
Constraints on atmospheric dust PSD based on dozens of measurements

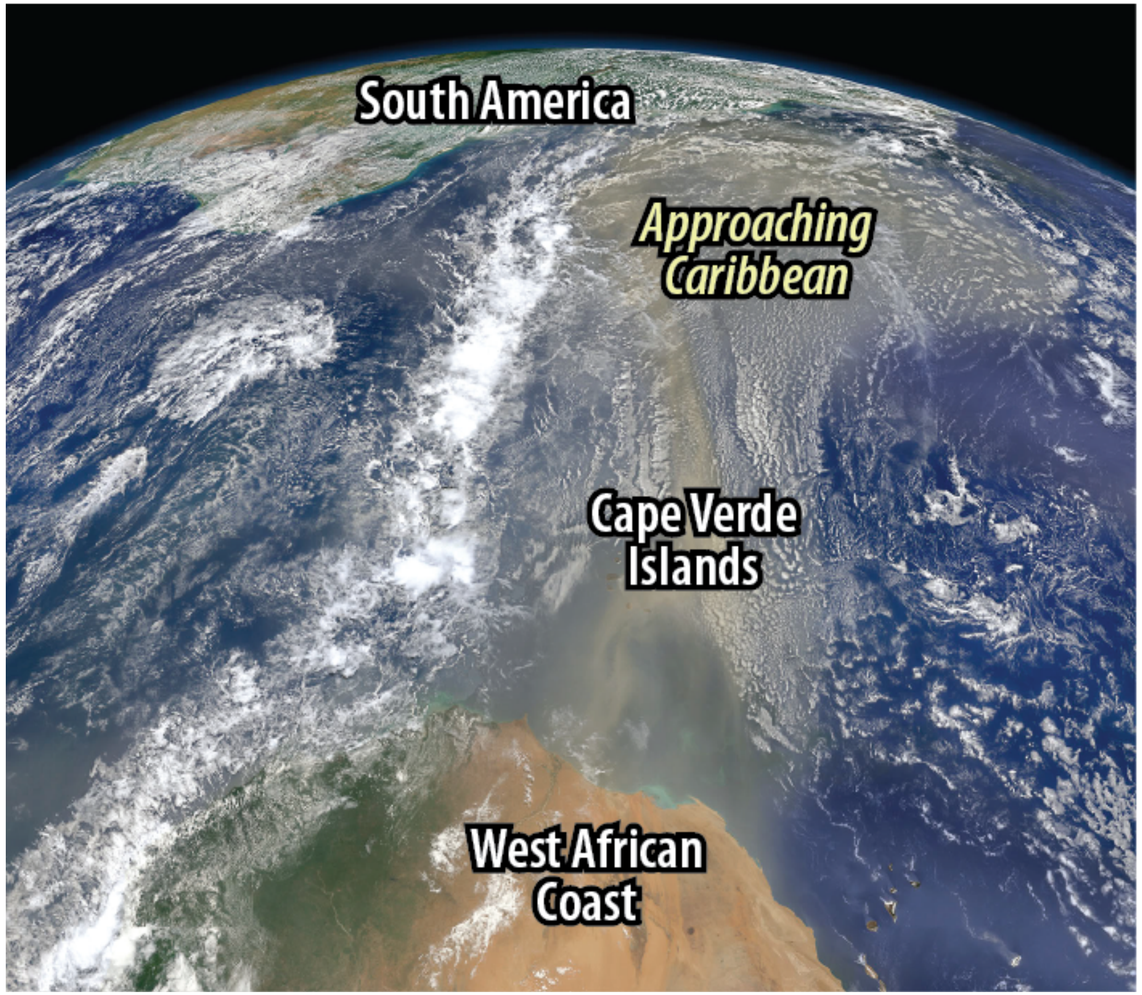


Dust-dominated AERONET retrievals of dust size distributions underestimate coarse dust









A Review of the Treatment of Dust Optical Properties in Earth System Modeling

October 12, 2021

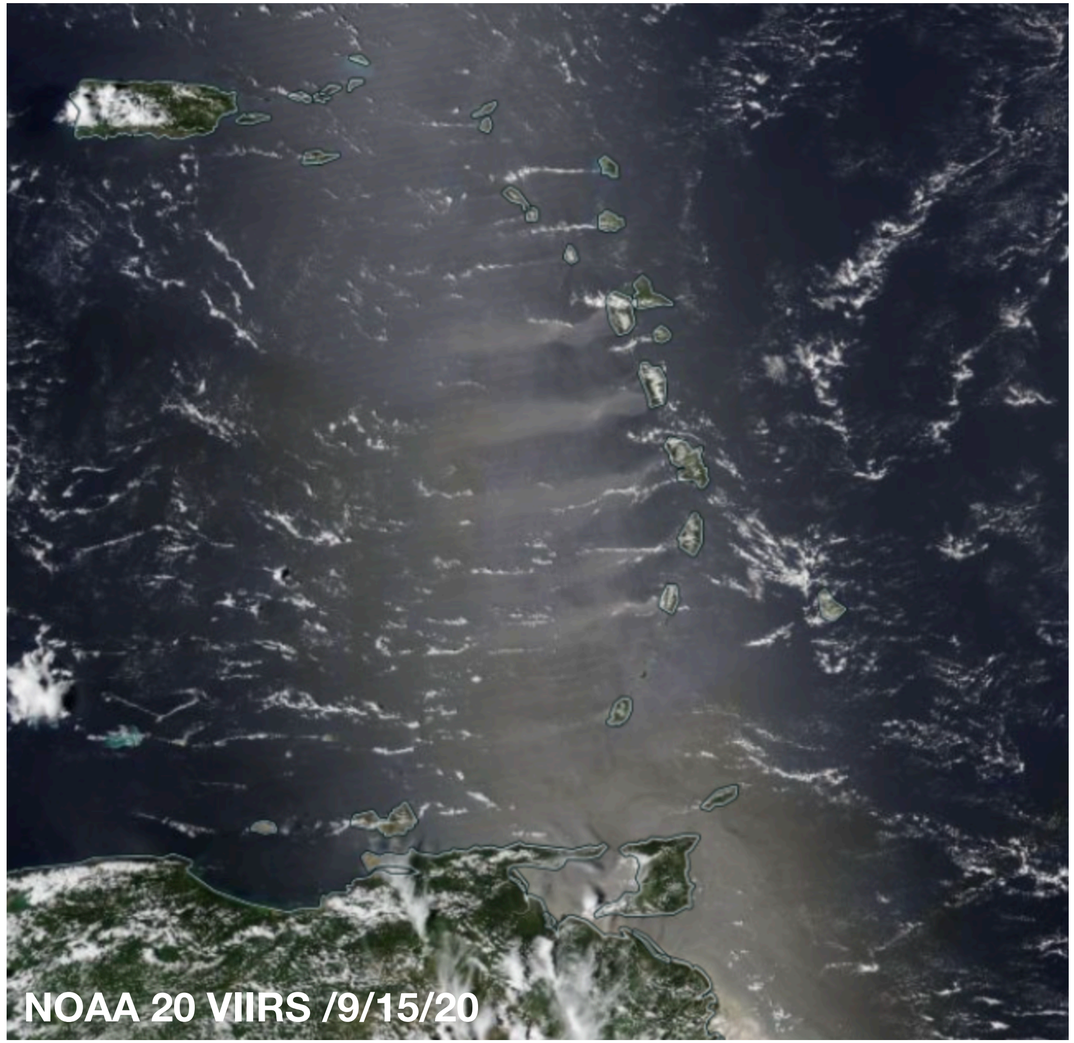
Pete Colarco, NASA GSFC/614

with a lot of useful conversations with: Patricia Castellanos, Rob Levy, Ed Nowottnick, Reed Espinosa, Osku Kemppinen, Ralph Kahn, Andy Sayer, Kirk Knobelspiesse, and others…

Special Thank To: Paul Ginoux, Oriol Jorba, Carlos Pérez García-Pando, Sam Rémy, Zak Kipling, Angela Benedetti, Jeff Reid, Peng Xian, Barry Baker, Jeff McQueen, Taichu Tanaka, Ron Miller, Susa Bauer, Melissa Brooks and Rostislav Kouznetsov

Motivation

- Most abundant aerosol species in the atmosphere
- Clearly visible from space
- Important to Earth's radiative balance
- Important to aerosol-cloud interactions
- Source of nutrients to land and ocean surfaces
- Impacts air quality and visibility



What We Did

- Surveyed a number of global aerosol models that treated dust
- Most of the models were drawn from the ICAP ensemble of near-real time global aerosol forecasting systems
- Asked all for details on how they approach the treatment of microphysics and optics in their models: sub-bin PSD assumptions, refractive indices, specifics of optical property calculations
- All of the models adopted either a bulk or sectional approach to dealing with dust mass and particle size distribution
- Subset of the models provided asked for specific optical quantities from their own calculation: MEE and SSA @ 550 nm

NASA GSFC/GEOS-GOCART

NOAA NCEP/GEFS-GOCART

ECMWF/IFS

FMI/SILAM

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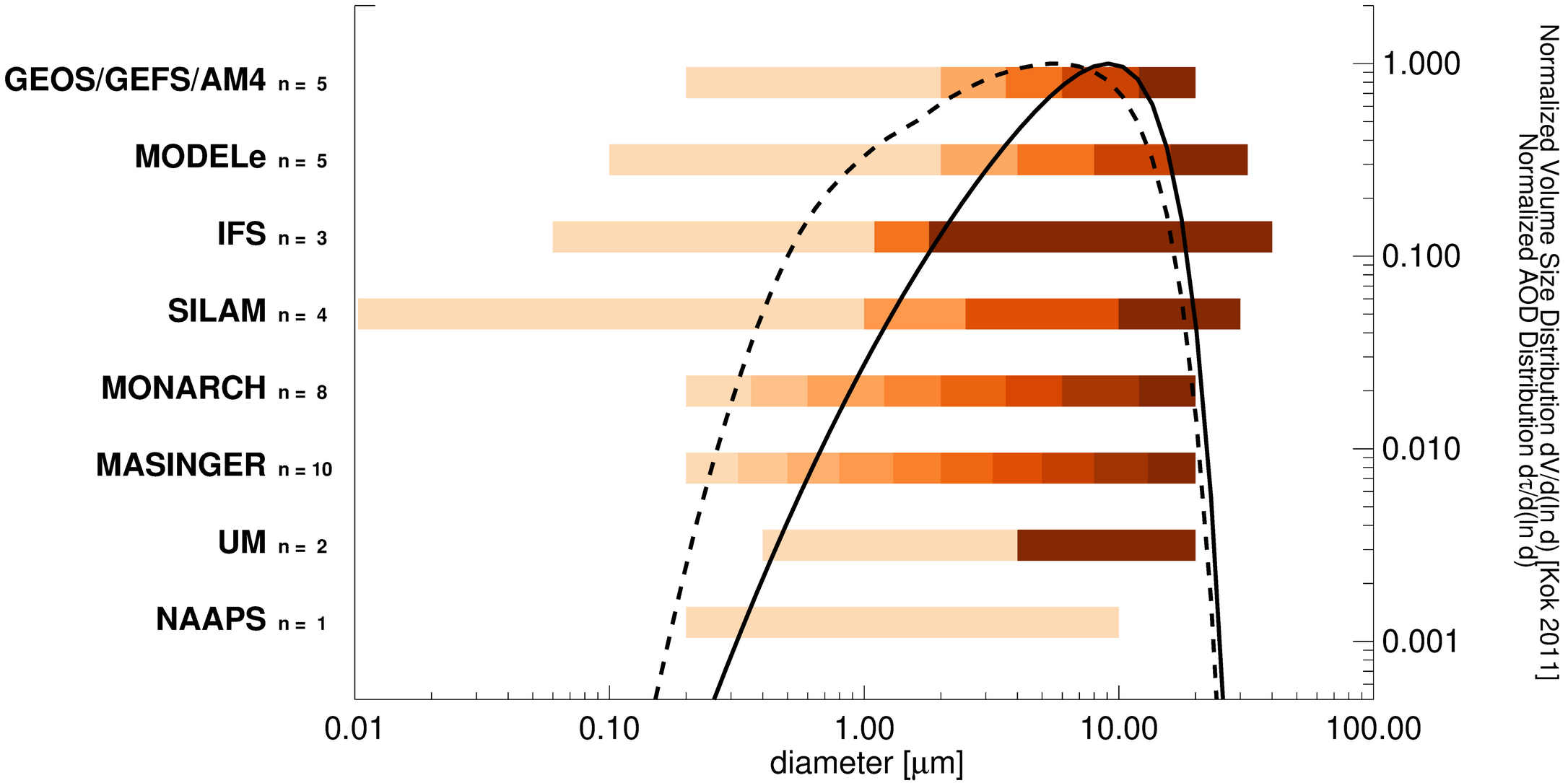
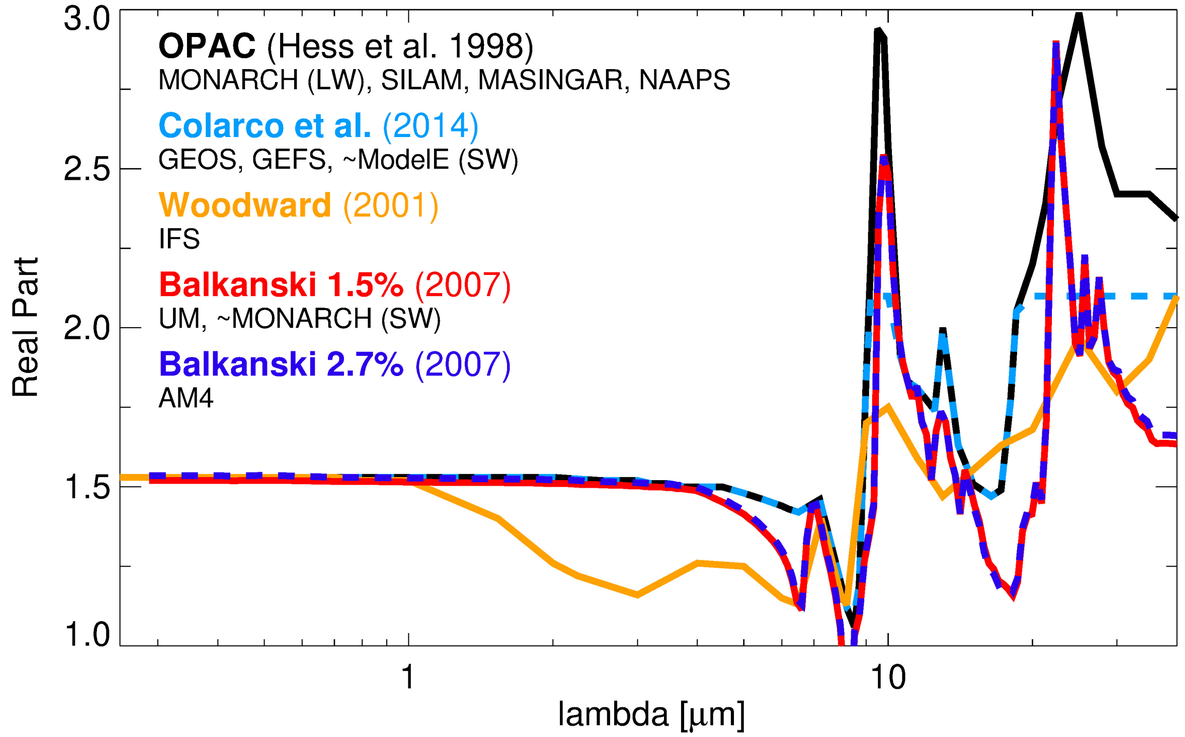
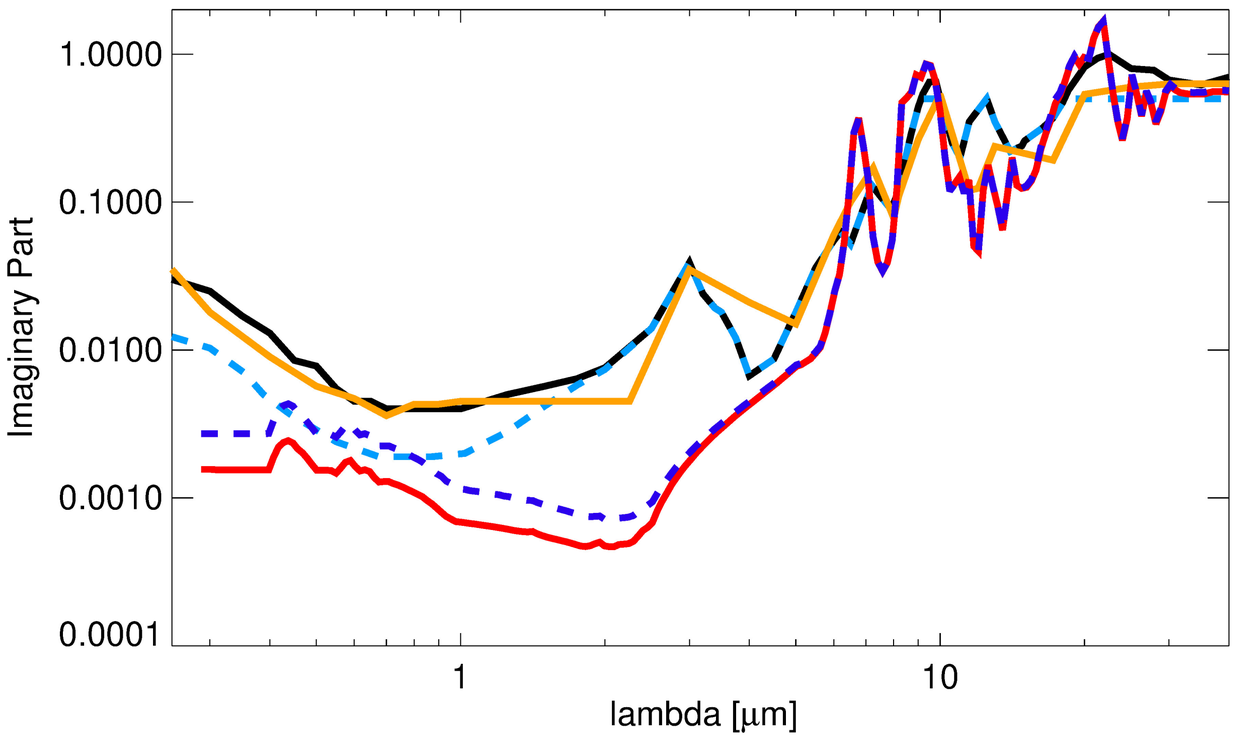
Model Treatment of Dust Particle Size Distribution



Dust Refractive Index





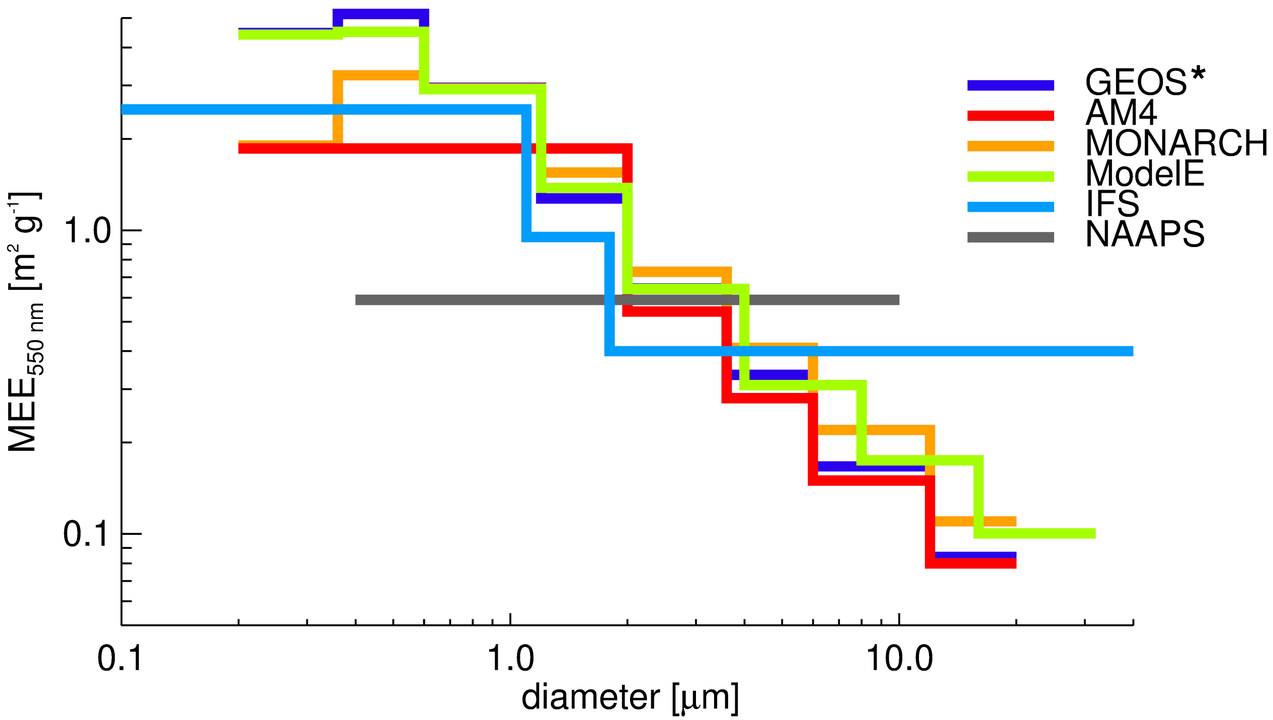
Calculation of dust optical properties for these models is generally

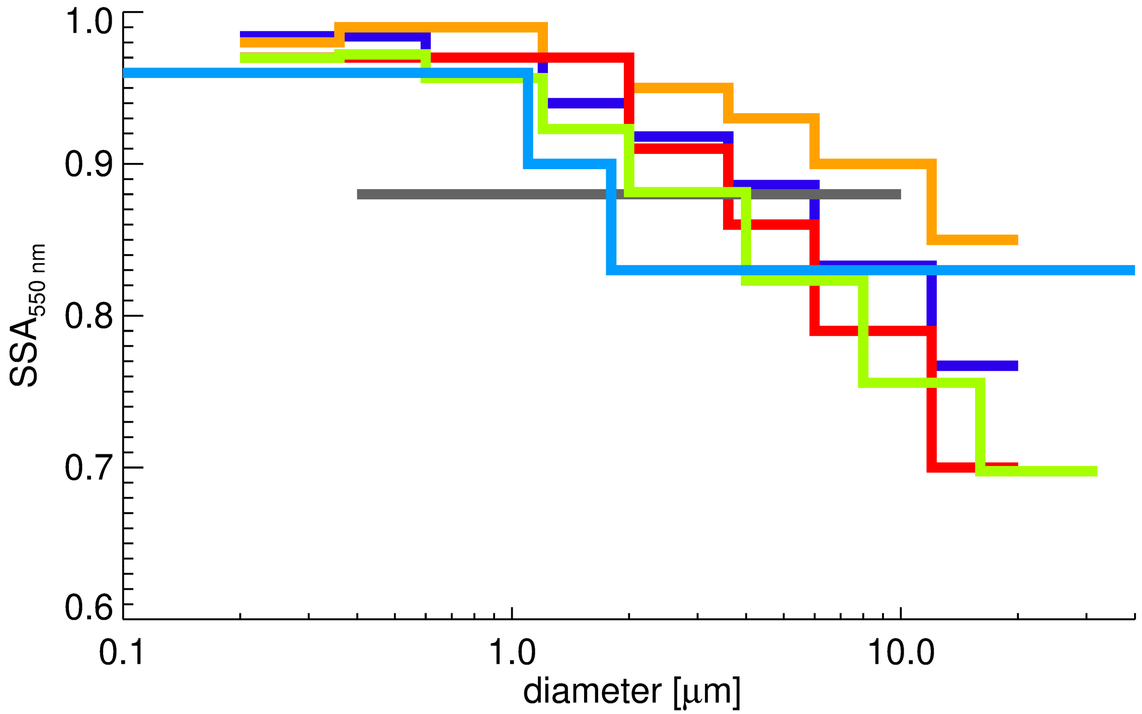
$$\sum_{\text{nbins}} \int \text{sub-bin distribution} \times f(\text{refractive index, shape})$$

Could be composition dependent, but in practice for these models is not

Mie theory (most), some non-spherical

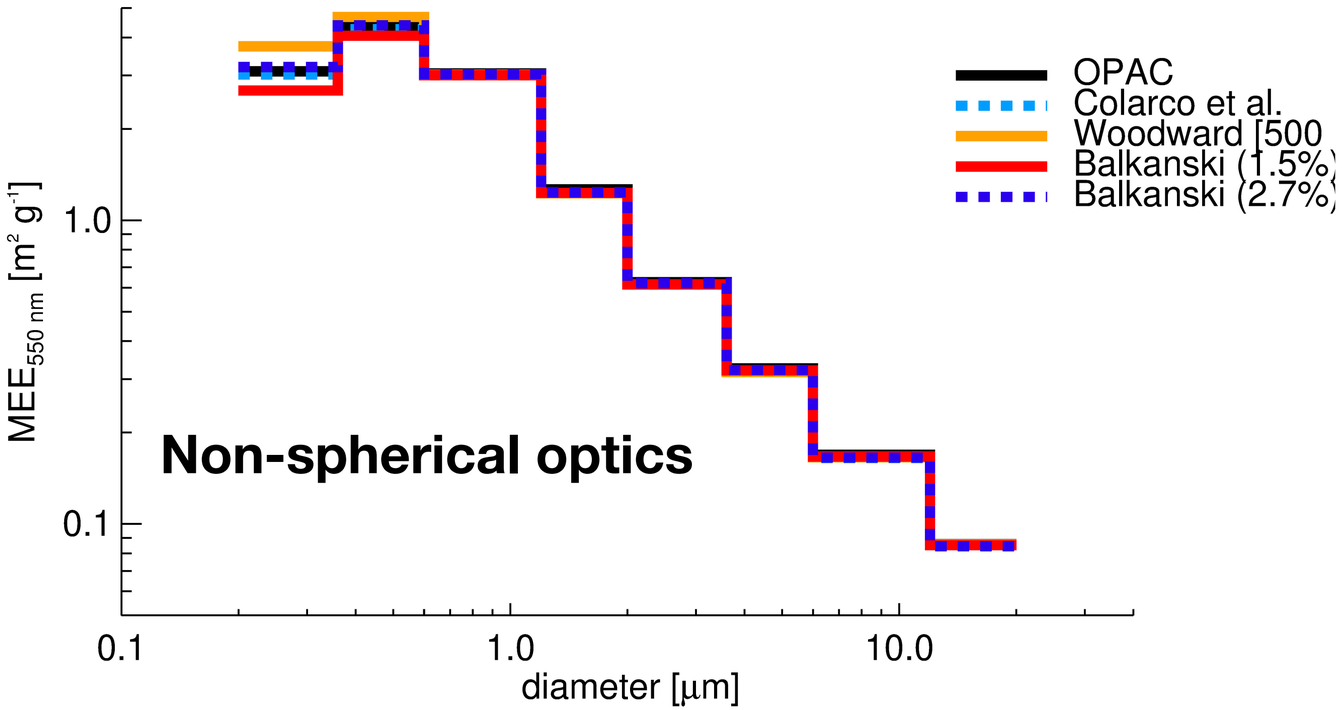
Size Resolved Optical Properties

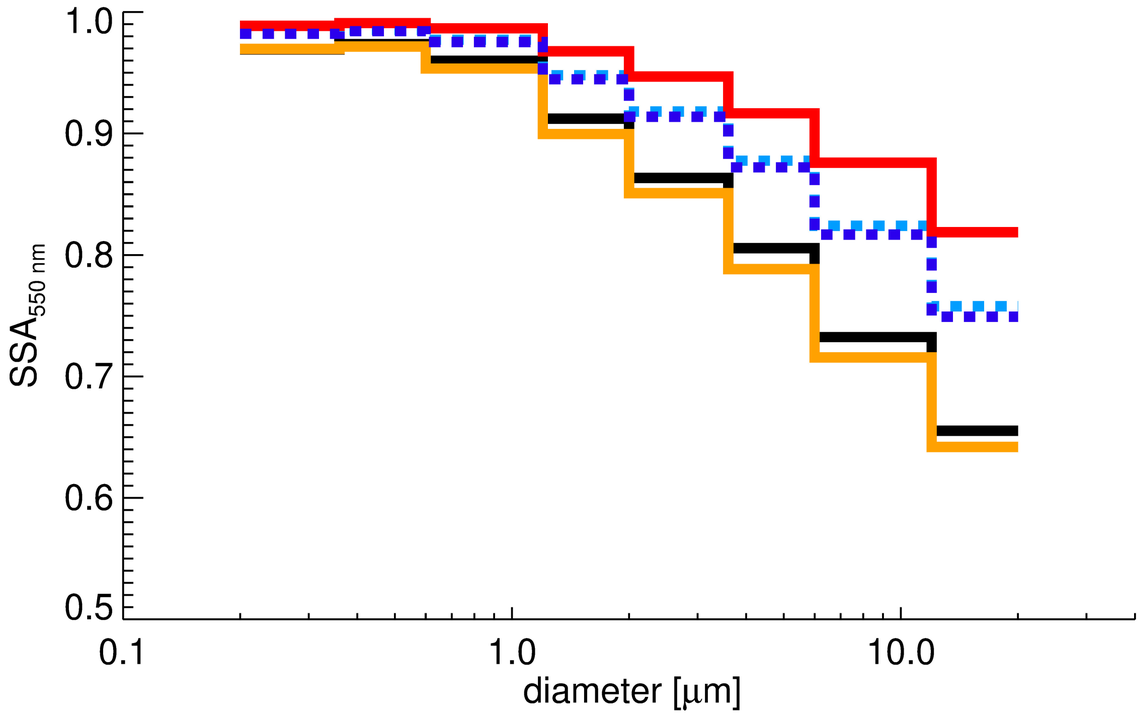




*GEOS explicitly uses spheroidal shapes in optical property calculations, all others assume spheres

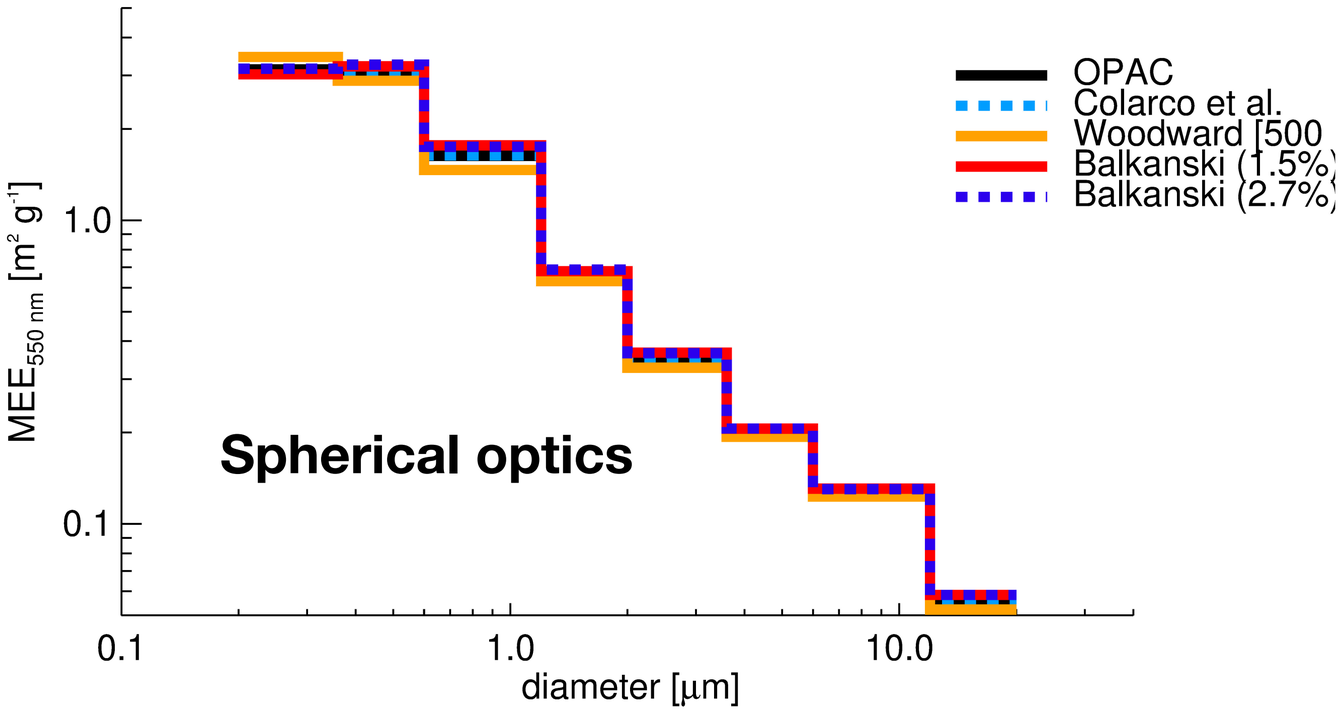
Calculated Dust MEE & SSA (non-spherical)

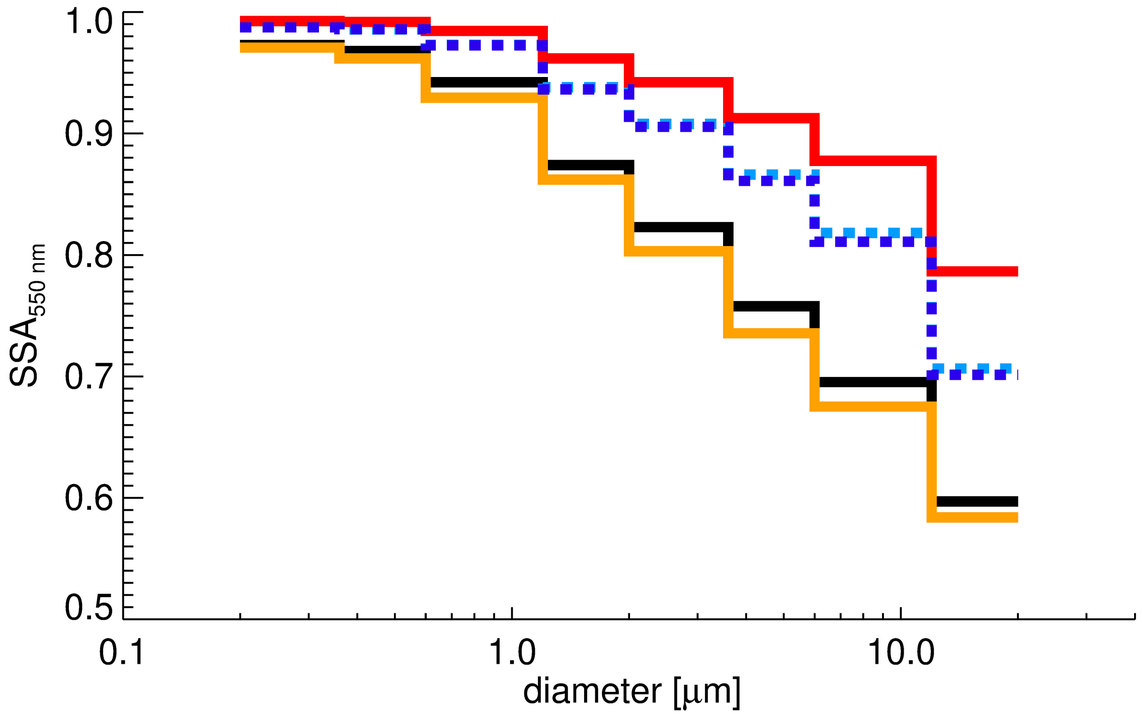




- Recalculate dust optical properties assuming GEOS framework, testing different refractive indices
- Low sensitivity in MEE to refractive index choice, expected because n_{real} approximately the same
- Much greater sensitivity to size-resolved SSA that tracks with n_{imag}

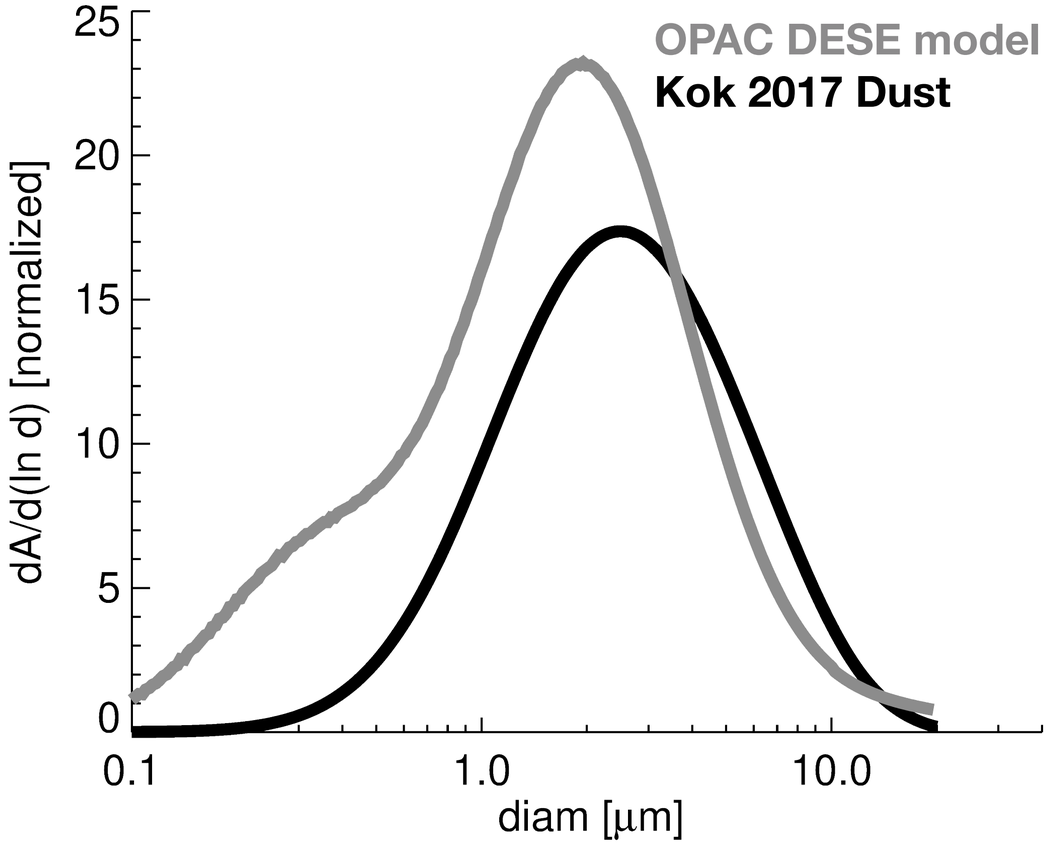
Calculated Dust MEE & SSA (spherical)





- Same but now using Mie theory/spherical optics
- MEE is a little smaller for spherical optics as expected
- Some impact also on size-resolved SSA

Toy Experiment



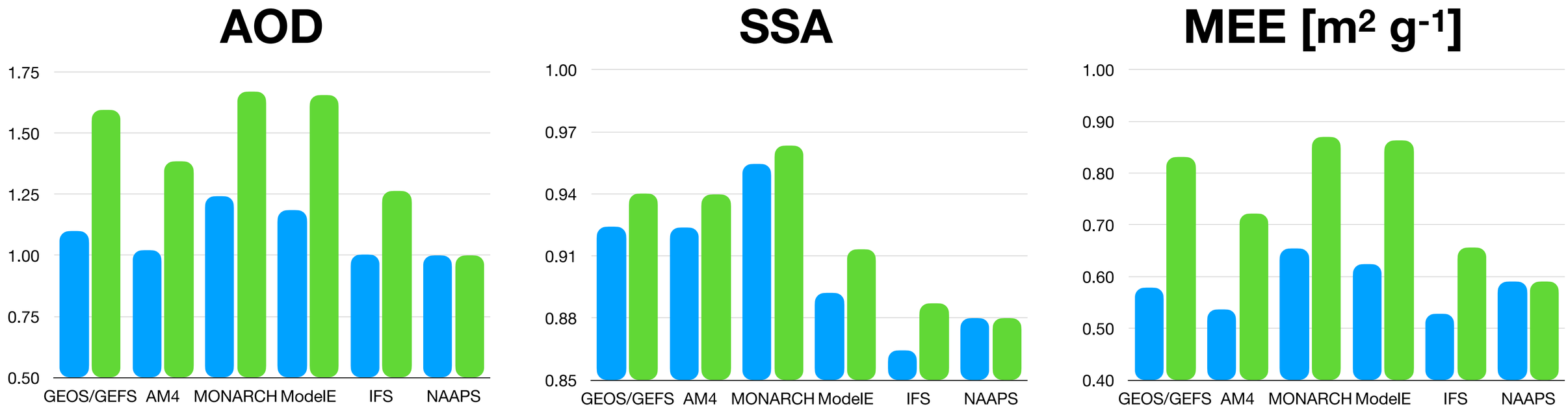
Plotted as a surface area distribution emphasizes optics

Previous slides show not much impact of refractive index choice on MEE

Want to explore convolution of reported size bins and per-bin MEE/SSA on integrated quantities

- Impose dust particle size distribution across reported size bins —> i.e., assume we know dust mass and size distribution
- Use provided per-bin MEE/SSA to calculate the total AOD and SSA
- Normalize mass loading so that NAAPS gives AOD = 1

Toy Experiment



Kok 2017

OPAC DESE

Models are all similar in AOD for **Kok 2017distribution**

- All models get ~100% of mass and >96% of surface area

Much larger disparity for **OPAC DESE distribution**

- NAAPS has ~85% of surface area; others all close to 100%

Residual disparities are down to coarseness of PSD and particular optics

Conclusions

- Surveyed a series of global dust models for how they cope with dust microphysical and optical properties

- Models reported here take a sectional approach, and in general the size range of particles considered is adequate to express the total mass loading and for the most part the optical properties

- Refractive index as used in the models surveyed is not a prime driver of the mass extinction efficiency (MEE) at 550 nm, but does explain diversity in single scattering albedo (SSA)

- For models that report their per-bin MEE and SSA we illustrate with imposed size distributions how the limited number of size bins and the particulars of their optical calculations result in possibly quite large diversity in the AOD, SSA, and effective MEE

- We suggest further work to refine the number and spacing of size bins needed to adequately express the dust mass distribution and hence its optical properties