

# A Correlation-Based Inversion Approach for Aerosol Remote Sensing

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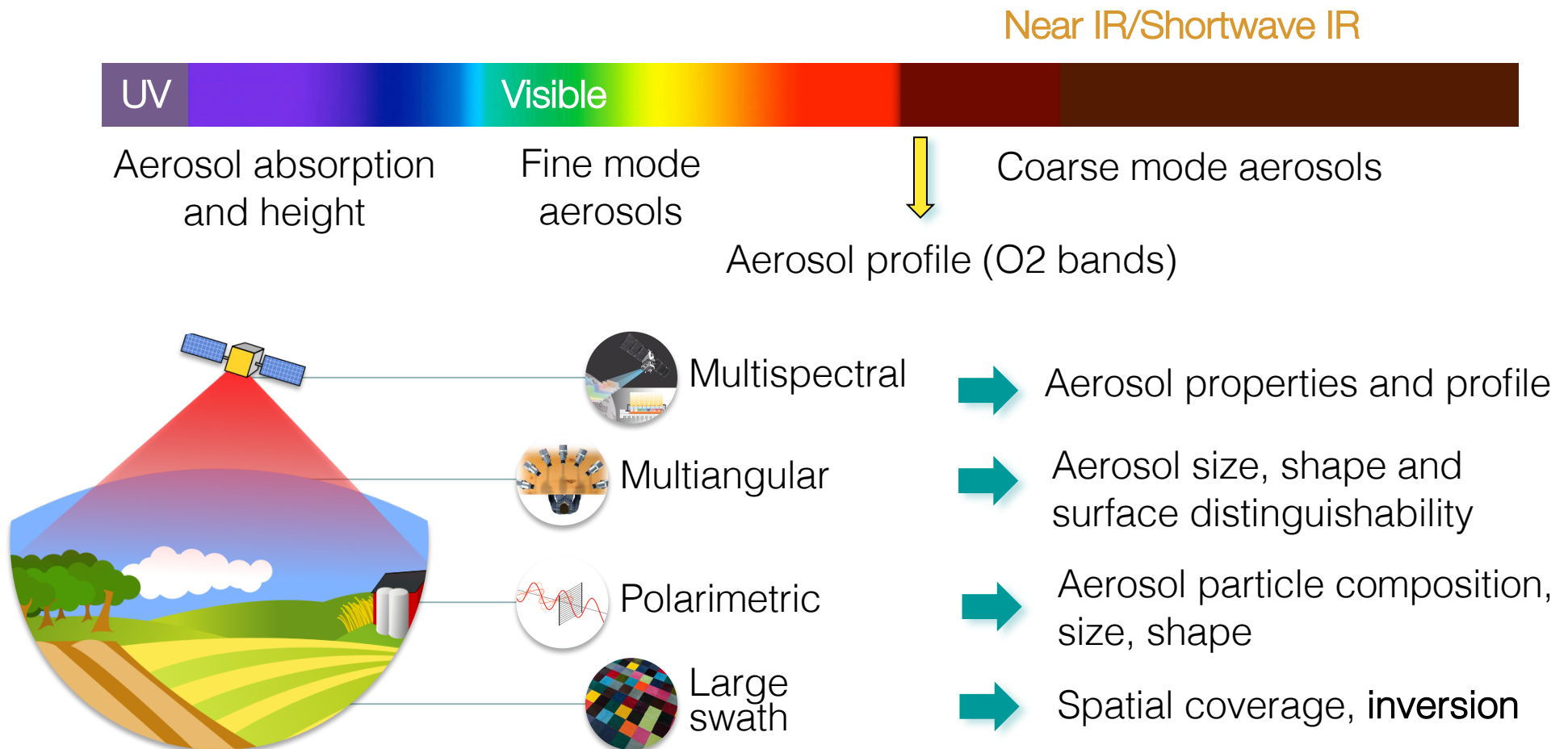
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# Multi-angle polarimetry for remote sensing

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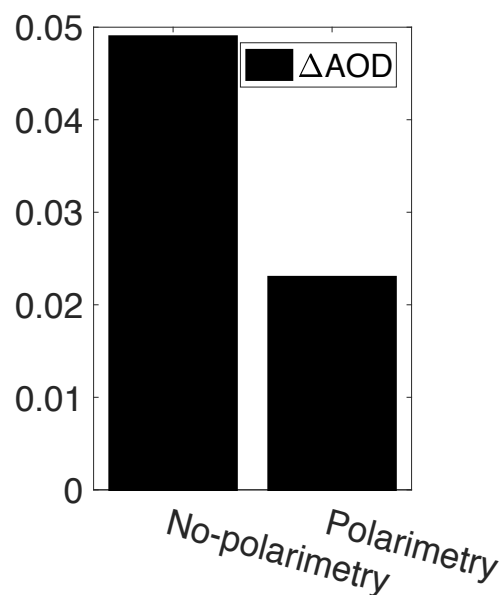
Space-borne multi-angle spectro-polarimetric measurements (POLDER, 3MI, MAIA, SPEXone, HARP2, DPC, etc.) provide multi-dimensional constraints to anchor aerosol distributions and their optical and microphysical properties.



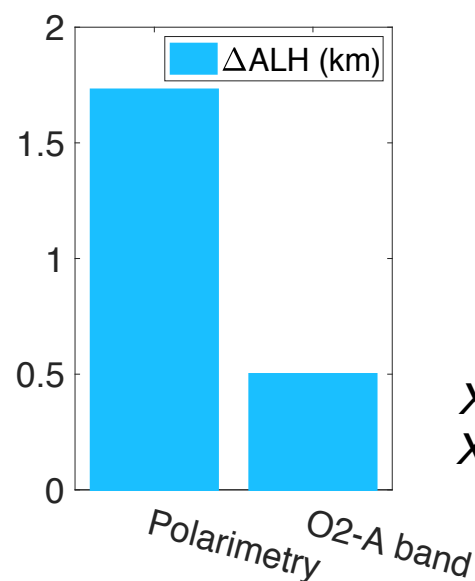
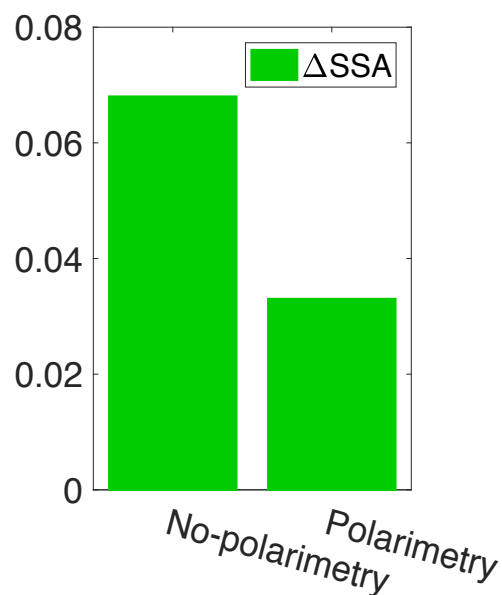
# Multiangle polarimetry: benefits

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Multi-angle polarimetry and hyperspectral measurements strongly constrain the retrieval of aerosol abundance, absorption and height.



AirMSPI retrieval test



1 nm bandwidth in O2-A band (EPIC)

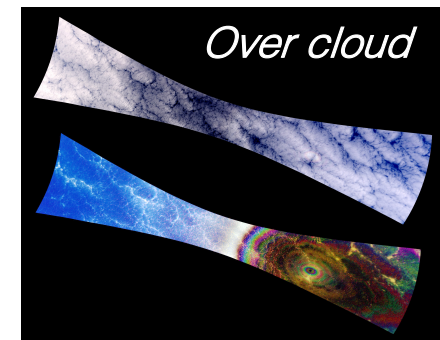
*Xu F. et al. 2017*  
*Xu R. et al. 2017*

*Also informed by community efforts on retrieving observations from POLDER, SPEX airborne, AirHARP, RSP, etc which integrate subsets of multi-angle, polarimetry, multi-spectral measurements*

# Algorithm challenges and opportunities

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- Aerosol remote sensing is subjected to ill-posedness
  - *Solution is non-unique due to insufficient information in observations*
  - *High dimensionality of parameter space causes inversion instability and large computational burden*
- We utilize aerosol spatial and temporal correlations and developed
  - *a correlation-based inversion (CBI) approach that optimizes over a reduced parameter space (Xu et al. 2019)*
  - *a fast multi-pixel radiative transfer (RT) modeling approach*

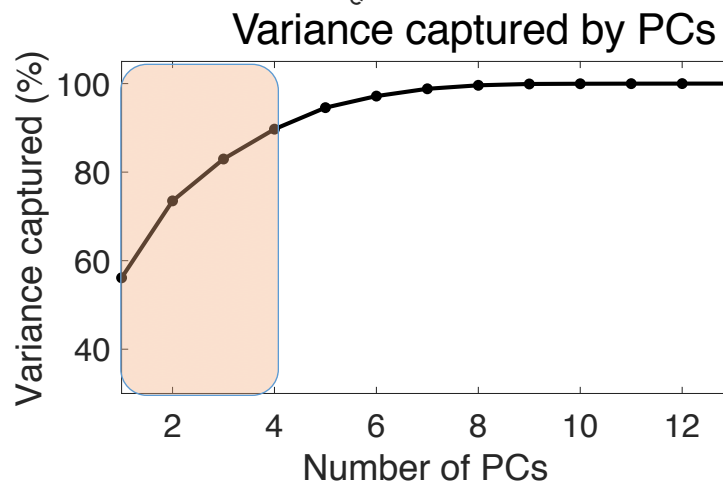
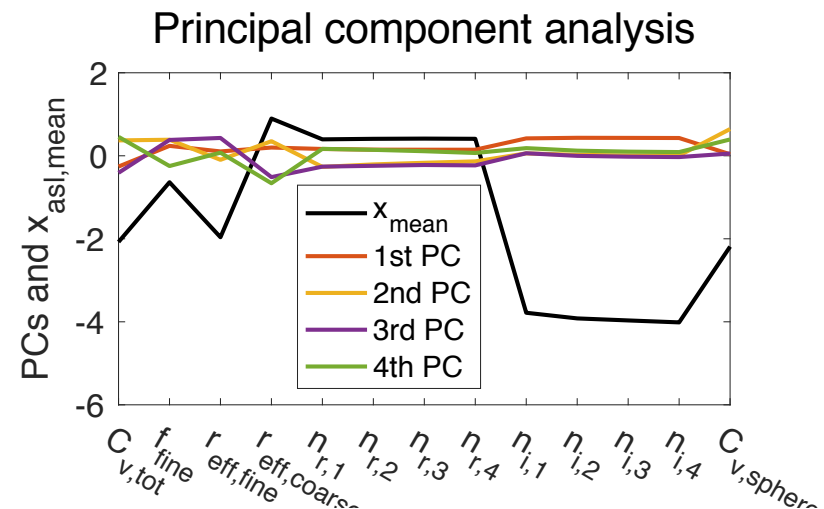
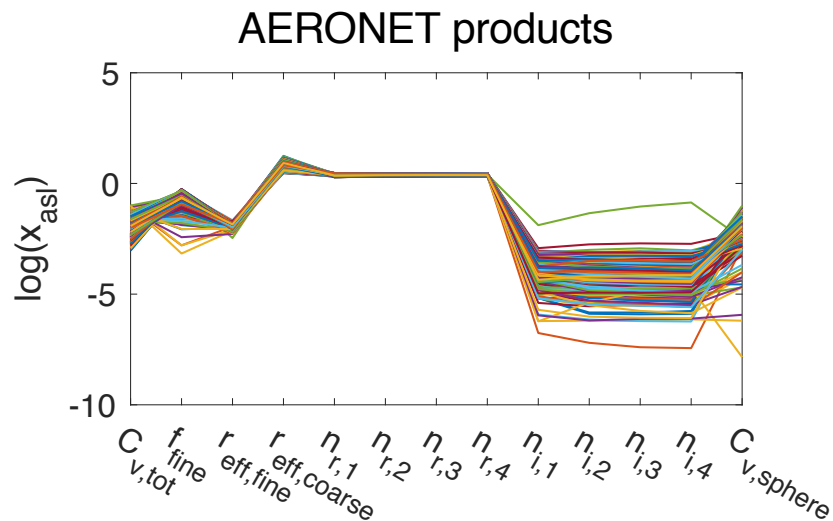


*Three types of lower boundaries considered in correlation-based aerosol retrievals*

# Spatio-temporal correlation in aerosol properties

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Aerosols in a 2000 km domain around AERONET **Namibe** site, Angola



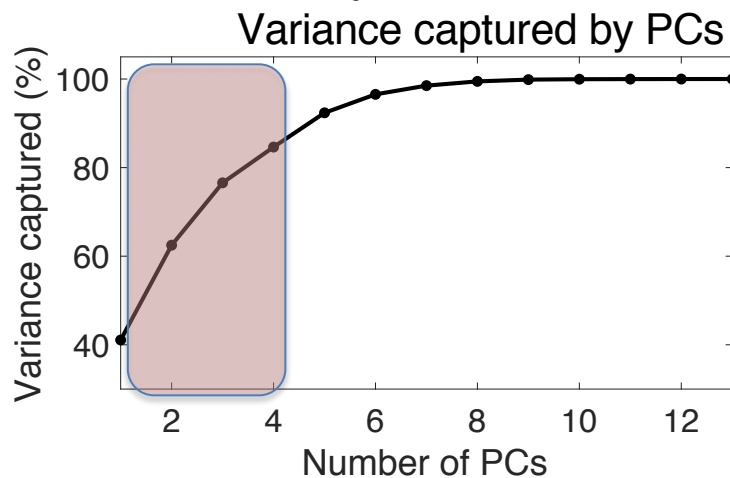
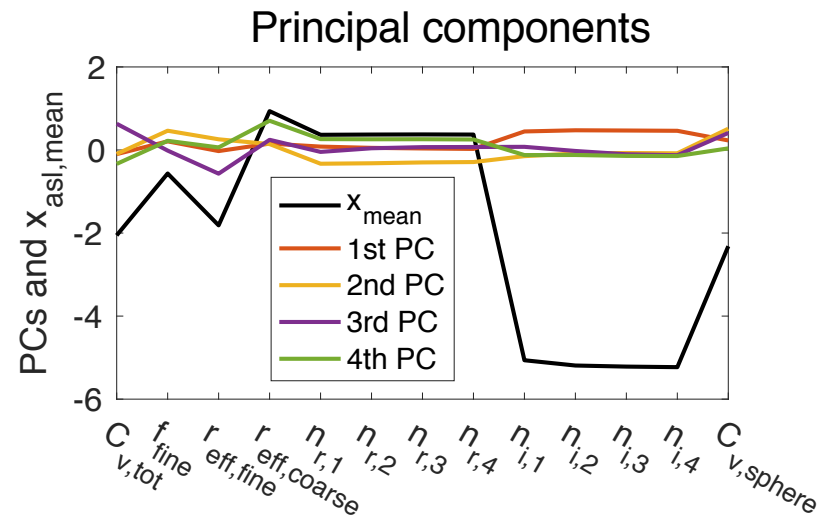
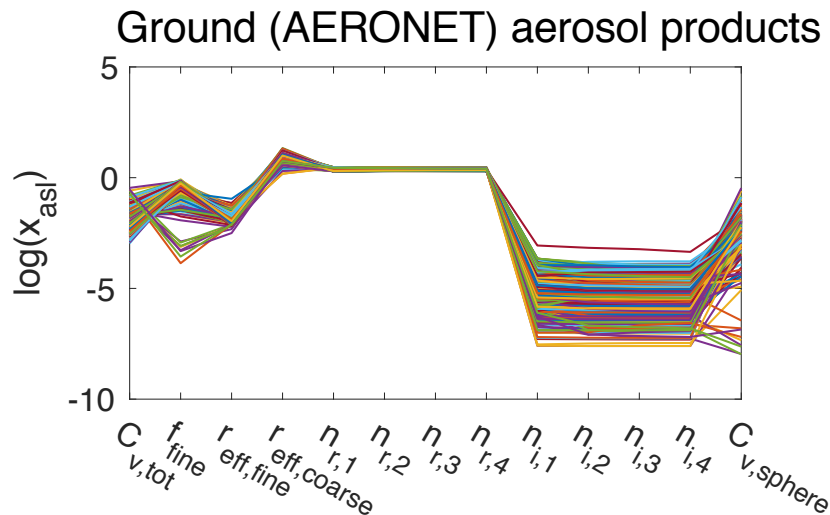
Observation: aerosol parameters are highly correlated in nature but a few principal components (PCs) capture >85% temporal and spatial variance of aerosol properties.



# Correlations in aerosol properties

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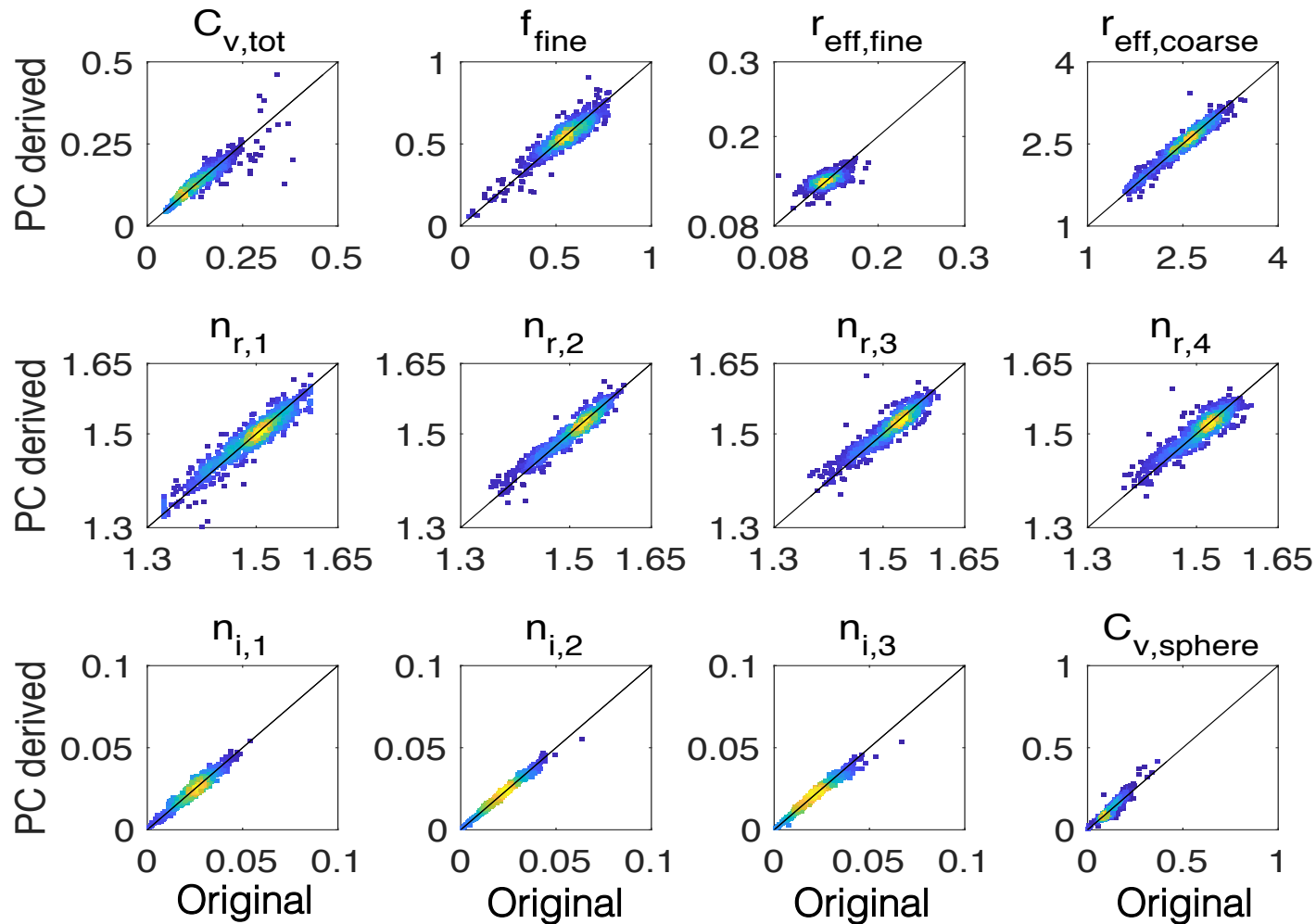
2000 km domain around AERONET **Fresno** site, California



Aerosol parameters are highly correlated in nature but a few principal components (PCs) capture ~85-90% temporal and spatial variance of aerosol properties.

# Reconstructed fields from dominating PCs

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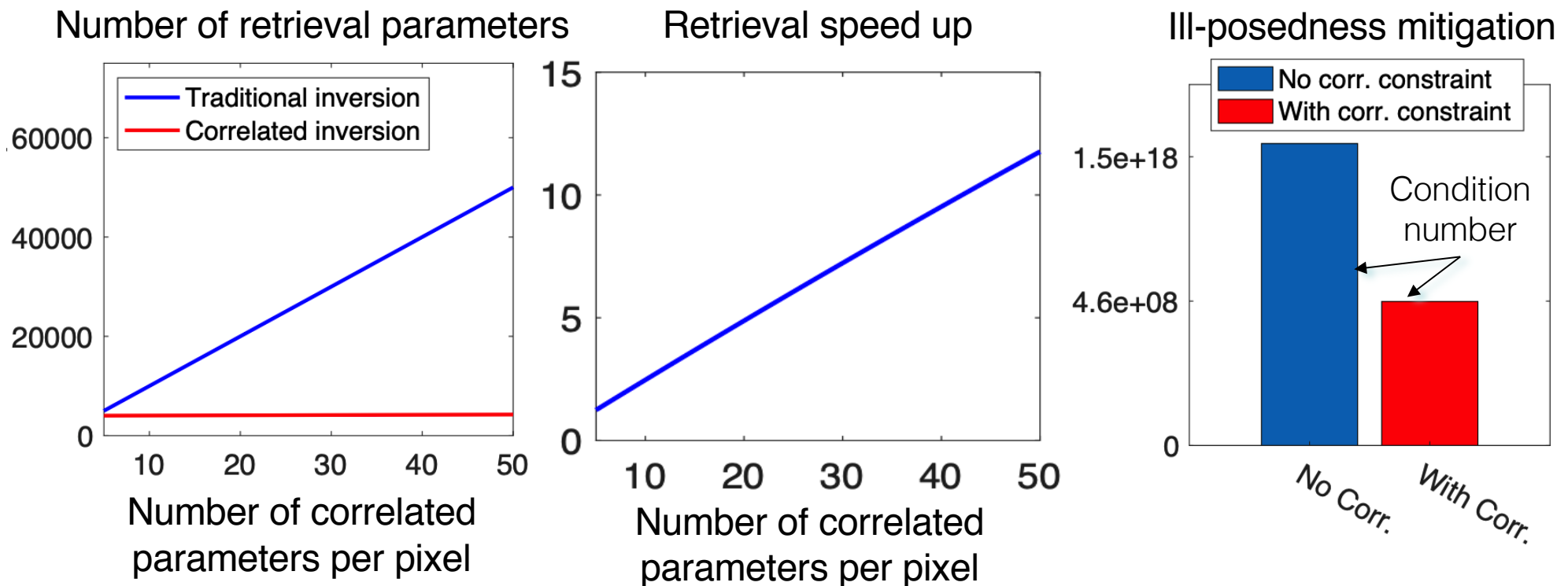
Reconstruction formula:  $x(i) = \bar{x}(i) + \sum_{n=1}^{N_{PC}} x_n(i)$  for  $i^{\text{th}}$  correlated aerosol property

# Benefits of correlation based inversion

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**Traditional inversion:** fast parameter space increase as func. of number of pixels  
**Correlated inversion:** slow parameter space increase as func. of number of pixels

Assuming 1000 pixel retrieval





# Correlation-based inversion features

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- Reduces aerosol parameter space by retrieving principal components (PCs)
  - Total parameter space reduces by 2 magnitudes for an 1000x1000 pixel image*
- Builds in a few retrieval flexibilities, e.g.
  - *retrieve PC weights and PC vectors simultaneously*
  - *retrieve PC weights, but PC vectors fixed as informed by a priori analysis of reliable climatology*
  - *start with correlation constraints and then relax them when approaching the solution*
- Imposes multiple types of constraints to stabilize PC retrievals to ensure fast convergence to truth
  - Example: smooth aerosols spatial and spectral variations*
- Allows climatology/transport model to inform retrieval
- Incorporate a PC based fast RT model



# State vector and objective function in CMPI

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State vector:  $\mathbf{x} = [\mathbf{x}_{\text{correlated}}, \mathbf{x}_{\text{regular}}]$ , with  $\mathbf{x}_{\text{correlated}} = [\mathbf{v}_{\text{mean}}, \mathbf{w}_{\text{pixel1-M}}, \mathbf{v}_{\text{PC1-N}}]$

Cost **function** for multi-pixel  
data fit

Constraints on smooth spatial & spectral variations in  
**regular** parameter space (Dubovik et al. 2011)

$$\psi_{\text{Total}} = \left[ \sum_{i=1}^{N_{\text{pixel}}} \psi_f(\mathbf{x}_i) \right] + \gamma_1 \mathbf{x}_{\text{regular}}^T \mathbf{\Omega}_{(x,y,z)}^{\text{regular}} \mathbf{x}_{\text{regular}} + \gamma_2 \mathbf{x}_{\text{regular}}^T \mathbf{\Omega}_{\lambda}^{\text{regular}} \mathbf{x}_{\text{regular}}$$

$$+ \gamma_3 [\mathbf{w}; \mathbf{v}]^T \mathbf{\Omega}_{(x,y,z)}^{\text{correlated}} [\mathbf{w}; \mathbf{v}] + \gamma_4 [\mathbf{w}; \mathbf{v}]^T \mathbf{\Omega}_{\lambda}^{\text{correlated}} [\mathbf{w}; \mathbf{v}]$$

Constraints on  
smooth spatial &  
spectral variations  
in **correlated**  
parameter space  
(Xu et al. 2019)

$$+ \gamma_5 \mathbf{v}^T \mathbf{T}^{\text{ort}} \mathbf{v} + \gamma_6 \mathbf{w}^T \mathbf{O}^{\text{zero}} \mathbf{w} + \gamma_7 \mathbf{w}^T \mathbf{U}^{\text{unit}} \mathbf{w}$$

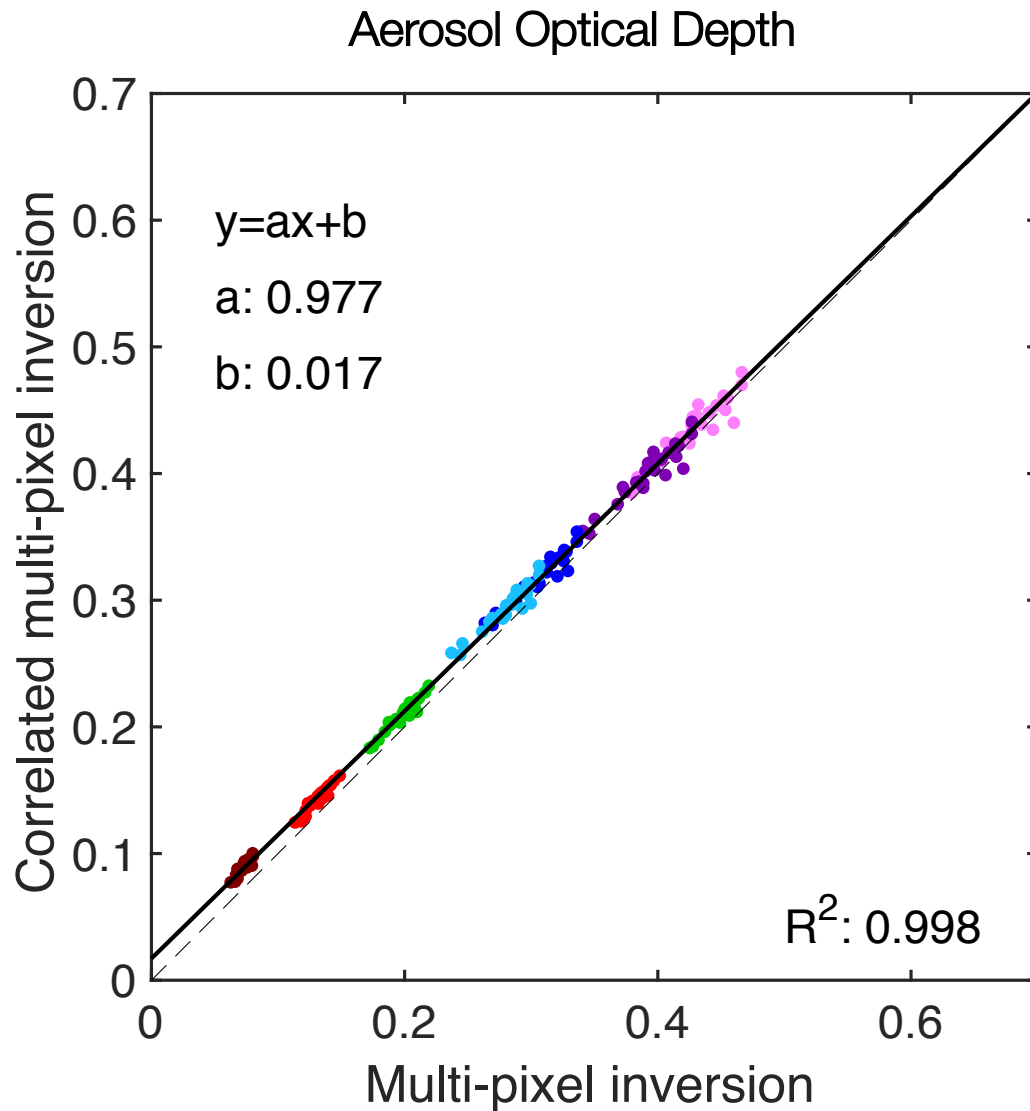
Mutual orthogonality  
constraint on PC vectors ( $\mathbf{v}$ )

Zero-sum PC weight  
constraint ( $\mathbf{w}$ )

Unity-norm PC vector  
constraint ( $\mathbf{w}$ )

# Comparison to multi-pixel inversion w/o correlation

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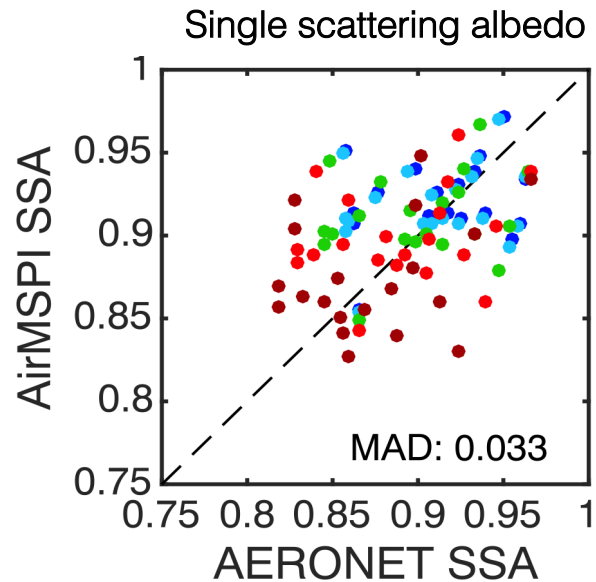
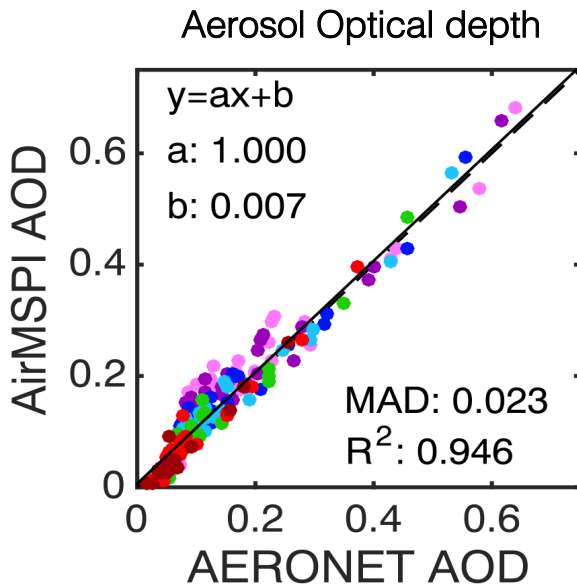
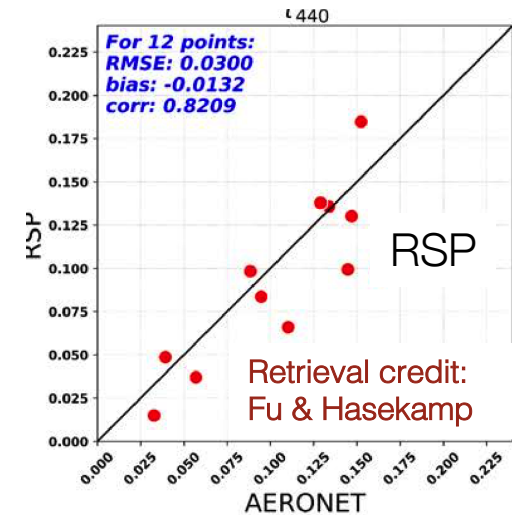
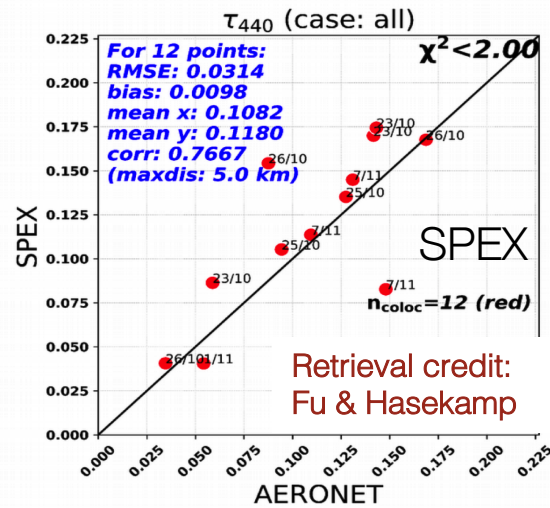
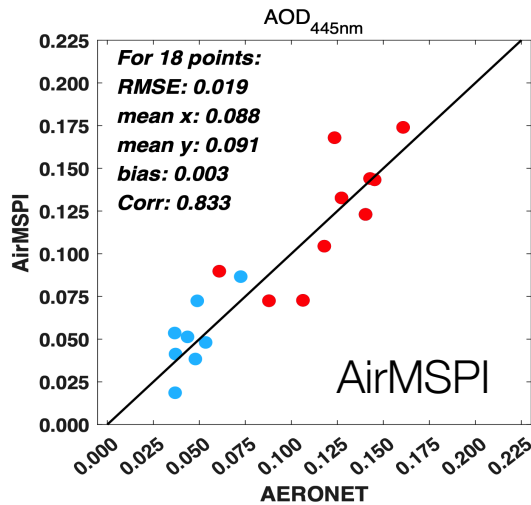


Pixel-by-pixel comparison of AODs retrieved using correlated and non-correlated multi-pixel inversion approach shows consistency

- 355 nm
- 380 nm
- 445 nm
- 470 nm
- 555 nm
- 660 nm
- 865 nm

# Retrieval practice

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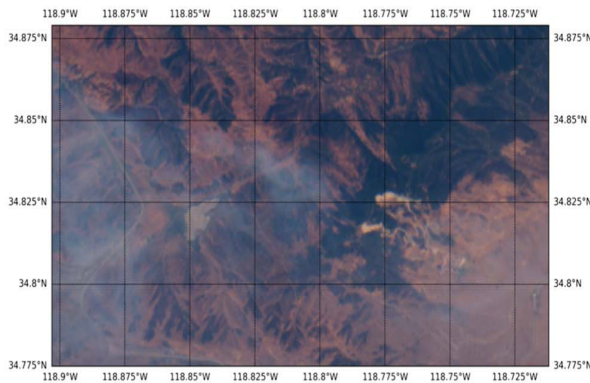
- Testing data acquired by RSP, SPEX airborne and AirMSPI instruments during NASA multiple field campaigns
- Collocated data with AERONET sites adopted for retrieval validation

# Fast multi-pixel PCA-RT model

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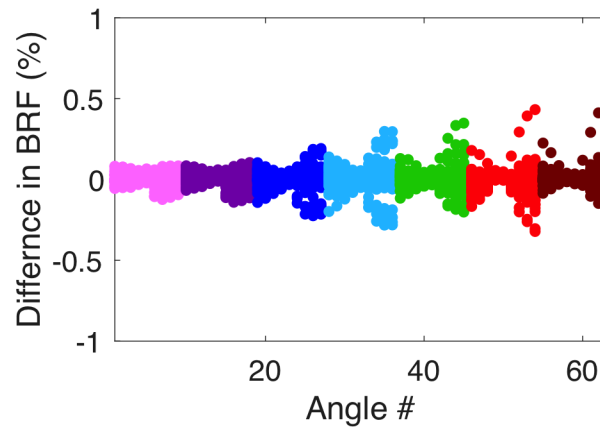
$$Y(\mathbf{x}_p) \approx Y(\bar{\mathbf{x}}) + \sum_{k=1}^{N_{\text{PC}}} \left[ \frac{Y(\bar{\mathbf{x}} + \delta \times \mathbf{v}_k) - Y(\bar{\mathbf{x}} - \delta \times \mathbf{v}_k)}{2\delta} w_{p,k} + \frac{Y(\bar{\mathbf{x}} + \delta \times \mathbf{v}_k) - 2Y(\bar{\mathbf{x}}) + Y(\bar{\mathbf{x}} - \delta \times \mathbf{v}_k)}{2\delta^2} w_{p,k}^2 \right]$$

$Y$ : pixel resolved atmospheric radiation field     
  $\bar{\mathbf{x}}$ : field mean     
  $\mathbf{v}$ : PC vectors (image-effective)     
  $w$ : PC weights (pixel-resolved)     
  $\delta$ : perturbation



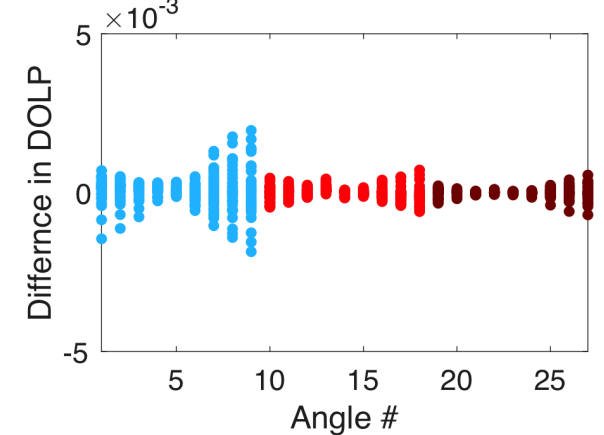
Algorithm heritage:  
 PCA-RT for hyperspectral  
 RT modeling (Liu et al.  
 2006; Natraj et al. 2007)

PCA-RT error (%) in multi-pixel  
 TOA angular **BRF** in 7 bands



*Xu et al., 2019*

PCA-RT error in multi-pixel  
 TOA angular **DOLP** in 3 bands



# Summary

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We developed a correlated-based inversion (CBI) approach that

- ❖ capitalizes on the spatial and temporal correlation of aerosol properties
  - to reduce the aerosol parameter space by retrieving PCs
  - to allow multiple types of constraints to impose to stabilize PC retrievals
  - to enable a PCA-RT model for fast radiative transfer modeling
- ❖ CBI preliminary application to polarimetric observations achieves mean absolute errors  $\sim 0.015$ - $0.03$  for AOD and  $\sim 0.03$ - $0.04$  for SSA
- ❖ CBI application to OCO-2 data is targeted for an accuracy  $\sim 0.68$ km for aerosol layer height retrieval
- ❖ CBI is current under optimization for use by the next-generation polarimeters

# Looking forward ...

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- ❖ Adapting the correlation-based inversion approach to retrieve aerosol composition, more aerosol shape parameters and ocean constituent properties by combining observations and a priori analysis of other model and climatology observation in PC space
- ❖ Constituting new basic shapes for capturing retrieval parameter correlation and transform retrieval from regular parameter space to other types of linear/non-linear spaces
  - Challenges: Mapping traditional a priori constraints used from regular parameter space to new spaces is non-trivial
- ❖ Seeking intrinsic relations between correlation-based retrieval and some machine learning approaches
- ❖ ...

# Acknowledgement

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We thank discussions with and/or earlier work done on

- ❖ **Optimization approach**

by J. Martonchik, P. Litvinov, O. Hasekamp, K. Knobelspiesse, S. Stamnes, M. Garay, J. Wang, W. Hou, X. Xu, etc.

- ❖ **Radiative transfer modeling**

by J. Chowdhary, P. Yang, A. Davis, X. Liu, V. Natraj, P. Zhai, etc.

- ❖ **Validation data supply**

by AERONET, RSP & SPEX airborne teams

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Article

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**Abstract:** Aerosol retrieval algorithms used in conjunction with remote sensing are subject to ill-posedness. To mitigate non-uniqueness, extra constraints (in addition to observations) are valuable for stabilizing the inversion process. This paper focuses on the imposition of an empirical correlation constraint on the retrieved aerosol parameters. This constraint reflects the empirical