ORACLES field campaign observations of clouds and aerosols above cloud by the Research Scanning Polarimeter

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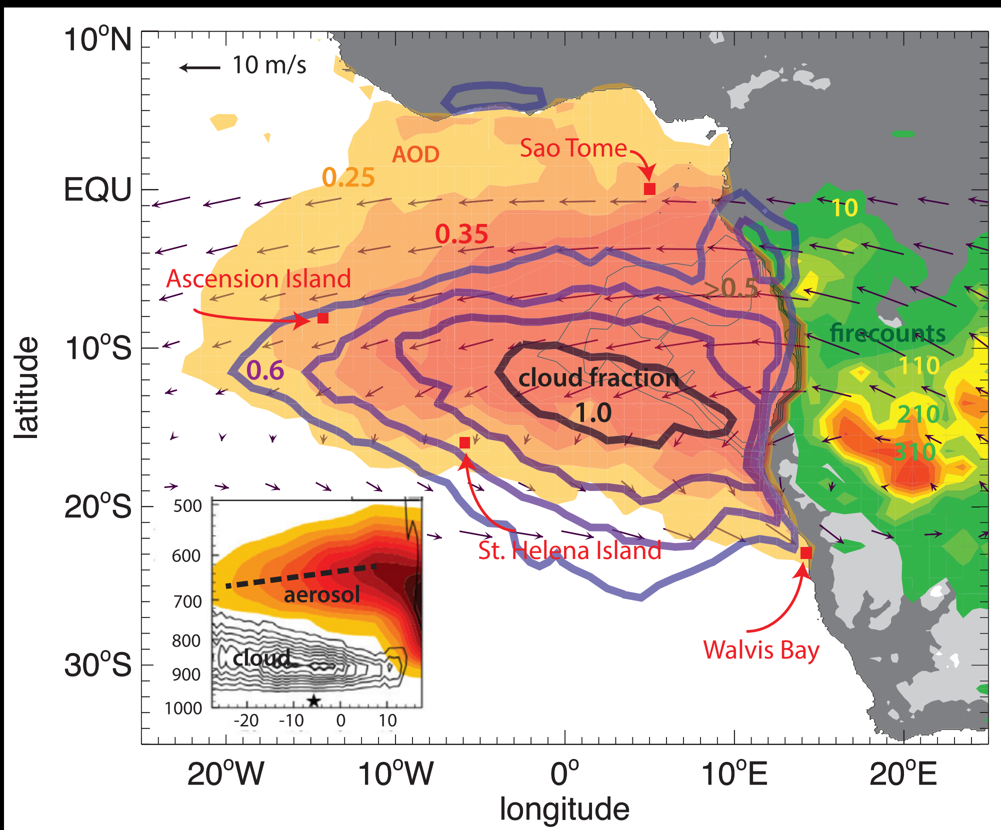
ORACLES: ObseRvations of Aerosols above Clouds and their intEractionS

NASA Earth venture airborne mission to study aerosols above clouds where this frequently occurs: in the S.E. Atlantic ocean



Zuidema, P., Redemann, J., Haywood, J., Wood, R., Piketh, S., Hipondoka, M. and Formenti, P., 2016. Smoke and clouds above the southeast Atlantic: Upcoming field campaigns probe absorbing aerosol's impact on climate. *Bulletin of the American Meteorological Society*, *97*(7), pp.1131-1135.

The SE Atlantic ocean has:
persistent clouds (due to upwelling)
+ massive smoke aerosol loads
= lots of Above Cloud Aerosols

Multi-angle polarimetry is the only available remote sensing technique that can simultaneously retrieve cloud and aerosol (absorption) properties

MASSIVE intra-model variability

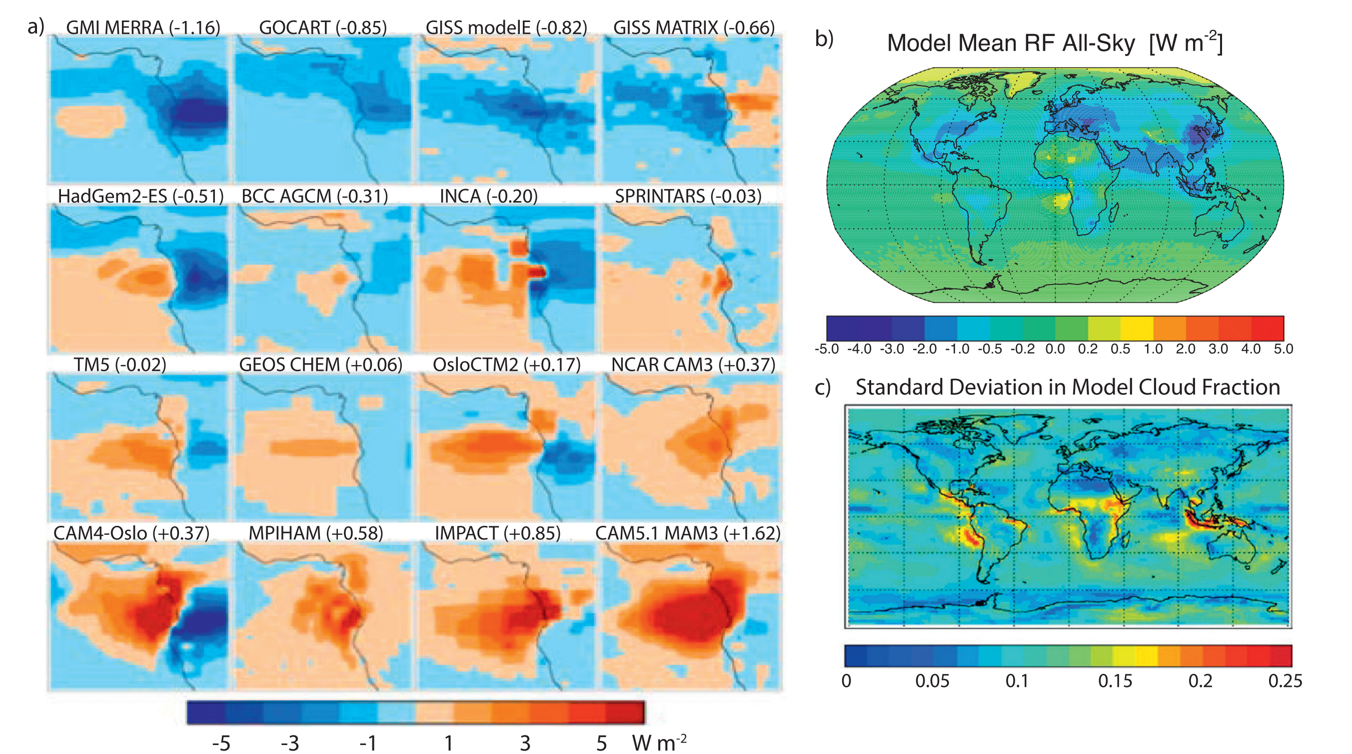
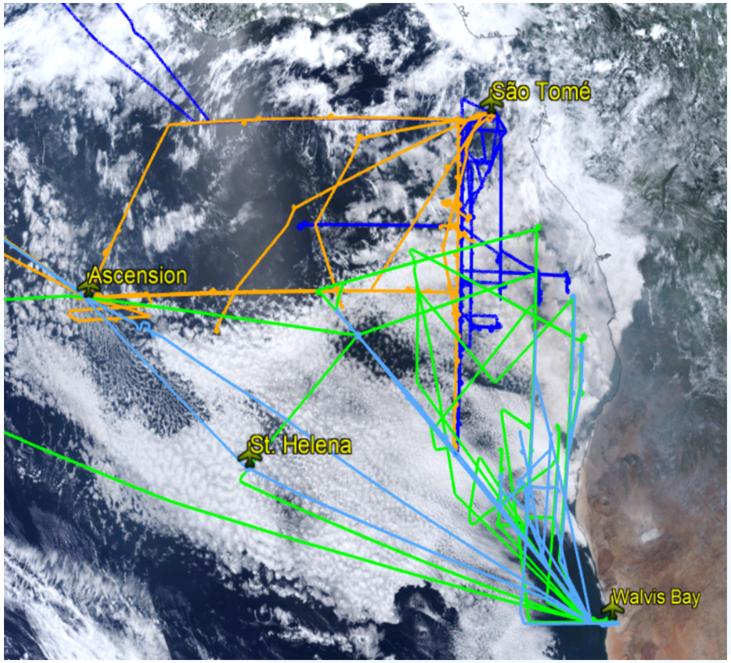


Fig. 2. Modeled Aug–Sep direct aerosol radiative forcing in (a) individual AeroCom models ordered by their regional- and annual-average difference from the (b) ensemble mean indicating the regional hotspot for BB aerosol forcing over the southeast Atlantic. (c) indicates the large diversity in the models' cloud fraction. The cloud fraction helps determine if the aerosol shortwave absorption influences the climate more than the aerosol scattering. More model details can be found in Stier et al. (2013).

From Zuidema, P., Redemann, J., Haywood, J., Wood, R., Piketh, S., Hipondoka, M. and Formenti, P., 2016. Smoke and clouds above the southeast Atlantic: Upcoming field campaigns probe absorbing aerosol's impact on climate. *Bulletin of the American Meteorological Society*, *97*(7), pp.1131-1135.



P-3: Profiling aircraft
2016, 2017 & 2018

ER-2: High-flying
2016 only

Science Questions

Q1: What is the direct radiative effect of the African biomass burning (BB) aerosol layer in clear and cloudy sky conditions over the SE Atlantic?

Q2: How does absorption of solar radiation by African biomass burning (BB) aerosol change atmospheric stability, circulation, and ultimately cloud properties?

Q3: How do BB aerosols affect cloud droplet size distributions, precipitation and the persistence of clouds over the SE Atlantic?

https://espo.nasa.gov/oracles

Instrument	Aircraft	Measurements
SSFR	P-3	Solar flux, Irradiance
	ER-2	
4STAR	P-3	Aerosol Optical Depth, H2O
APR3'	P-3	Radar Reflectivity, Linear Depolarization Radar, Doppler Velocity
AMPR	P-3	Brightness Temperature
HIGEAR	P-3	Particle Absorption, Cloud Condensation Nuclei, Particle Scattering, Aerosol Size Distribution, Black Carbon
COMA	P-3	CO, CO2, H2O
UND-2DS	P-3	SPEC Two-Dimensional Stereo Optical Array Probe
UND-CIP	P-3	DMT Cloud Particle Imager
UND-HVPS	P-3	SPEC High Volume Precipitation Spectrometer Version 3
UND-CAS	P-3	DMT Cloud Aerosol Spectrometer
UND-PCASP	P-3	DMT Passive Cavity Aerosol Spectrometer
KING	P-3	
PDI	P-3	Flight Probe Dual Range Phase Doppler Interferometer Data
RSP	P-3	Polarimetric Imagery
	ER-2	
TAMMS	P-3	Aircraft position, Temperature, Pressure, H2O
Water isotopes	P-3	Water Vapor Isotopes
AirMSPI	ER-2	Polarimetric Imagery
eMAS	ER-2	Imagery
HSRL2	ER-2	Aerosol Depolarization Ratio, Aerosol Scattering Ratio, Aerosol Backscattering, Aerosol Extinction

Research Scanning Polarimeter (RSP)

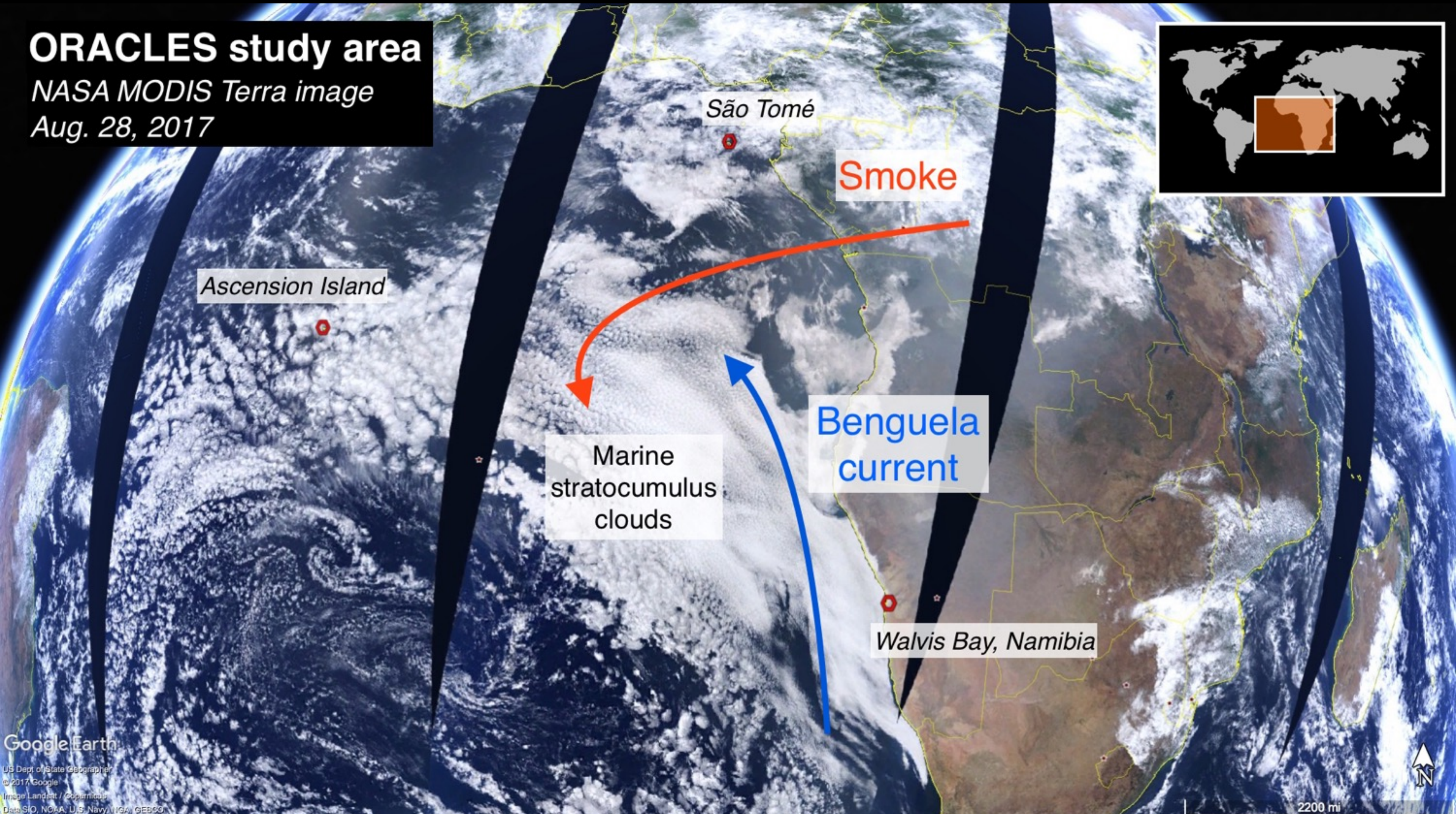
VIS-SWIR (9 channel)

highly accurate ($\sigma_{DoLP} < 0.0015$)

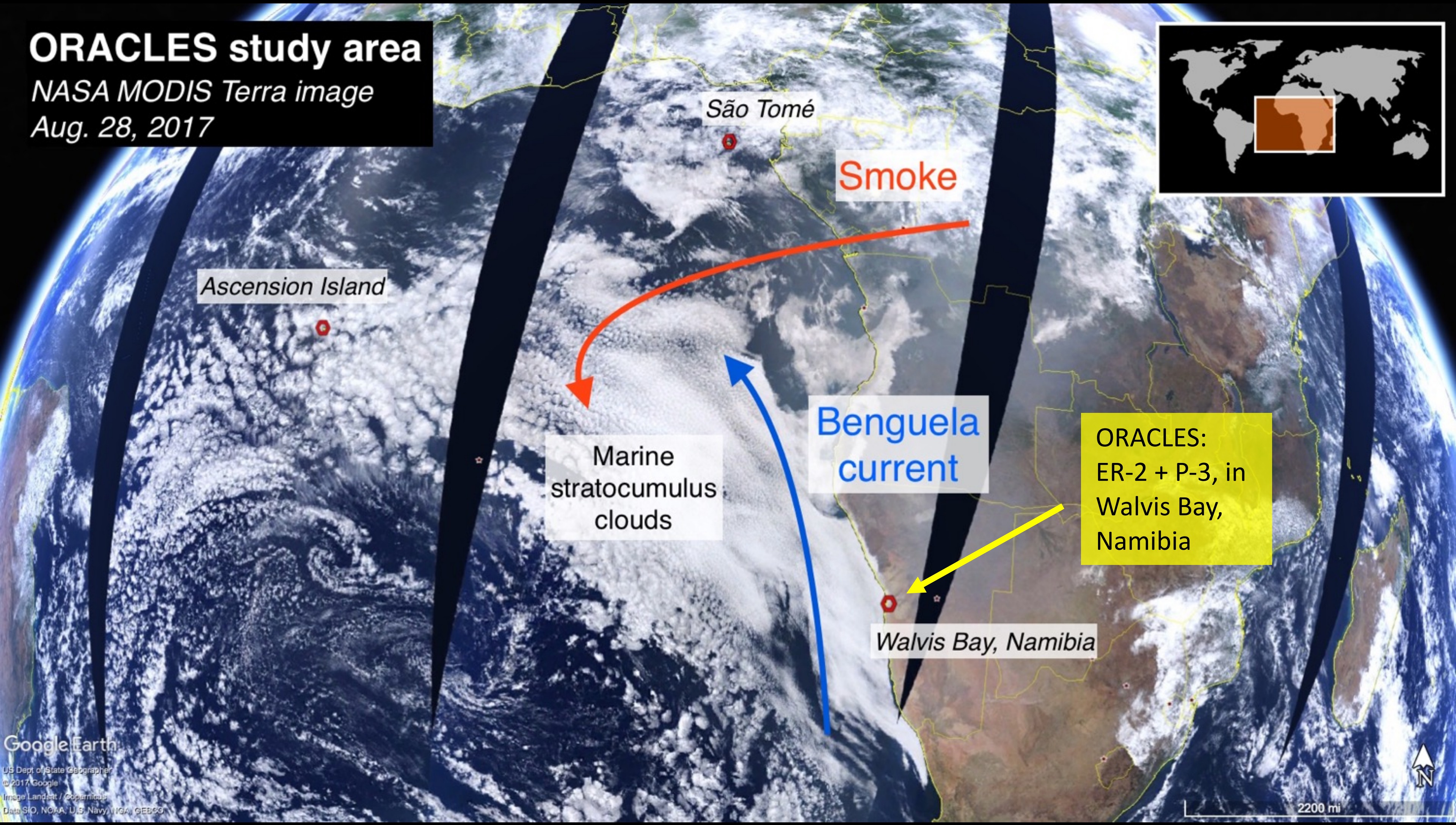
PI: Brian Cairns

multi-angle (~150 views)

along track scanner

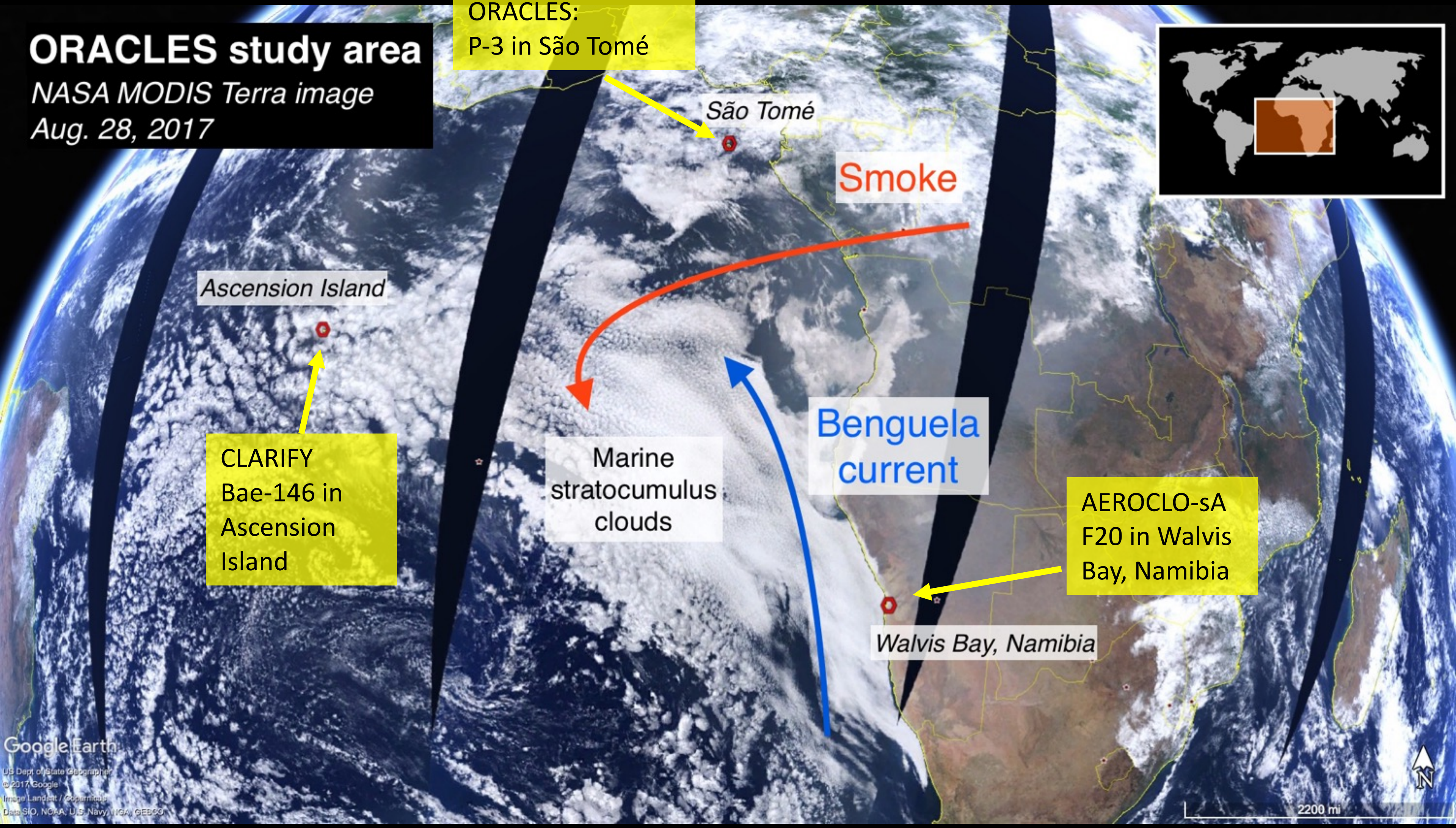

ORACLES study area
NASA MODIS Terra image
Aug. 28, 2017
São Tomé
Smoke
Ascension Island
Benguela
current
Marine
stratocumulus
clouds
Walvis Bay, Namibia
Google Earth
US Dept of State Geographer
© 2017 Google
Image Landsat / Copernicus
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
2200 mi
N

2016

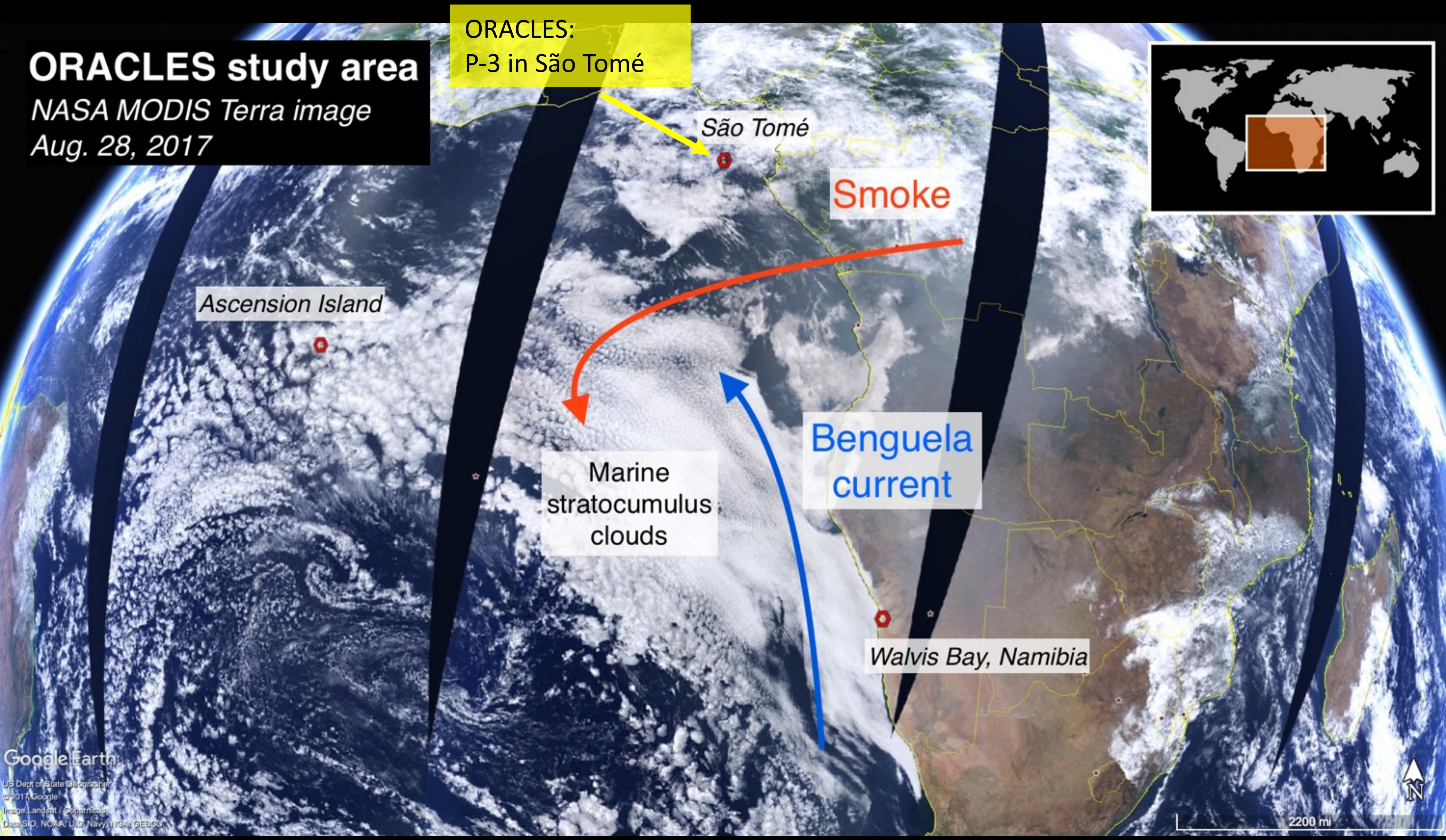


ORACLES study area
NASA MODIS Terra image
Aug. 28, 2017
São Tomé
Smoke
Ascension Island
Benguela current
Marine stratocumulus clouds
ORACLES: ER-2 + P-3, in Walvis Bay, Namibia
Walvis Bay, Namibia
Google Earth
2200 mi
N

2017


ORACLES study area
NASA MODIS Terra image
Aug. 28, 2017
ORACLES:
P-3 in São Tomé
São Tomé
Smoke
Ascension Island
CLARIFY
Bae-146 in
Ascension
Island
Marine
stratocumulus
clouds
Benguela
current
AEROCLO-sA
F20 in Walvis
Bay, Namibia
Walvis Bay, Namibia
Google Earth
2200 mi

2018



ORACLES study area
NASA MODIS Terra image
Aug. 28, 2017
ORACLES:
P-3 in São Tomé
São Tomé
Smoke
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Benguela current
Walvis Bay, Namibia
Google Earth
US Dept of State Geographer
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Image Landsat / Copernicus
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
2200 mi
N

How do polarimetric algorithms work?

Retrieval of liquid cloud droplet size distribution goes back a long way…

GEOPHYSICAL RESEARCH LETTERS, VOL. 25, NO.11, PAGES 1879-1882, JUNE 1, 1998

Cloud droplet effective radius from spaceborne polarization measurements

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Abstract. The spaceborne POLDER instrument provided the first quantitative measurements of the Earth reflectance polarization characteristics. Many POLDER images of polarized light show cloudbow type features over cloud fields for scattering angles between 150 and 170°. This unexpected observation is attributed to the polarized radiance generated by single scattering by cloud droplets. It shows that, in many cases, the cloud droplet size distribution is very narrow. The multidirectional polarized radiance measurements can be inverted for an accurate estimate of the cloud droplet radius.

(East) is the African continent, with more vegetati North (top) which is evidenced by the redish col reflectance at 0.86 µm). A few cloud fields appear areas over the land. On the left side of the figu Atlantic ocean, which is covered by a variable a clouds. This area is well known for a very high occu stratocumulus.

The bottom image corresponds to the exact same displays the perpendicular component of the radiance. In the Stokes vector representation of (I,Q,U,V), it is the second component of the vector (the reference direction is the plane of scattering (defined by the solar and viewing directions). The white band which

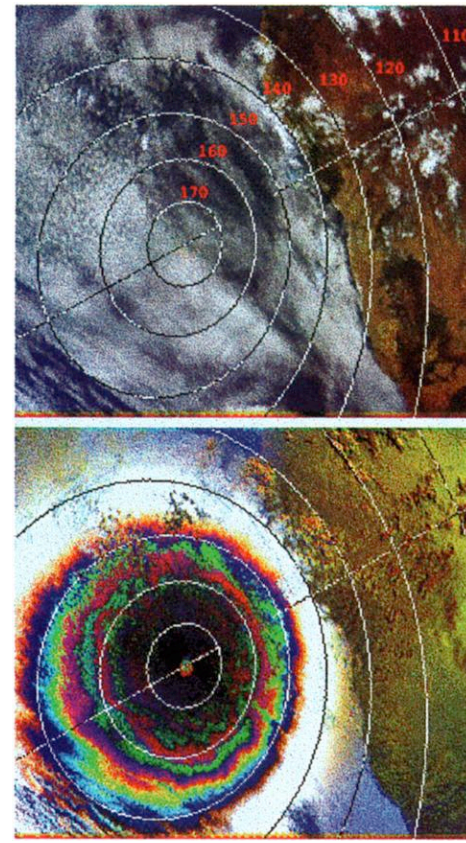
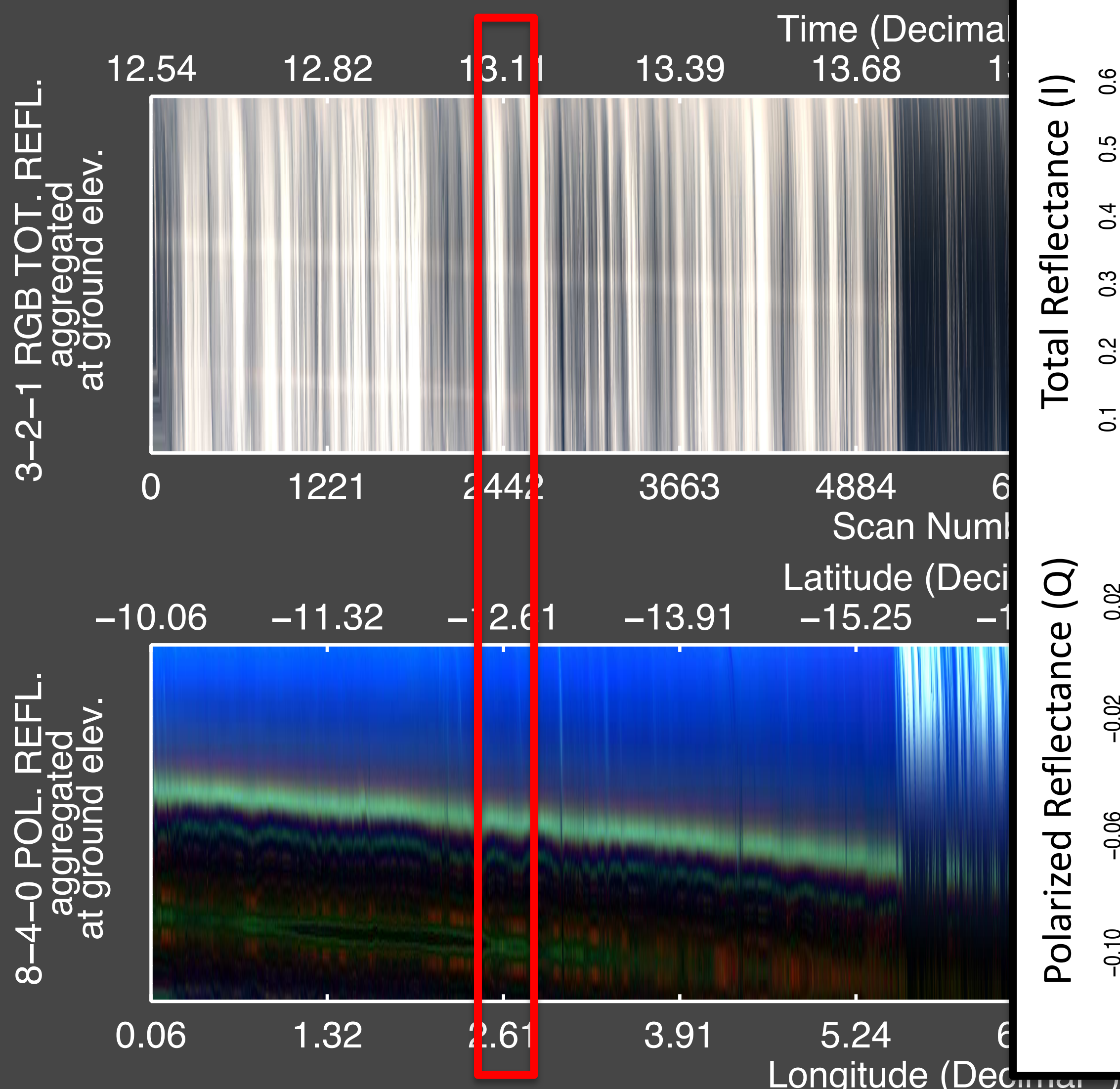


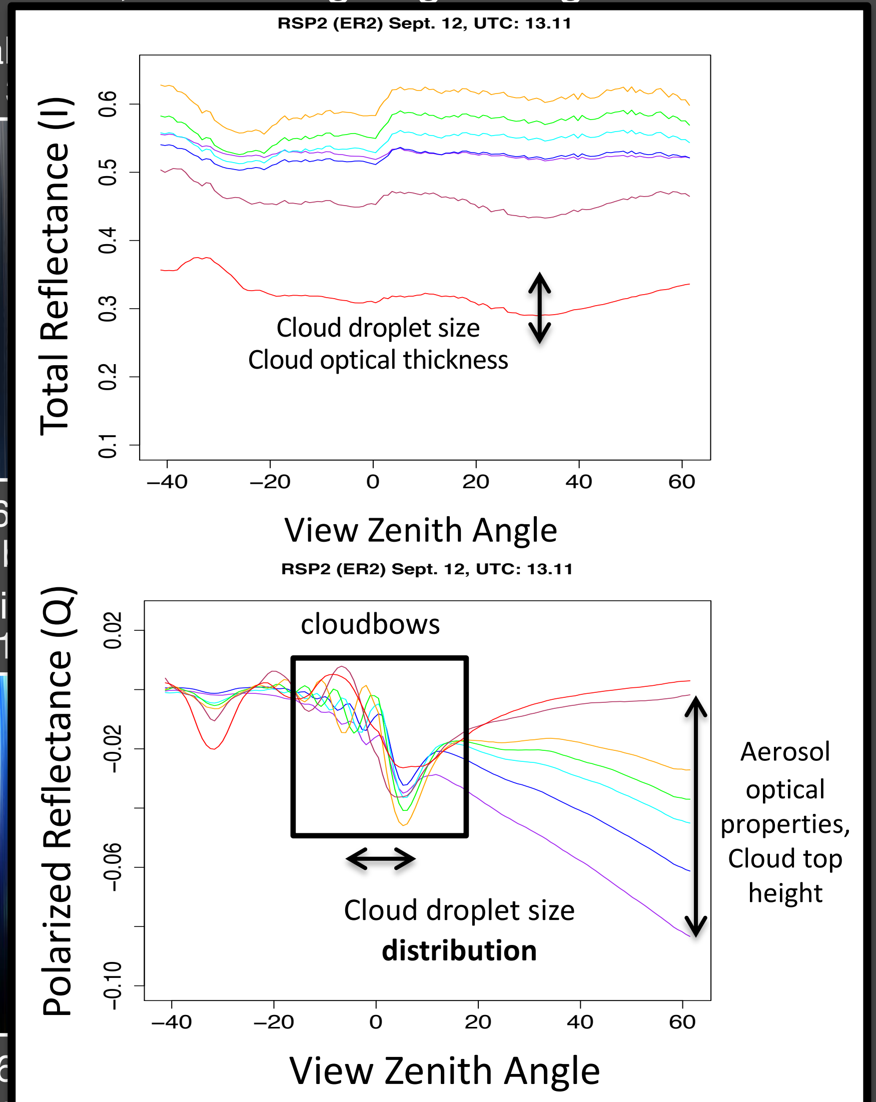
Figure 1. Three color composite (Blue : 0.43 µm, Green : 0.67 µm, Red : 0.86 µm) of POLDER measurements acquired by the CCD matrix over the Atlantic ocean and Southern Africa on Nov. 3rd, 1996. The top figure is for the total reflectance, whereas the bottom figure represents the polarized reflectance. The curved lines indicate the scattering angle in 10° increments (smaller radius line is for 170°). The straight line is the principal plane. For each spectral band, the scale is from 0 to 0.8 in reflectance, and from 0.08 in polarized reflectance.

How do polarimetric algorithms work: RSP

2016/09/12, 10989 scans: 12:32:15 to 15:06:21 UTC

Average Rel. Azimuth in central 60% of scans: –16°; Scattering angle range: 51°–178°





Aerosol above cloud (polarimetric) remote sensing ORACLES (only) results

- **AirMSPI, 2016 ER-2:**
  - Xu, F., van Harten, G., Diner, D.J., Davis, A.B., Seidel, F.C., Rheingans, B., Tosca, M., Alexandrov, M.D., Cairns, B., Ferrare, R.A. and Burton, S.P., 2018. Coupled Retrieval of Liquid Water Cloud and Above-Cloud Aerosol Properties Using the Airborne Multiangle SpectroPolarimetric Imager (AirMSPI). *Journal of Geophysical Research: Atmospheres*, *123*(6), pp.3175-3204.

  ORACLES specific algorithm

- **RSP, 2016 ER-2, 2017-8 P-3**
  - Stamnes, S., C. Hostetler, R. Ferrare, S. Burton, X. Liu, J. Hair, Y. Hu, A. Wasilewski, W. Martin, B. van Diedenhoven, J. Chowdhary, I. Cetinic, L. Berg, K. Stamnes, and B. Cairns, 2018: Simultaneous polarimeter retrievals of microphysical aerosol and ocean color parameters from the "MAPP" algorithm with comparison to high spectral resolution lidar aerosol and ocean products. *Appl. Opt.*, 57, no. 10, 2394-2413, doi:10.1364/AO.57.002394.

    Aerosol above ocean retrieval technique, data not yet archived

  - Pistone, K., Redemann, J., Doherty, S., Zuidema, P., Burton, S., Cairns, B., Cochrane, S., Ferrare, R., Flynn, C., Freitag, S., Howell, S., Kacenelenbogen, M., LeBlanc, S., Liu, X., Schmidt, K. S., Sedlacek III, A. J., Segal-Rosenhaimer, M., Shinozuka, Y., Stamnes, S., van Diedenhoven, B., Van Harten, G., and Xu, F.: Intercomparison of biomass burning aerosol optical properties from in-situ and remote-sensing instruments in ORACLES-2016, Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2019-142, in review, 2019.

    Results of MAPP in this paper

  - Segal-Rozenhaimer, M., D. J. Miller, K. Knobelspiesse, J. Redemann, B. Cairns, and M. D. Alexandrov. 2018. "Development of neural network retrievals of liquid cloud properties from multi-angle polarimetric observations." *Journal of Quantitative Spectroscopy and Radiative Transfer*, 220: 39-51 [10.1016/j.jqsrt.2018.08.030]

    Our cloud only NN

  - Miller, D. J., Segal-Rozenhaimer, M., Knobelspiesse, K., Redemann, J., Cairns, B., Alexandrov, M., van Diedenhoven, B., and Wasilewski, A.: Low-level liquid cloud properties during ORACLES retrieved using airborne polarimetric measurements and a neural network algorithm, Atmos. Meas. Tech. Discuss., https://doi.org/10.5194/amt-2019-327, in review, 2019.

    V2 of our cloud only NN

Full aerosol above cloud algorithm in training…

(Multi-angle) Polarimetry is especially useful for ORACLES (4 reasons)

1. Cloud properties are usually estimated using reflectance ratios to give cloud optical depth (COD) and effective radius… but are confounded by aerosols above cloud. “bi-spectral” or “Nakajima-King”

2. Explicit retrievals of aerosols above clouds usually must assume aerosol absorption (e.g. Jethva et al., 2013, Meyer et al., 2015; Sayer et al., 2016).

3. Polarimetric remote sensing of cloud bows: cloud droplet size distribution, COD easily constrained once size is known. Less affected by aerosol above cloud. Applied to POLDER by Waquet et al, 2009, 2013, Peers et al, 2016. Constrained by limits of POLDER angular sampling.

4. Applied to RSP data, which has many more view angles by Knobelspiesse et al., 2011. Constrained by existing data at the time and computational limits.

How do these algorithms work?

Bi-spectral and polarimetric retrievals are similar but not the same (see Miller et al, 2018)

What happens if we try to combine the above Bi-spectral and polarimetric retrievals, plus solve for aerosols? Can we use machine learning to lessen the computational burden?

We teach a computer to connect observations to physical parameters, based on (in our case) a synthetically generated “training set”

- Advantage: VERY fast algorithm
- Disadvantage: lack of physical relationship

Goals

- Improve other approaches – establish a starting point for optimal estimation
  - ***Di Noia, A., et al.*** *"Use of neural networks in ground-based aerosol retrievals from multi-angle spectropolarimetric observations.", 2015*
- We can learn from blind exploration of measurement/retrieval space
- Experience – machine learning may be useful for other remote sensing problems

Machine learning (ML) can mean many things…

What lessons did we learn that are useful for others who might make ML algorithms?

…hopefully transcend this
(but in truth there is a lot of this)

https://xkcd.com/1838

What does one need to do?

- Choose an approach (we used Neural Networks, more details later)
- Gather or create a training set (we use radiative transfer simulations)
- Define inputs, outputs, parameterizations, assumptions
- Coding, generate "transfer function", apply to observations
- Assessment

...repeat

Much of the literature is intended for non-scientific applications. It is also rapidly evolving. Identifying tightly constrained goals of your ML approach is key. Finding examples of similar problems is important.

We found to the following to be useful:

Di Noia, A., Hasekamp, O.P., van Harten, G., Rietjens, J.H.H., Smit, J.M., Snik, F., Henzing, J.S., de Boer, J., Keller, C.U. and Volten, H., 2015. Use of neural networks in ground-based aerosol retrievals from multi-angle spectropolarimetric observations. *Atmospheric Measurement Techniques*, *8*(1).

Di Noia, A., Hasekamp, O.P., Wu, L., Diedenhoven, B.V., Cairns, B. and Yorks, J.E., 2017. Combined neural network/Phillips–Tikhonov approach to aerosol retrievals over land from the NASA Research Scanning Polarimeter. *Atmospheric Measurement Techniques*, *10*(11), pp.4235-4252.

Di Noia, A. and Hasekamp, O.P., 2018. Neural Networks and Support Vector Machines and Their Application to Aerosol and Cloud Remote Sensing: A Review. In *Springer Series in Light Scattering* (pp. 279-329). Springer, Cham. Available here: https://link.springer.com/chapter/10.1007/978-3-319-70796-9_4

NN version 1: cloud only test

Journal of Quantitative Spectroscopy & Radiative Transfer 220 (2018) 39–51

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journal homepage: www.elsevier.com/locate/jqsrt

Development of neural network retrievals of liquid cloud properties from multi-angle polarimetric observations

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ABSTRACT

We present a neural network (NN) based algorithm for the retrieval of liquid low-level marine stratocumulus cloud microphysical property parameters (cloud optical depth, cloud droplet size effective radius and variance) from airborne multi-angle polarimetric measurements. We establish our retrieval method for the Research Scanning Polarimeter (RSP) airborne instrument, which measures both polarized and total reflectance in the spectral range of 410–2260 nm, scanning along the flight track at ~150 viewing zenith angles spanning the angular range between −60° and 60°. In this study, we present the development of the algorithm, including the optimization and selection of input parameters and the network architecture. We perform a sensitivity study to test the effect of random and correlated instrument noise on the retrieval performance, and to assess which of the measured radiometric quantities (i.e., total reflectance, polarized reflectance, degree of linear polarization and combinations thereof) are best suited for marine stratocumulus liquid cloud property retrievals using simulated RSP data. Finally, we show the application of this method to airborne observations from the ObseRvations of Aerosols above CLouds and their intEractionS (ORACLES) 2016 field campaign, which primarily encountered low altitude marine clouds. Retrieved cloud optical depth compares favorably ($r^2 = 0.96$) to standard algorithms, but cloud droplet size effective radius less so ($r^2 = 0.45$), providing an assessment of the NN approach strengths and limitations. Specifically, the latter seemed to be affected by the cloud macro-structure and the liquid cloud droplet vertical distribution.

Segal-Rozenhaimer, M., D. J. Miller, K. Knobelspiesse, J. Redemann, B. Cairns, and M. D. Alexandrov. 2018. "Development of neural network retrievals of liquid cloud properties from multi-angle polarimetric observations." *Journal of Quantitative Spectroscopy and Radiative Transfer*, 220: 39-51 [10.1016/j.jqsrt.2018.08.030]

Feed forward back propagation multi-layer perceptron (MLP) NN

Trained on:

- Cloud optical thickness
- Cloud droplet effective radius
- Cloud droplet effective variance
- Solar zenith angle
- Relative azimuth angle (limited range of cloud/aircraft distances)

What should be the inputs? And how to manage measurement uncertainty and large input vectors?

Archived for 2016, ER-2 and 2017 P-3 here:
https://data.giss.nasa.gov/pub/rsp/ORACLES_2016/NeuralNetworkCloud/
https://data.giss.nasa.gov/pub/rsp/ORACLES_2017/NeuralNetworkCloud/

NN version 1: cloud only test

What should be the inputs?

How to account for measurement uncertainty?

How to manage large datasets?

Tested with different combinations of inputs

Input Label	# input variables	R_{eff} RMSE	V_{eff} RMSE	COD RMSE
Ri	30	1.01	0.016	2.21
Qi	30	0.93	0.008	9.04
Rp	20	0.74	0.006	10.85
DoLP	100	0.54	0.006	1.71
Ri-Qi	60	0.78	0.010	0.45
Ri-Rp	50	0.60	0.009	0.97
Ri-DoLP	130	0.37	0.006	1.16
Qi-Rp	50	0.80	0.005	6.88
Qi-DoLP	130	0.35	0.004	0.81
Rp-DoLP	120	0.45	0.004	1.18

There are different ways to represent polarimetric data. Some (unexpected) combinations offered surprisingly good results.

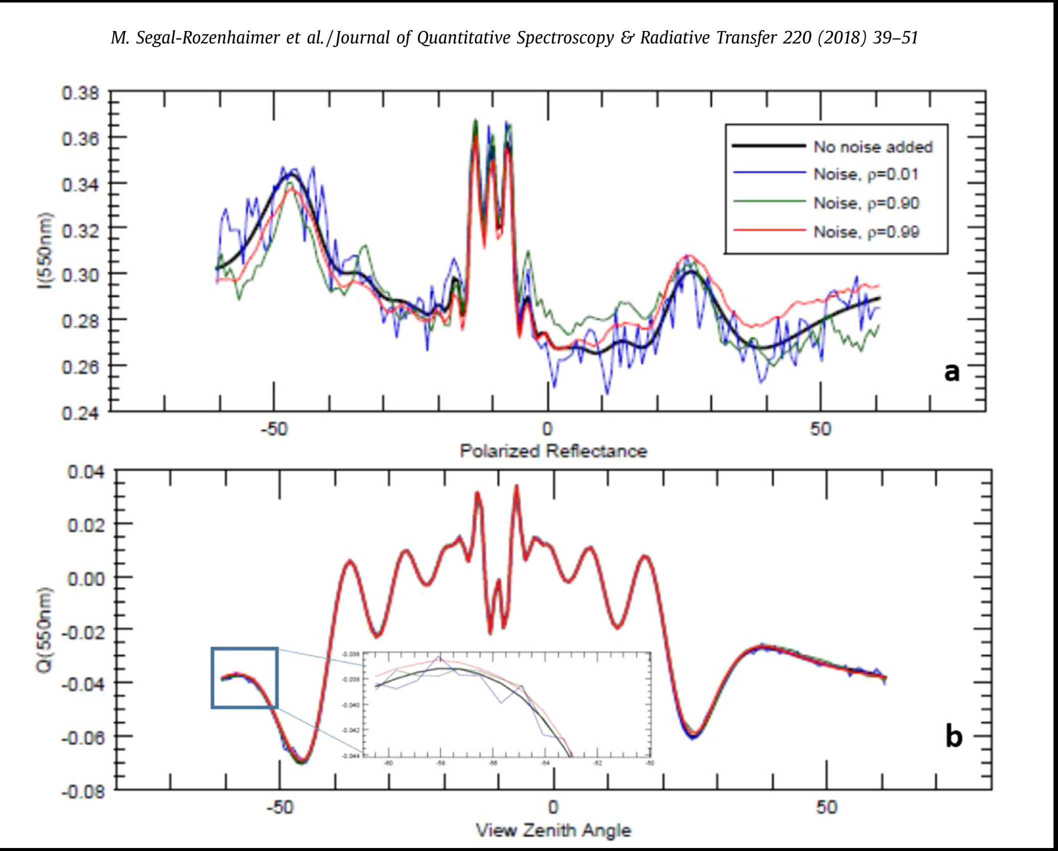
Lesson: If you have the means to test your results, don't be too prescriptive on inputs

NN version 1: cloud only test

What should be the inputs?

How to account for measurement uncertainty?

How to manage large datasets?



We added ‘random errors’ to our training set, copied and repeated many times

Consequence: training set size grew by 100x

Lesson: if training with synthetic data, consider how to represent measurement errors. V2 dealt with this in a better way.

NN version 1: cloud only test

What should be the inputs?

How to account for measurement uncertainty?

How to manage large datasets?

Input:

[7 waveln x 125 view angles x 2]
+ Geometry

↓

60 to 130 principal components
+ Geometry

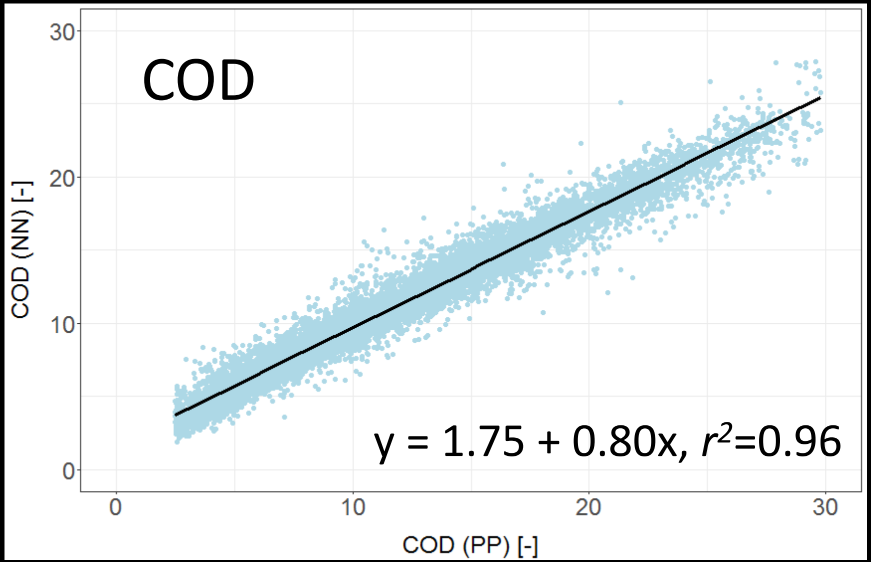
inputs reduced with principal components

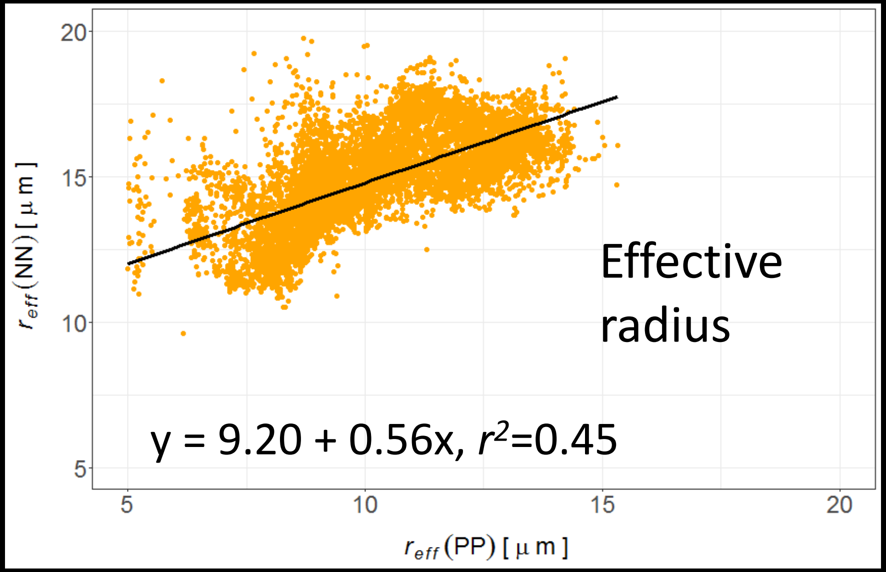
Consequence: are we missing phenomena? How best to manage?

Lesson: we started with custom built routines. V2 uses TensorFlow. Utilize (rapidly advancing) publicly available software.

NN version 1: cloud only test

We validated our NN with field observations from ORACLES 2016 ER-2 observations that use the standard RSP algorithms: Parametric (PP-polarimetric based), Nakajima-King (NK-total reflectance based), and Rainbow Fourier Transform (RFT), (Alexandrov et al., 2012,2015)





It works!

COD better than effective radius. No effective variance sensitivity.

Lesson: start small (cloud only) if one has external comparison data

NN version 2: cloud only

Still work only with clouds, but a number of improvements:

- More extensive, realistic training set
- "standardize" by measurement uncertainty – far smaller training set needed
- Utilize TensorFlow (open source) NN Python routines
- Tested different "activation functions"

https://doi.org/10.5194/amt-2019-327
Preprint. Discussion started: 16 September 2019

Atmospheric Measurement Techniques Discussions
Open Access
EGU

Low-level liquid cloud properties during ORACLES retrieved using airborne polarimetric measurements and a neural network algorithm

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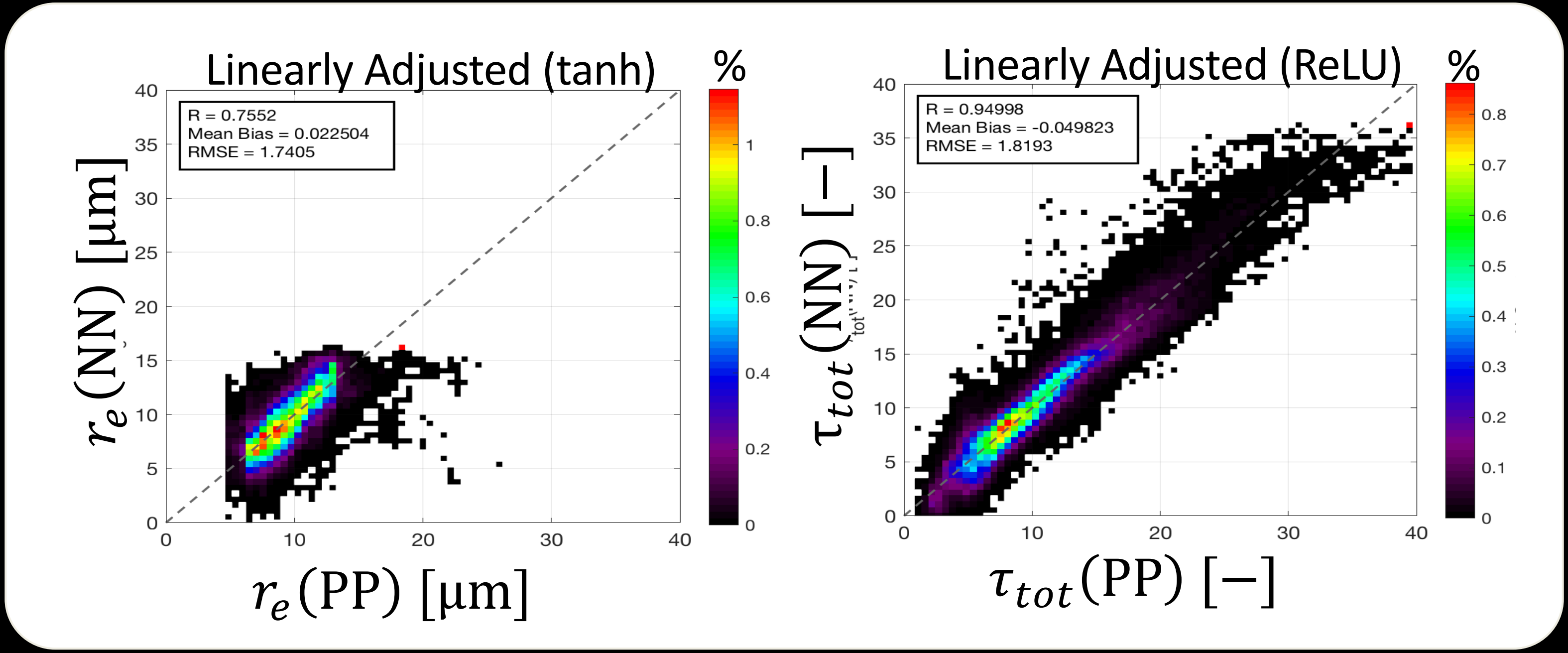
tensorflow.org

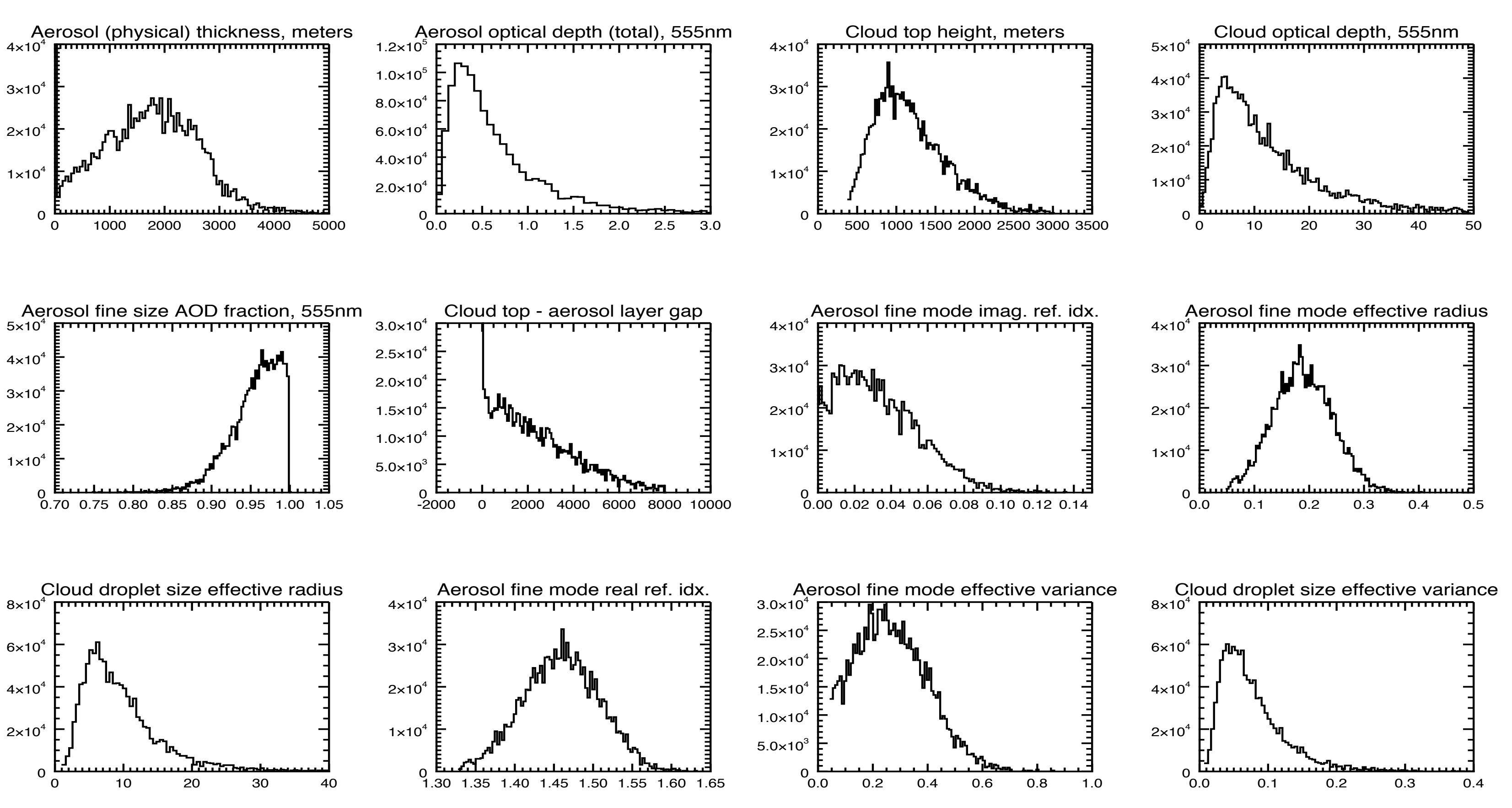
Miller, D. J., Segal-Rozenhaimer, M., Knobelspiesse, K., Redemann, J., Cairns, B., Alexandrov, M., van Diedenhoven, B., and Wasilewski, A.: Low-level liquid cloud properties during ORACLES retrieved using airborne polarimetric measurements and a neural network algorithm, Atmos. Meas. Tech. Discuss., https://doi.org/10.5194/amt-2019-327, in review, 2019.

NN version 2: cloud only

- Agrees with standard algorithms (polarimetric and bispectral) as well as they agree with each other
- Uses different NN for each product, aircraft
- (correctable) bias appears to be due gases not in training set
- Behaves more like polarimetric retrieval when clouds are homogeneous, like bi-spectral when clouds are broken
- Full, gas corrected dataset to be posted soon to data.giss.nasa.gov/pub/rsp/



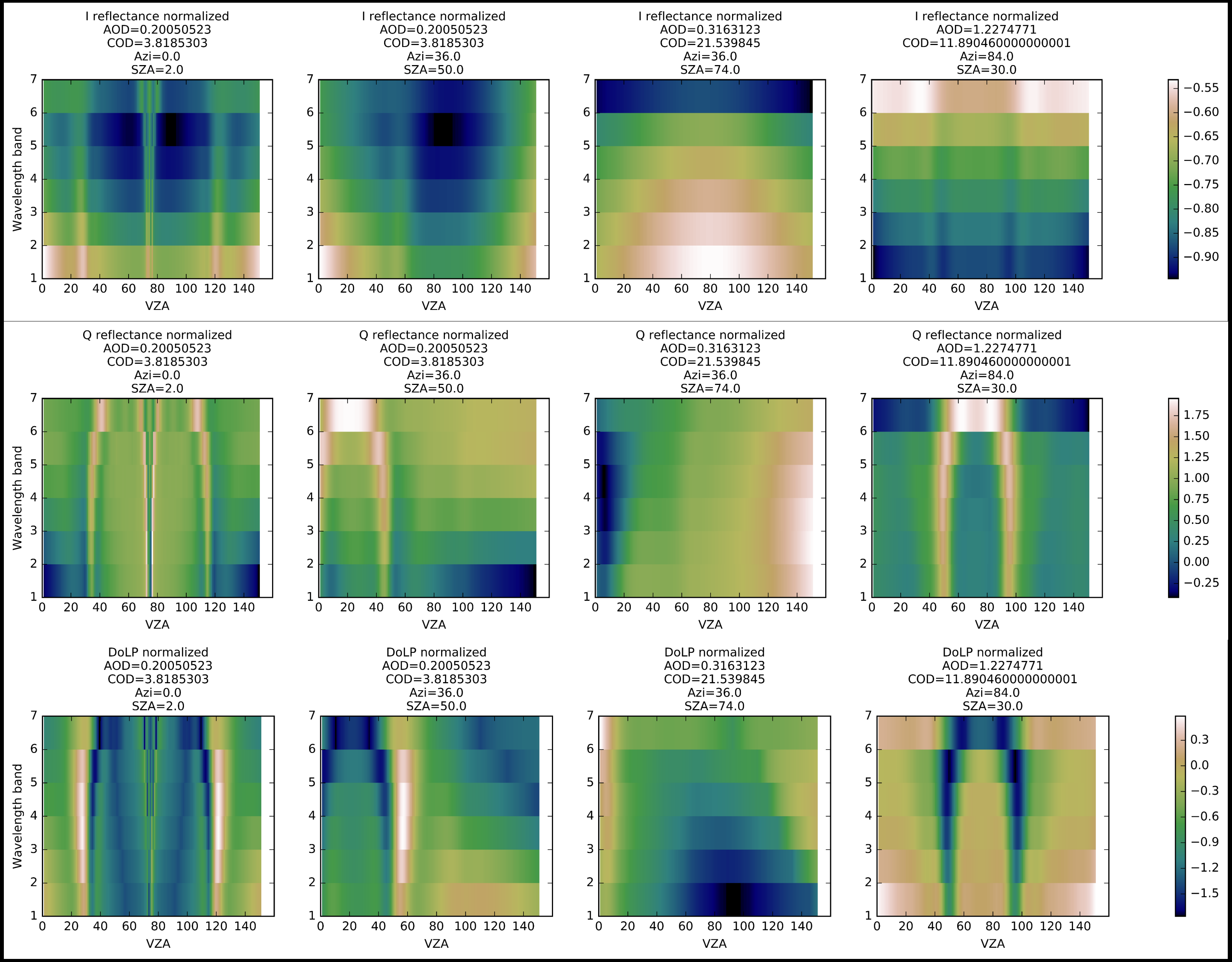
NN version 3: aerosol above cloud



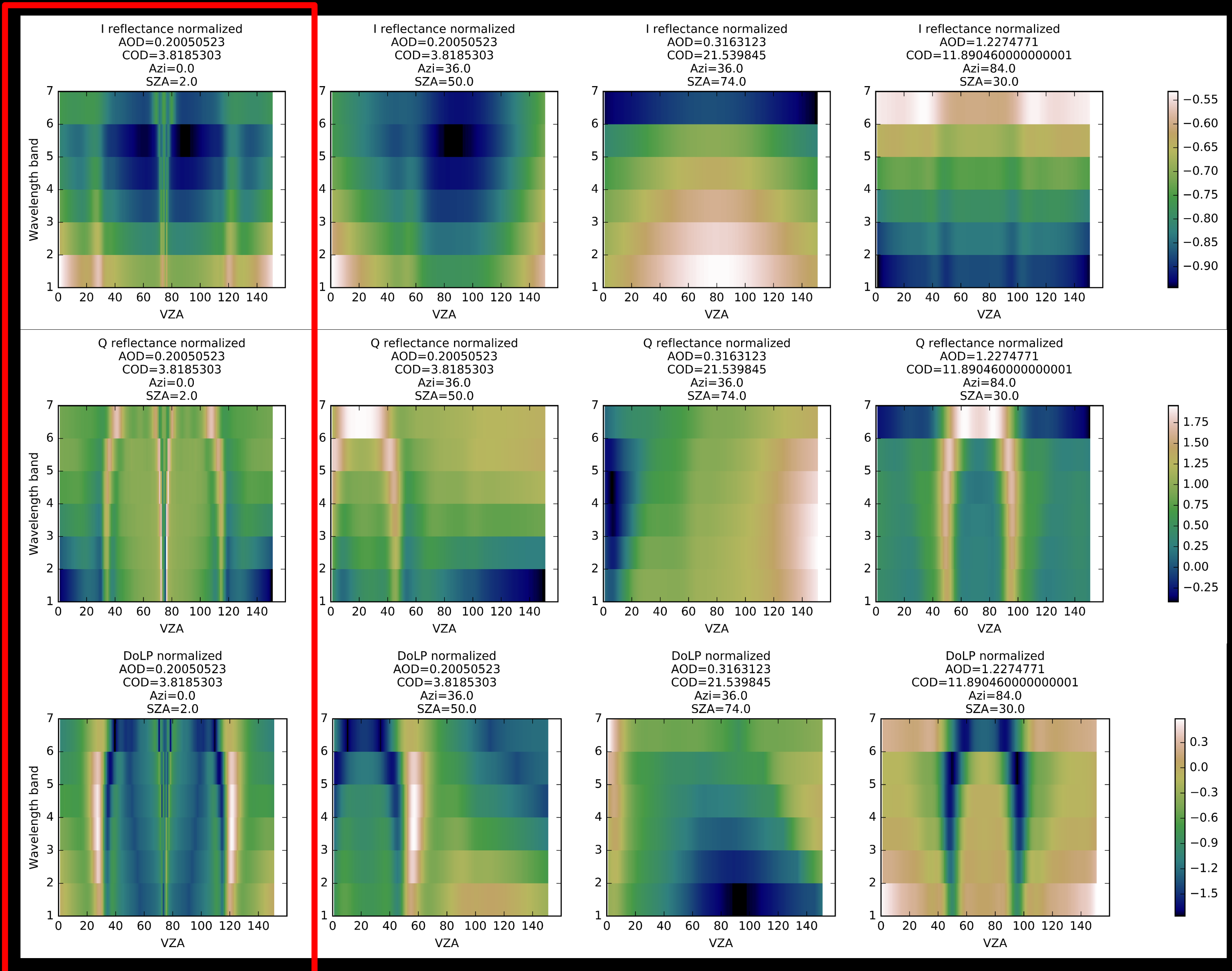
Two major changes

- Training set uses randomly distributed parameters within a defined distribution, not a fixed grid. ~10,000 cases, 15gb
- Convolutional Neural Networks: treat data as 'image'

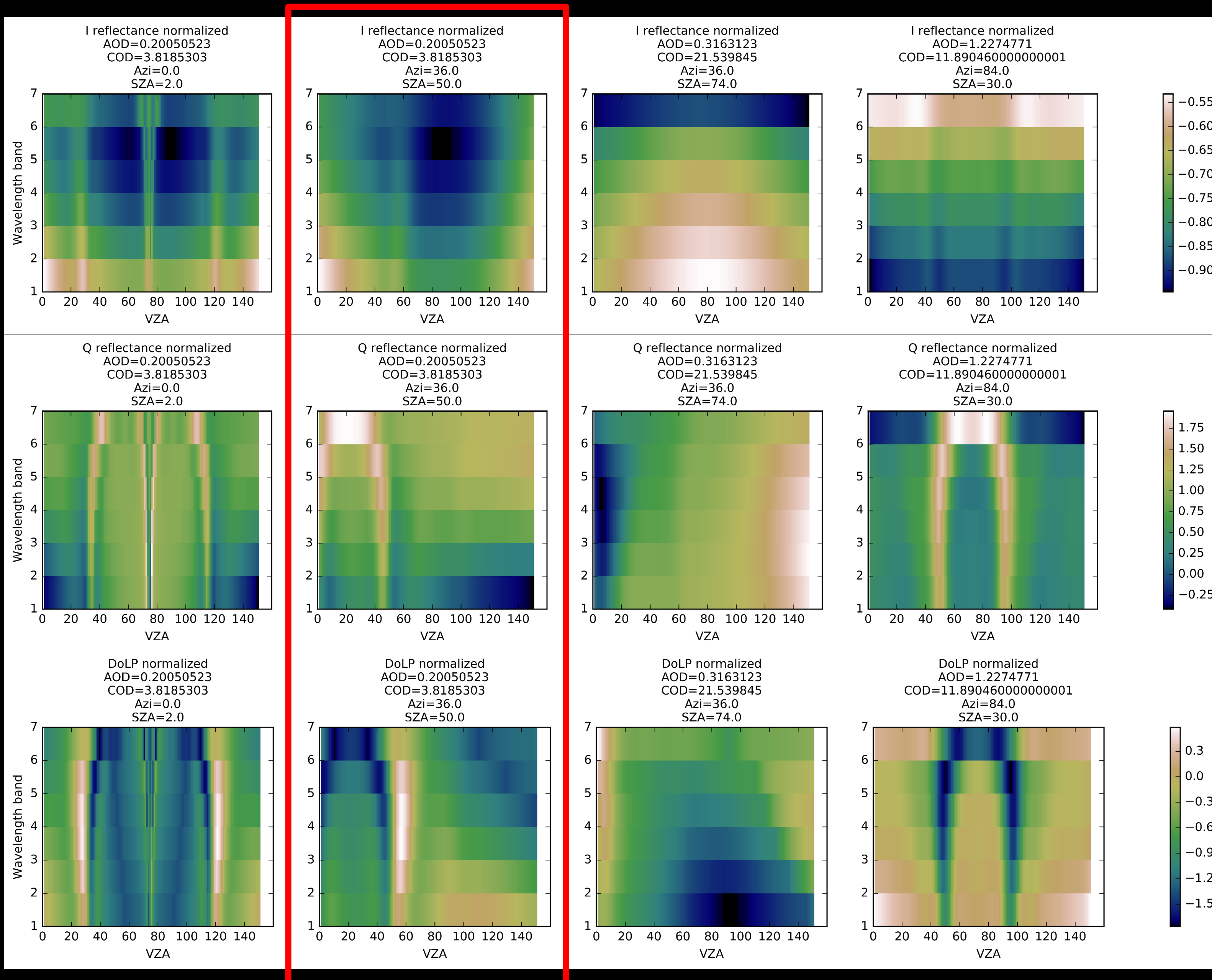
Some examples of I, Q and DoLP from the training LUT:



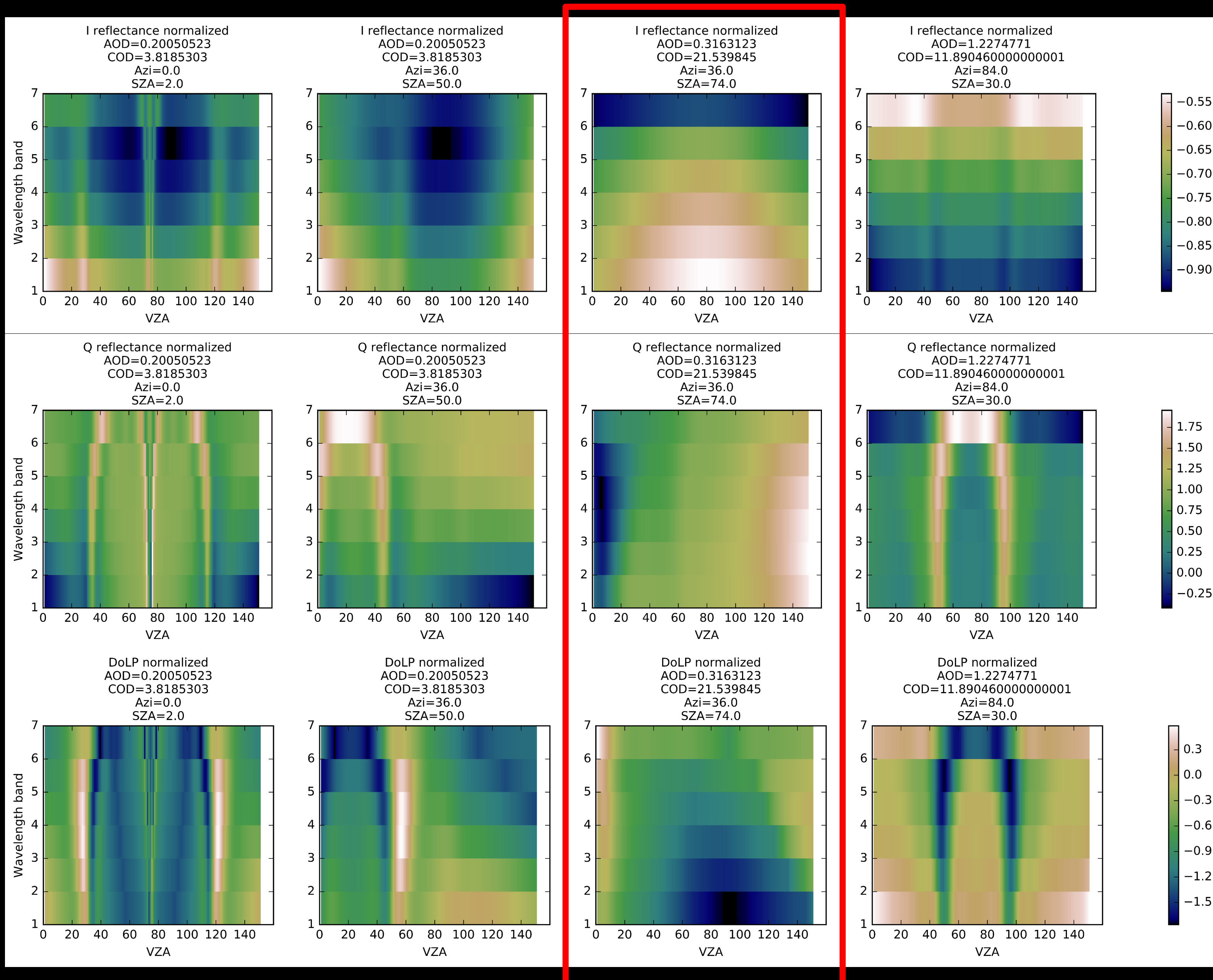
Some examples of I, Q and DoLP from the training LUT:



Some examples of I, Q and DoLP from the training LUT:



Some examples of I, Q and DoLP from the training LUT:



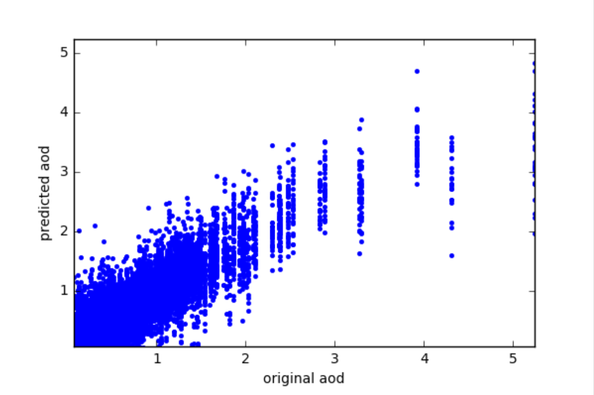
V3 status

Convolutional Neural Networks use kernels similar to those in image processing to represent the spatial relationships in inputs

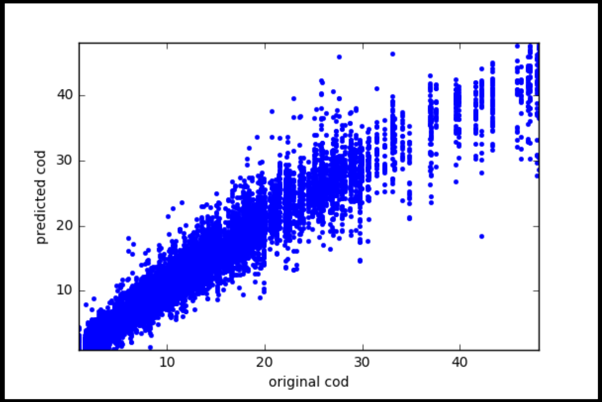
We are currently in 'hyperparamer' testing stage, examining best kernels

Training set much larger now, we may need to use supercomputing facilities. Note that once NN is trained, application is fast.

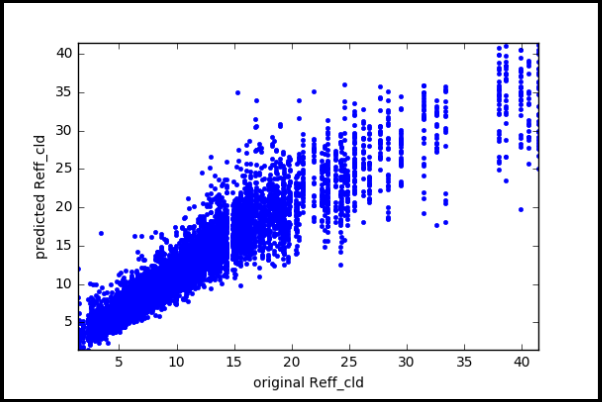
AOD



COD



R_{eff}



Conclusions

- We successfully created two generations of NN's for multi-angle polarimetry
- Clouds only at first because that can be validated. Now creating aerosol above cloud NN with what we have learned.

Some lessons

- Be prepared to iterate, and update your methods as you learn (and as new techniques become available)
- Don't be overly prescriptive
- Start small with something you can validate, then build