Jet Propulsion Laboratory
California Institute of Technology

Pulling 3D Cloud Structure Out of Passive Overhead Imagery: Observational and Computational Challenges

Anthony B. Davis (Jet Propulsion Laboratory, California Institute of Technology, Pasadena, Ca, USA)
Nicolas Ferlay (Laboratoire d'Optique Atmosphérique, U. de Lille, CNRS, Lille, France)
Quentin Libois (CNRM, Météo-France, U. de Toulouse, CNRS, Toulouse, France)
Aviad Levis and *Yoav Schechner* (Technion - IIT, Viterbi Faculty of Electrical Engineering, Haifa, Israel)

Mini-tutorial on "Quantitative Image Analysis"
SIAM Conference on Computational Science & Engineering (CSE19), 2/25-3/1/2019, Spokane, Wa

Outline

- **Atmospheric remote sensing in 3D … from 2D data**
  - *Why not just use active (radar/lidar) systems?*
  - Go beyond geometry (“shape-from-x”) with physics
- ***Depth from oxygen absorption spectroscopy***
  - *Why solar (VNIR) rather than thermal (TIR)?*
  - *constrained inverse Laplace transformation*
  - *Shannon information content analysis*
- **Three-dimensional cloud optical tomography**
  - multi-angle image data exploitation with:
    - radiometric calibration
    - fast/staged forward model
    - adapted inversion technique
- **Conclusions/outlook**

Outline

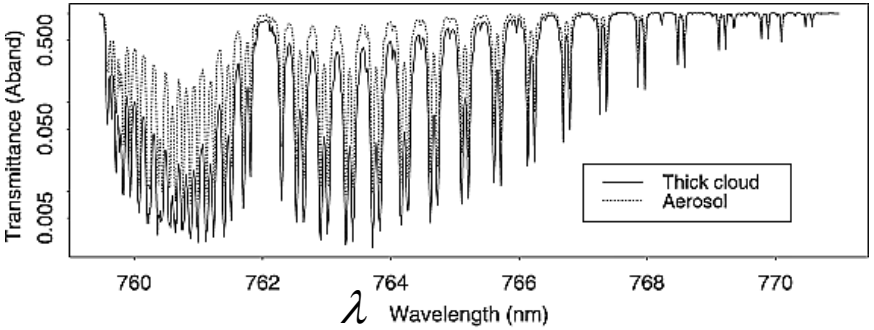
- **Atmospheric remote sensing in 3D … from 2D data**
  - *Why not just use active (radar/lidar) systems?*
  - Go beyond geometry (“shape-from-x”) with physics
- ***Depth from oxygen absorption spectroscopy***
  - *Why solar (VNIR) rather than thermal (TIR)?*
  - *constrained inverse Laplace transformation*
  - *Shannon information content analysis*
- **Three-dimensional cloud optical tomography**
  - multi-angle image data exploitation with:
    - radiometric calibration
    - fast/staged forward model
    - adapted inversion technique
- **Conclusions/outlook**

Depth vision from O_2 spectroscopy

- **Selected collaborators:**
  - Nicolas Ferlay (CNRS/LOA)
  - Quentin Libois (CNRS/CRNM)

  - Yuekui Yang (NASA/GSFC)
  - Alexander Marshak (NASA/GSFC)
  - Qilong Min (SUNY-Albany)
  - Lee Harrison (SUNY-Albany)
  - Igor Polonsky (AER)
  - Klaus Pfeilsticker (U of Heidelberg)
  - Feng Xu (JPL/Caltech)

Differential Optical Absorption Spectroscopy (DOAS) for O_2 at high spectral resolution



From: Min Q., L. C. Harrison, P. Kiedron, J. Berndt, and E. Joseph, 2004: A high-resolution oxygen A-band and water vapor band spectrometer, *J. Geophys. Res.*, **109**, D02202.

wavenumber $\nu = c/\lambda$ **x-section** **density** **pathlength** ($L = ct$ in lidar)

$$I(\nu)/I_0 = \exp[-\sigma_\nu \; n \; L]$$

$$\text{known/not}: \begin{cases} ? \;\; \surd \;\; \surd \;\; \text{estimating molecular cross-sections in the laboratory} \\ \surd \;\; ? \;\; \surd \;\; \text{monitoring amounts of chemical effluent in situ} \\ \surd \;\; \surd \;\; ? \;\; \text{scattering/reflection diagnostics of media permeated with gas} \end{cases}$$

$$I(\nu) = I(k_\nu) = I_0 \int_0^\infty p(L) \; \exp[-k_\nu L] \, \mathrm{d}L \text{ (equivalence "theorem")} \Rightarrow \langle L^q \rangle = \frac{(-1)^q}{I_0} \left(\frac{\mathrm{d}^q I}{\mathrm{d}k_\nu^q} \right)_{k_\nu = 0}$$

Representing pathlength distribution

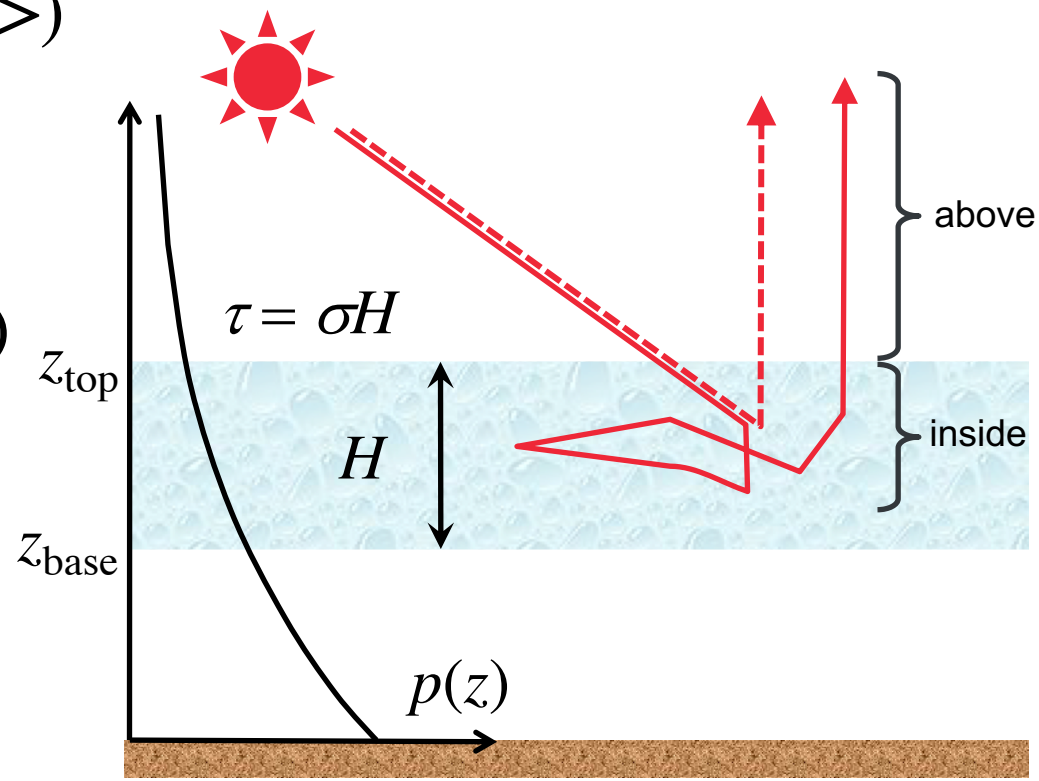
- **Lidar-like: single scattering**
  - Degenerate PDF: $p_D(ct) = \delta(ct - \langle ct \rangle)$
- **Solar-like: multiple scattering**
  - Gamma PDF:

$$p_a(ct) = (ct)^{a-1} \exp(-a\, ct/\langle ct \rangle) \times (a/\langle ct \rangle)^a / \Gamma(a)$$

where $a = \langle ct \rangle^2 / \mathrm{Var}[ct]$
$= 1/(\langle ct^2 \rangle / \langle ct \rangle^2 - 1)$

N.B. $p_D(ct) = p_{a \to \infty}(ct)$

- **… or combination**
  - for "above"+"inside"



EPIC/DSCOVR, at ≈10^6 miles away, Nov'17 new Moon

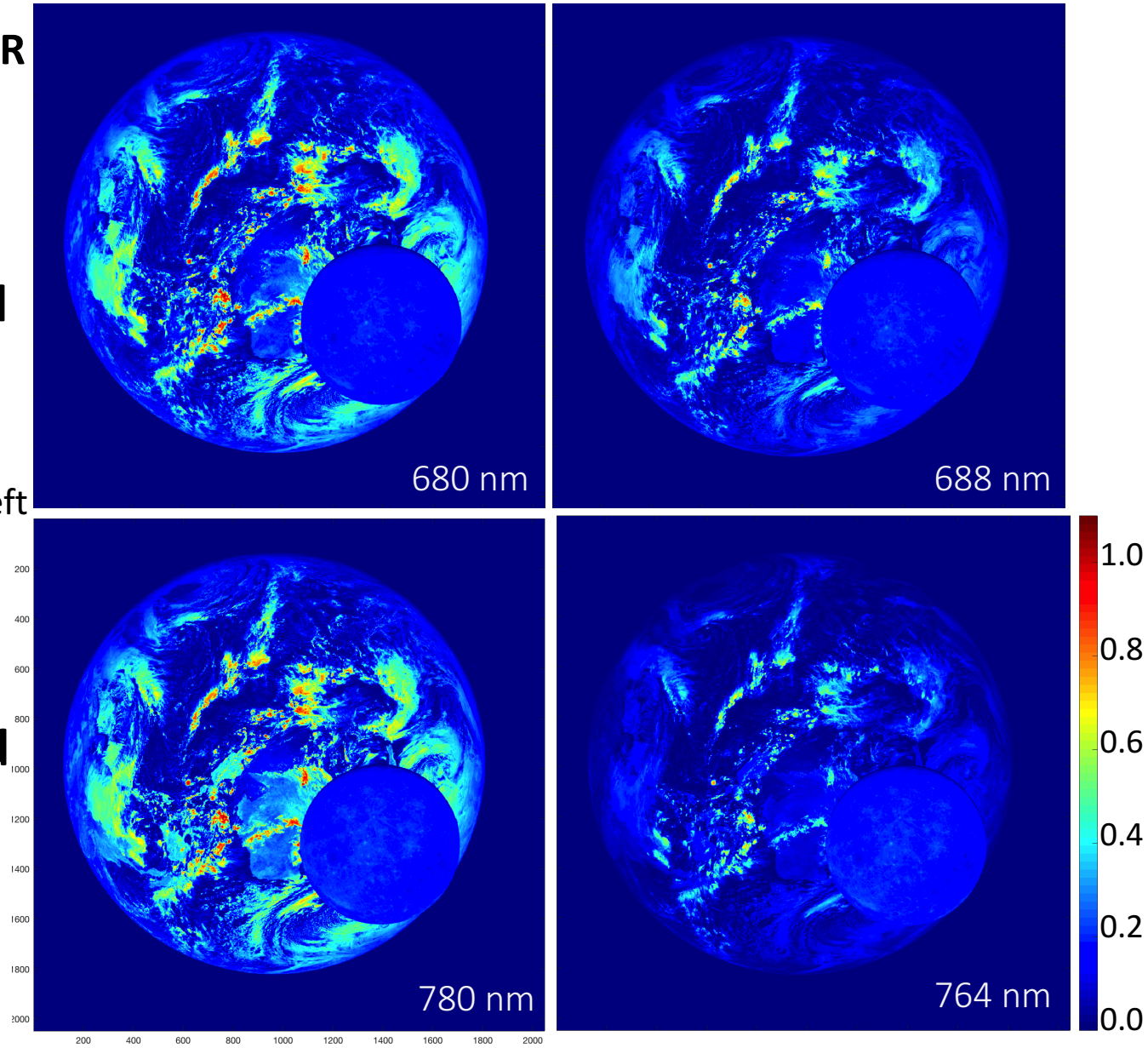
EPIC/DSCOVR
O_2 channels:

B-band
$\tau_{O2} \approx 0.3$

Reference on left
($\tau_{O2} = 0$)

A-band
$\tau_{O2} \approx 0.6$

2017-11-19



EPIC/DSCOVR, at ≈10^6 miles away, Nov'17 new Moon

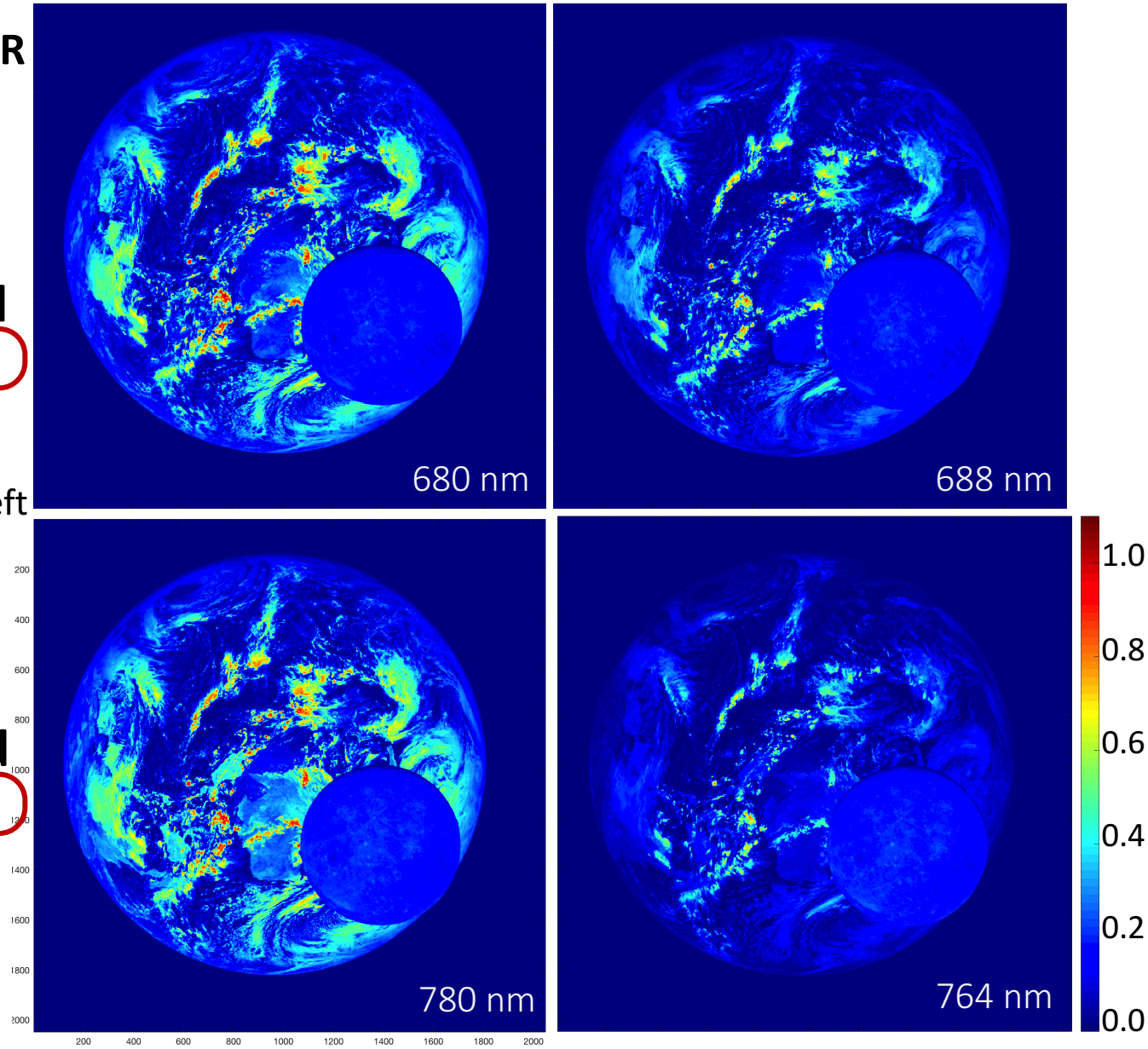
EPIC/DSCOVR
O_2 channels:

effective optical thicknesses

B-band
$\tau_{O2} \approx 0.3$

Reference on left
($\tau_{O2} = 0$)

A-band
$\tau_{O2} \approx 0.6$



2017-11-19

Statistical ("optimal estimation") formalism

Bayes' theorem:

PDF of total cost function =

PDF of forward model prediction error on observations $\mathbf{y}$

x PDF of prior uncertainty on state vector $\mathbf{x}$

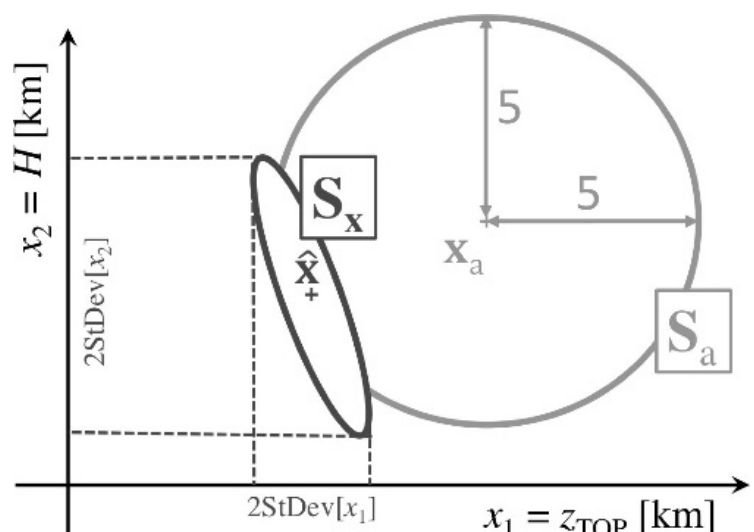
likelihood of y, given **x**

prior uncertainty on **x**

$$\underbrace{p(\mathbf{x}|\mathbf{y})}_{\textit{posterior}\text{ uncertainty on }\mathbf{x}\text{, given }\mathbf{y}} = \overbrace{p(\mathbf{y}|\mathbf{x})}^{\text{likelihood of y, given }\mathbf{x}}\ \overbrace{p(\mathbf{x})}^{\textit{prior}\text{ uncertainty on }\mathbf{x}}\ \underbrace{/\ p(\mathbf{y})}_{\text{unimportant}}$$

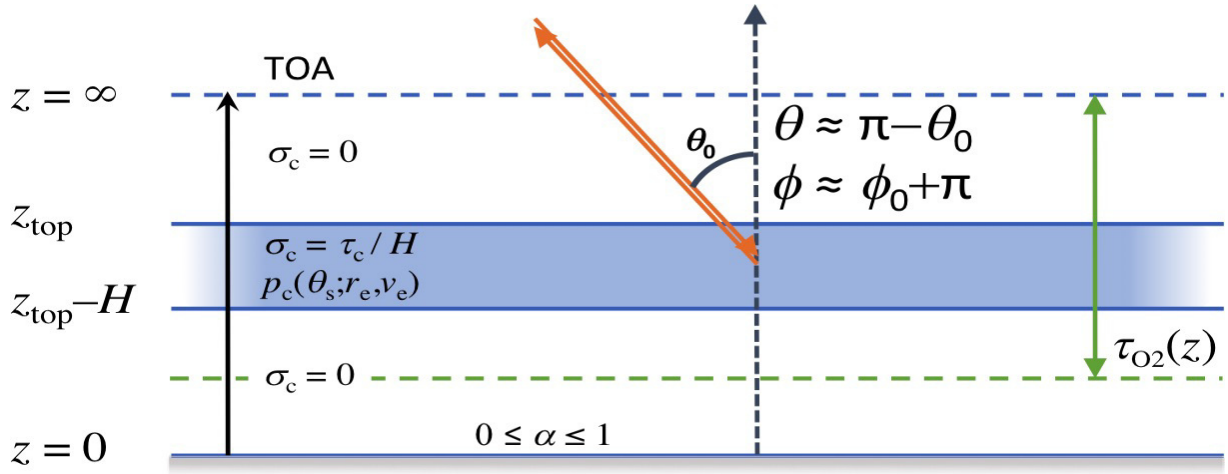
errors in $\mathbf{y}$ *space:* $\mathbf{S_y} = \mathbf{S_e} + \mathbf{S_b}$

sensor ↓ model ↓



Shannon information content / gain

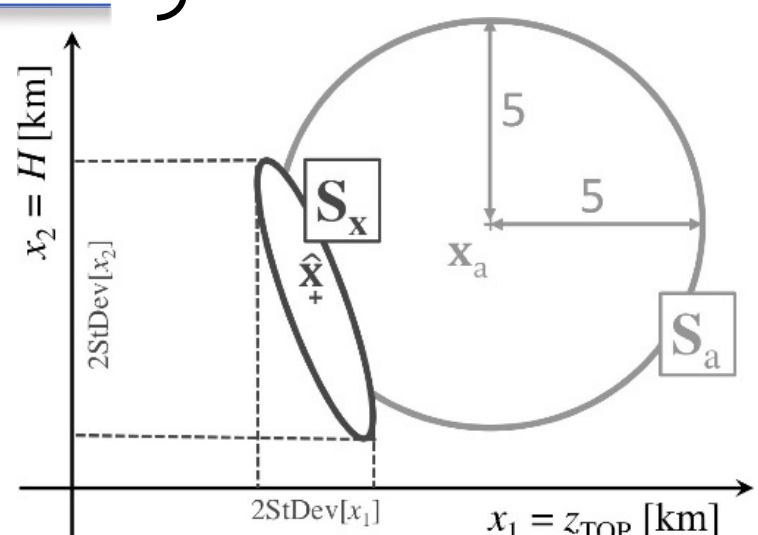
Information Content (IC) gain or Degrees-Of-Freedom (DOF) per cloud property = ratio of the areas of $\mathbf{S}_a$ and $\mathbf{S}_x$, projected onto one of the state/**x**-space axes



$$\mathbf{x}^T = (z_{top}, H)$$

$$\mathbf{y}^T = (I_{abs,l}/I_{ref,\lambda},\ \lambda = \text{A,B-bands})$$

Total information content/gain = Ratios of ellipses areas |**S**|, i.e., of products of minor and major axes of the prior-to-posterior PDFs



Bayesian IC analysis [Rodgers, 2000]: From forward physics-based model to UQ

$\mathbf{y} = \left[\mathrm{DOAS}_{0.5}, \mathrm{DOAS}_{1.9}, \mathrm{DOAS}_{2.6}\right]^{\mathrm{T}}$ are data, where subscript is $\tau_{\mathrm{O}_2,0}$ ($\lambda_{\mathrm{start}} \approx 755.75$ nm) with $\mu = 1$ ($m = 3$).

$\mathbf{S}_{\mathbf{y}} = \mathrm{diag}[(0.015\, y_i)^2]$ is measurement $m \times m$ error (co)variance matrix.

$\mathbf{S}_{\mathrm{a}} = \mathrm{diag}[250^2, 150^2]$ is $n \times n$ "apriori" uncertainty (co)variance matrix in mbar^2 for $\mathbf{x} = [p_{\mathrm{top}}, \Delta p]^{\mathrm{T}}$ ($n = 2$).

$\mathbf{S}_{\mathbf{b}} = \left(\mathrm{Max}[0.025, 0.15\ \tau_{\mathrm{a}}]\right)^2$ is 1×1 uncertainty (variance) on non-retrieved parameter τ_{a}.

$\mathbf{f}(\mathbf{x}, \mathbf{b}; \cdots)$ is the forward model for the DOAS ratio.

$\mathbf{K} = \dfrac{\partial \mathbf{f}}{\partial \mathbf{x}}, \mathbf{K}_{\mathbf{b}} = \dfrac{\partial \mathbf{f}}{\partial \mathbf{b}}$ are Jacobian matrices for retrieved ($m \times 2$) and non-retrieved ($m \times 1$) quantities.

$\mathbf{S}_{\mathbf{f}} = \mathbf{K}_{\mathbf{b}} \mathbf{S}_{\mathbf{b}} \mathbf{K}_{\mathbf{b}}^{\mathrm{T}}$ is forward model error $m \times m$ covariance matrix, from uncertainty on non-retrieved properties.

$\mathbf{S}_{\varepsilon} = \mathbf{S}_{\mathbf{y}} + \mathbf{S}_{\mathbf{f}}$ is total covariance error matrix for estimation of cost function: $(\mathbf{y} - \mathbf{f}(\mathbf{x}))^{\mathrm{T}} \mathbf{S}_{\varepsilon}^{-1} (\mathbf{y} - \mathbf{f}(\mathbf{x}))/2$.

$\mathbf{S}_{\mathbf{x}} = \left(\mathbf{K}^{\mathrm{T}} \mathbf{S}_{\varepsilon}^{-1} \mathbf{K} + \mathbf{S}_{\mathrm{a}}\right)^{-1}$ is the "posterior" error estimate for retrieved quantities in mbar^2.

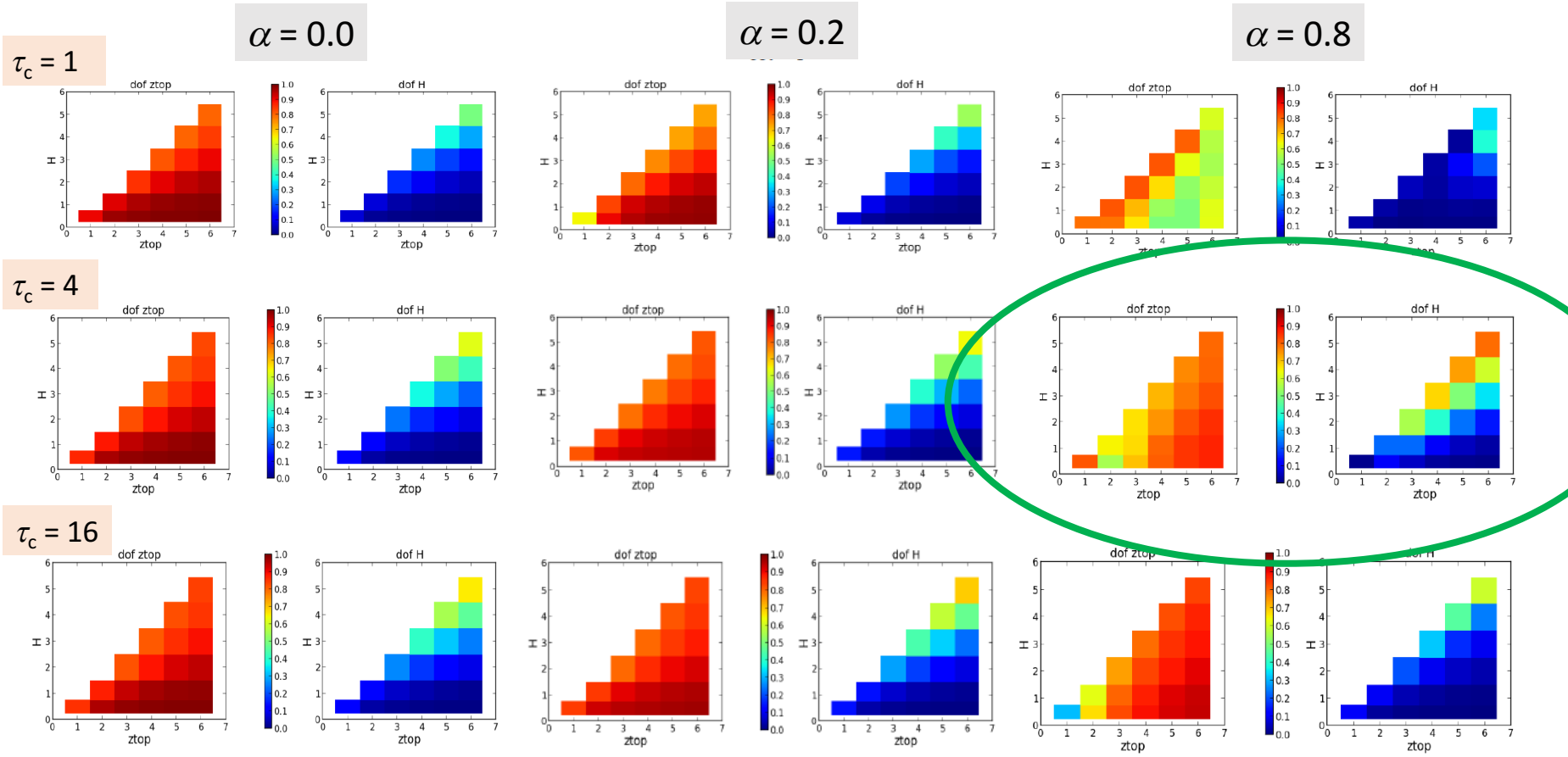
From there, uncertainty on each retrieved quantity is: $\sigma_i = \sqrt{S_{ii}}$ ($i = 1, \ldots, n$) in mbar.

A non-dimensional counterpart is the "Degree of Freedom" (DoF) for each quantity: A_{ii} ($i = 1, \ldots, n$) from

$\mathbf{A} = \mathbf{I} - \mathbf{S}_{\mathbf{x}} \mathbf{S}_{\mathrm{a}}^{-1}$. Note that DoF $\in [0,1]$ measures what the observations do to improve on the prior info.

A sweet spot for z_{top} <u>and</u> H retrieval?

→ moderately opaque clouds over bright surfaces …



… a possible application to arctic clouds?

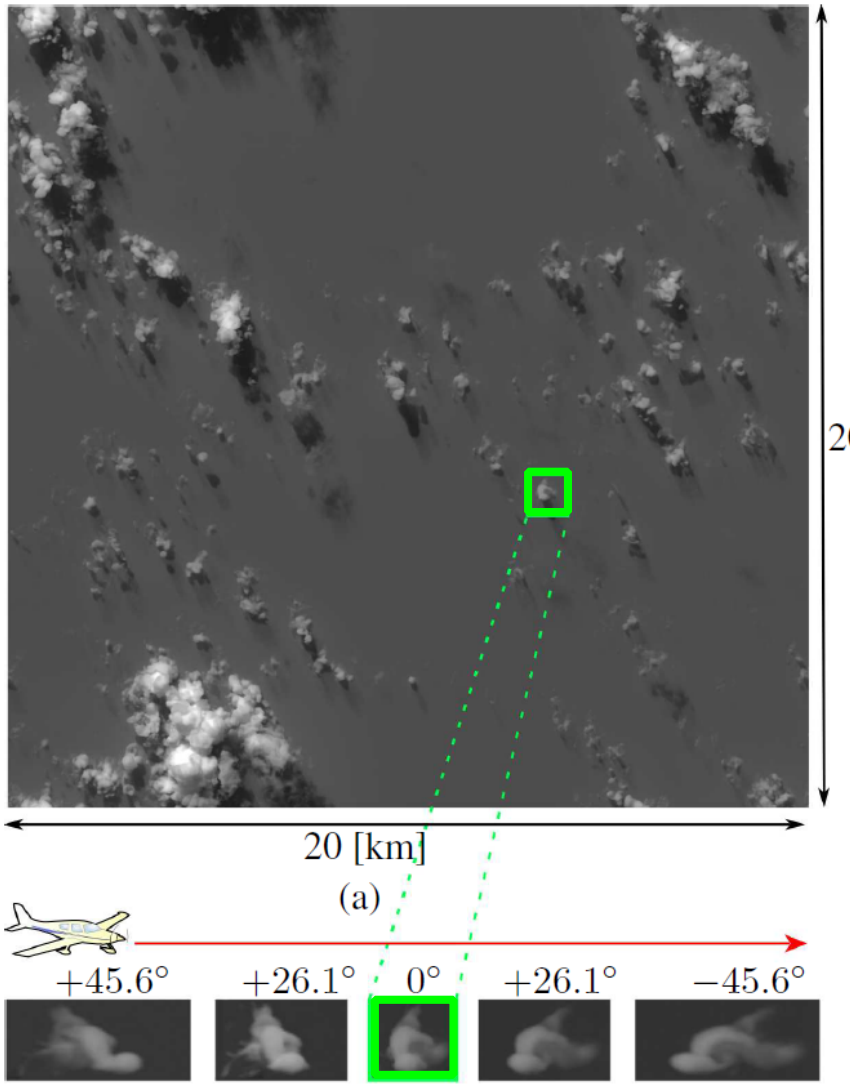
3D cloud optical tomography

- **Selected collaborators:**
  - Aviad Levis (Technion – IIT)
  - Yoav Y. Schechner (Technion – IIT)

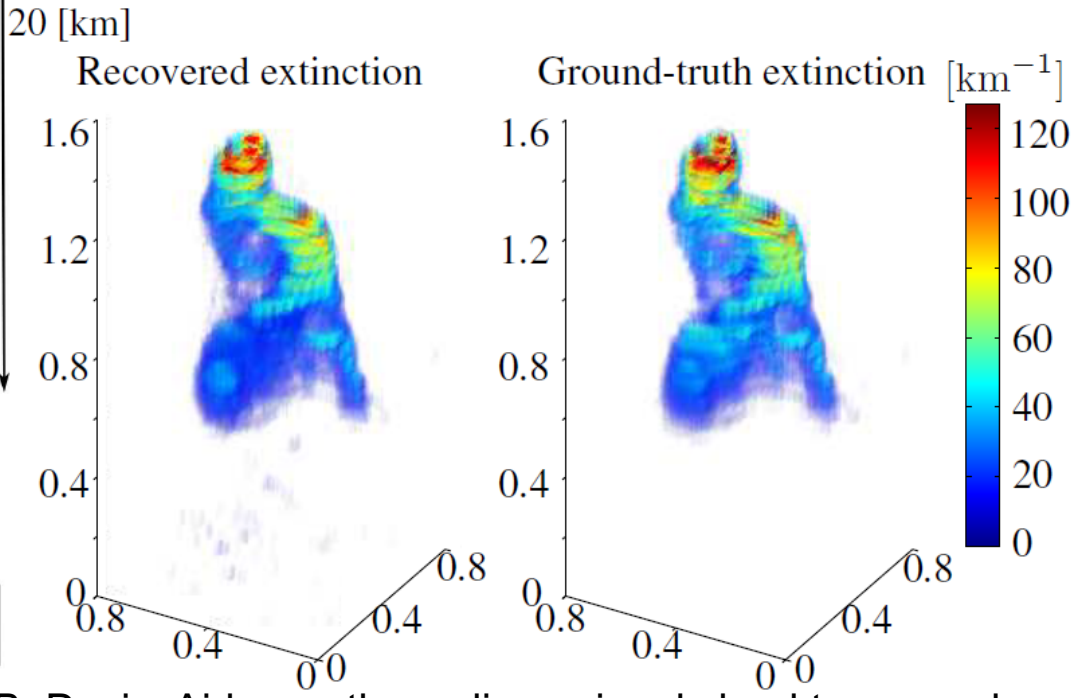
  - Zheng Qu (formerly, The Raytheon Company)
  - Georgios Matheou (U of Connecticut)
  - Feng Xu (JPL/Caltech)
  - David J. Diner (JPL/Caltech)
  - Linda Forster (JPL/Caltech and LMU)
  - Bernhard Mayer (LMU)
  - Claudia Emde (LMU)

Synthetic Data

LES+SHDOM generated cloud field



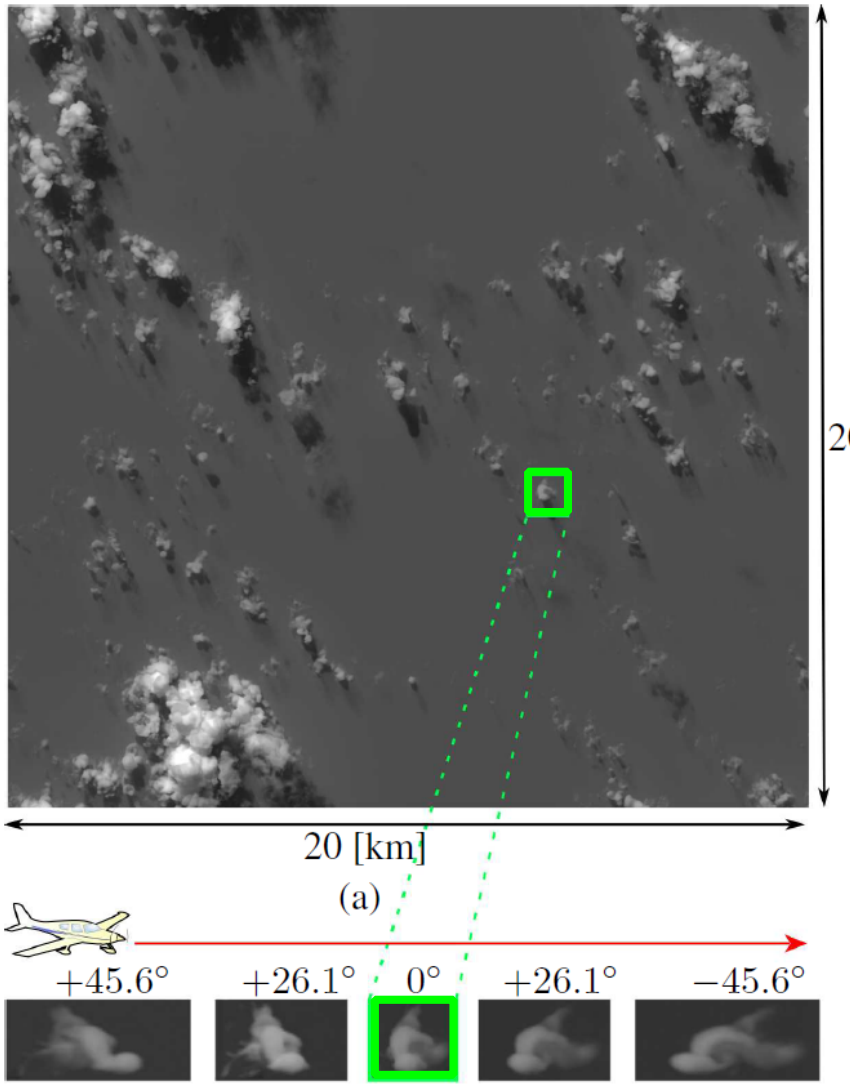
- 9 view angles:
  ±70.5°,±60.0°,±45.6°,±26.1°,0°
- Pixel resolution: 20 m
- SHDOM + photon & quantization noise
- Unknown extinction grid:
  (46,656 unknowns)



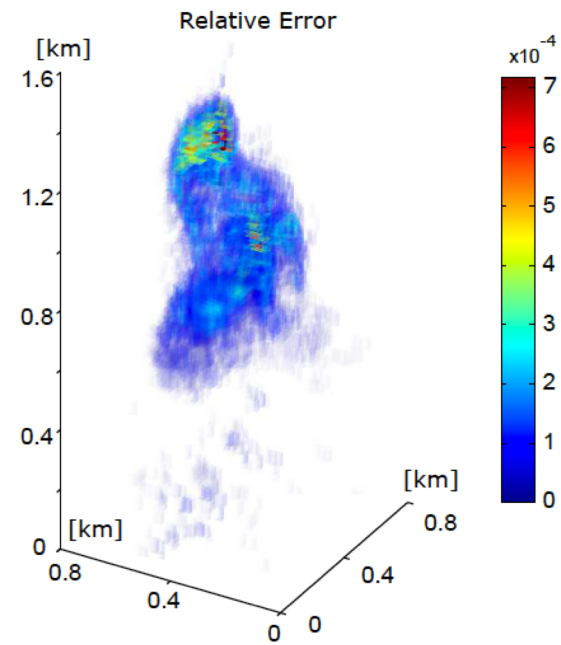
A. Levis, A. Aides, Y. Y. Schechner, and A. B. Davis, Airborne three-dimensional cloud tomography, *International Conference on Computer Vision (ICCV 2015)*, Santiago, Chile, 12/13/16, 2015.

Synthetic Data

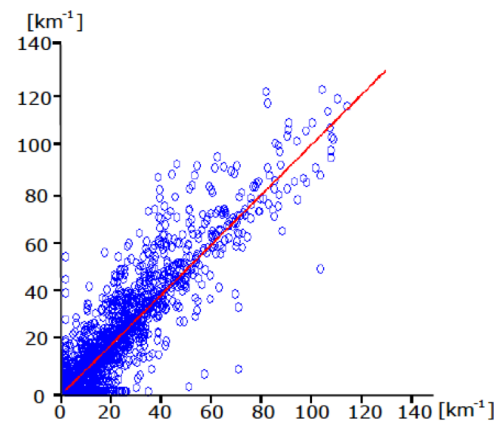
LES+SHDOM generated cloud field



- 9 view angles:
  ±70.5°,±60.0°,±45.6°,±26.1°,0°
- Pixel resolution: 20 m
- SHDOM + photon & quantization noise
- Unknown extinction grid:
  (46,656 unknowns)



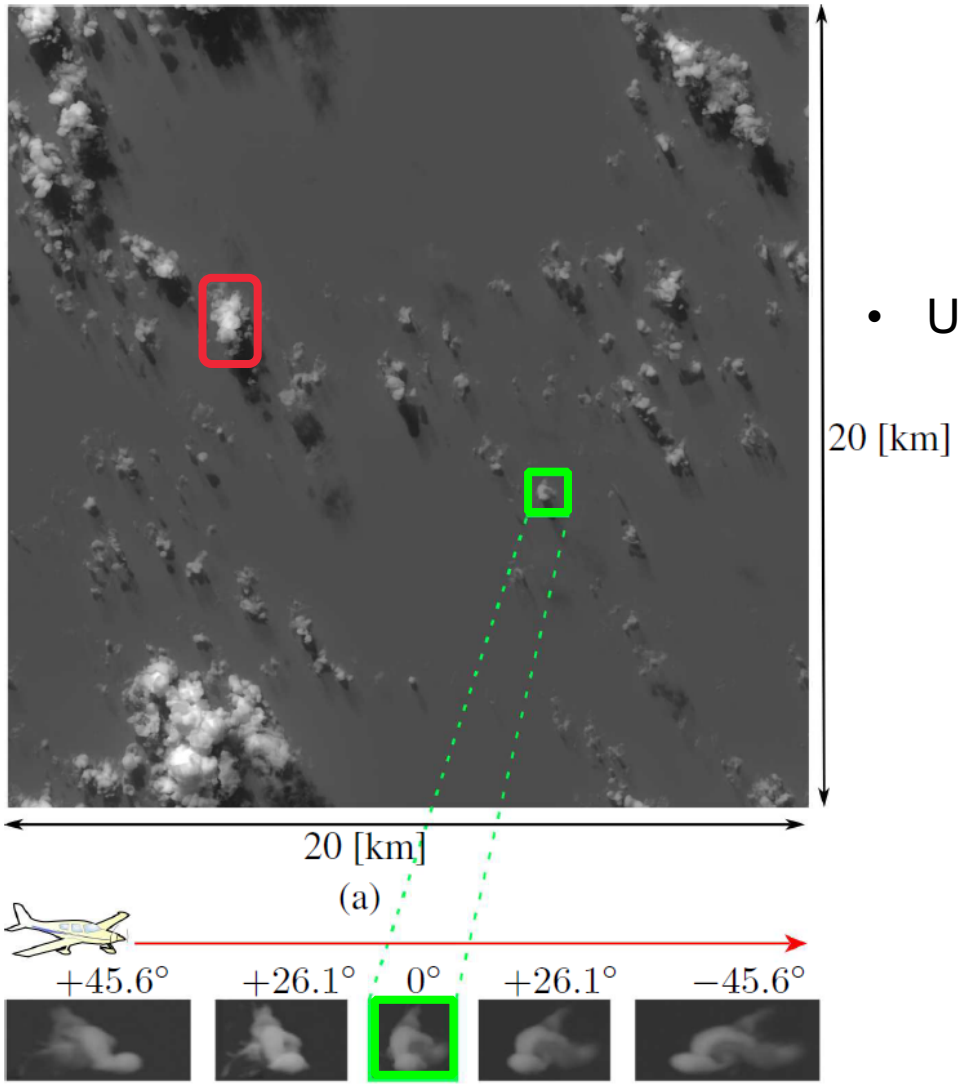
Correlation (R^2): 0.94

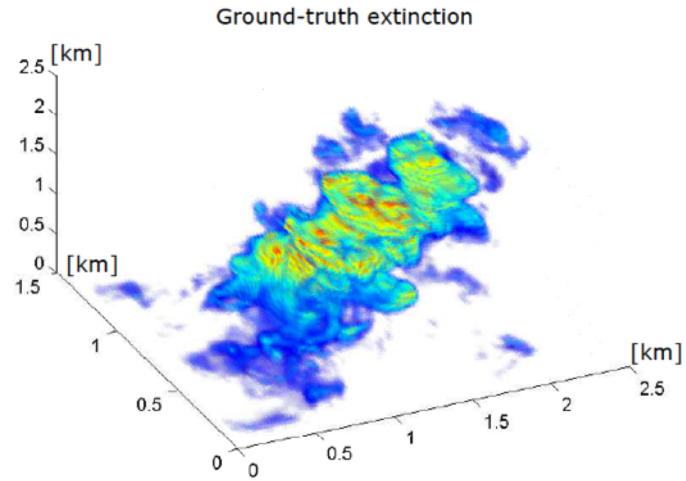


Errors: 5% on total mass; ±33% on local extinction.

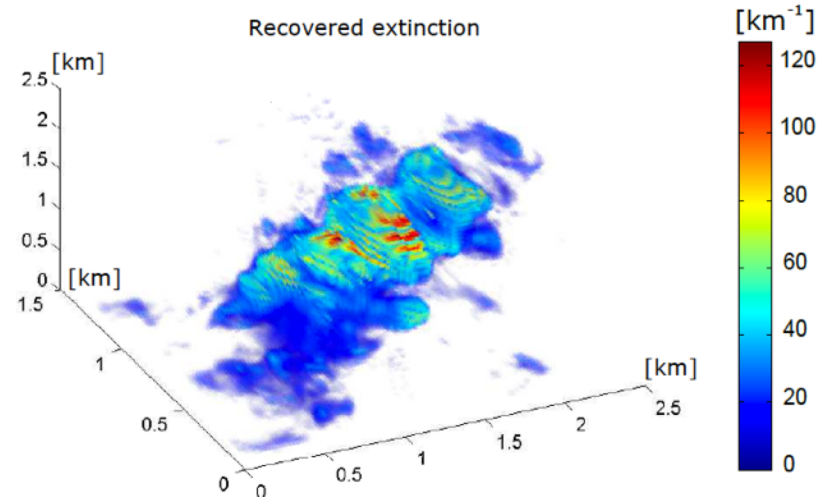
Synthetic Data

LES+SHDOM generated cloud field





- Unknown extinction grid: 66x111x43 (315,018 unknowns)

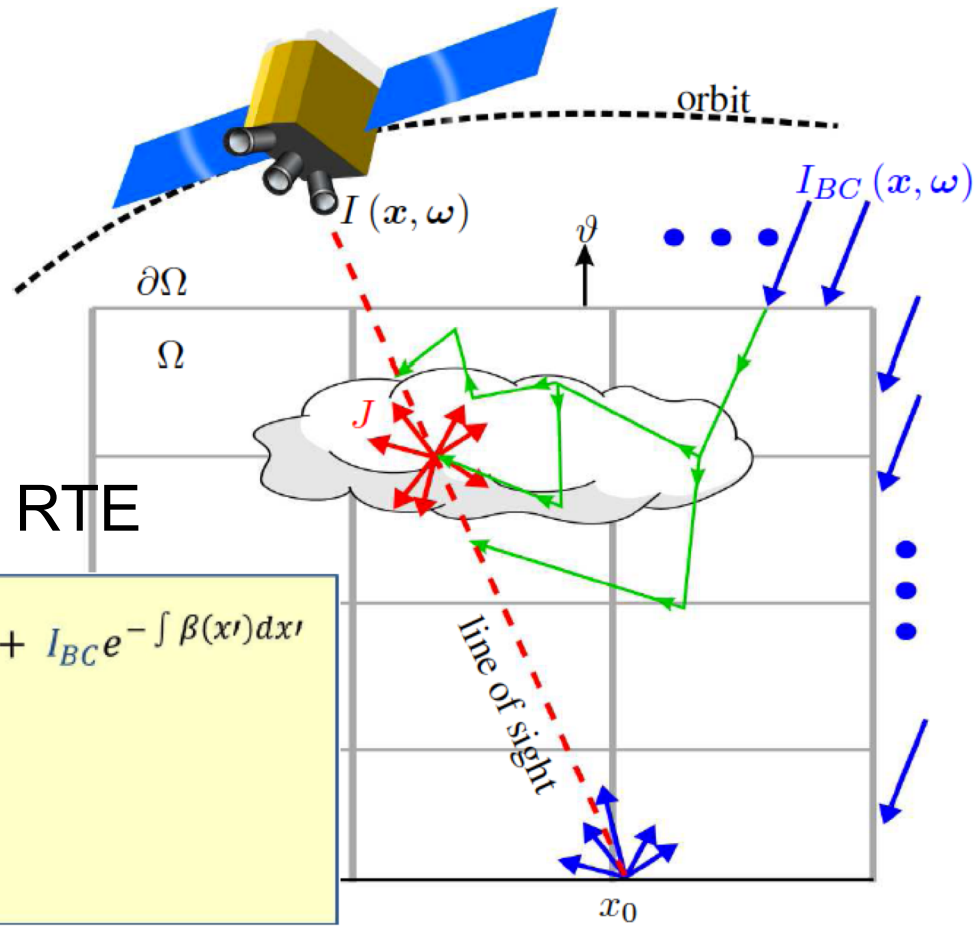


Errors:
30% on total mass;
±70% on local extinction.

Correlation (R^2): 0.76

Fine-scale cloud tomography

Two-level iterative solution



↓ "Formal" solution of 3D RTE

$$I(x,\omega) = \int J(x',\omega)\beta(x')\, e^{-\int \beta(r)dr} dx' + I_{BC} e^{-\int \beta(x')dx'}$$

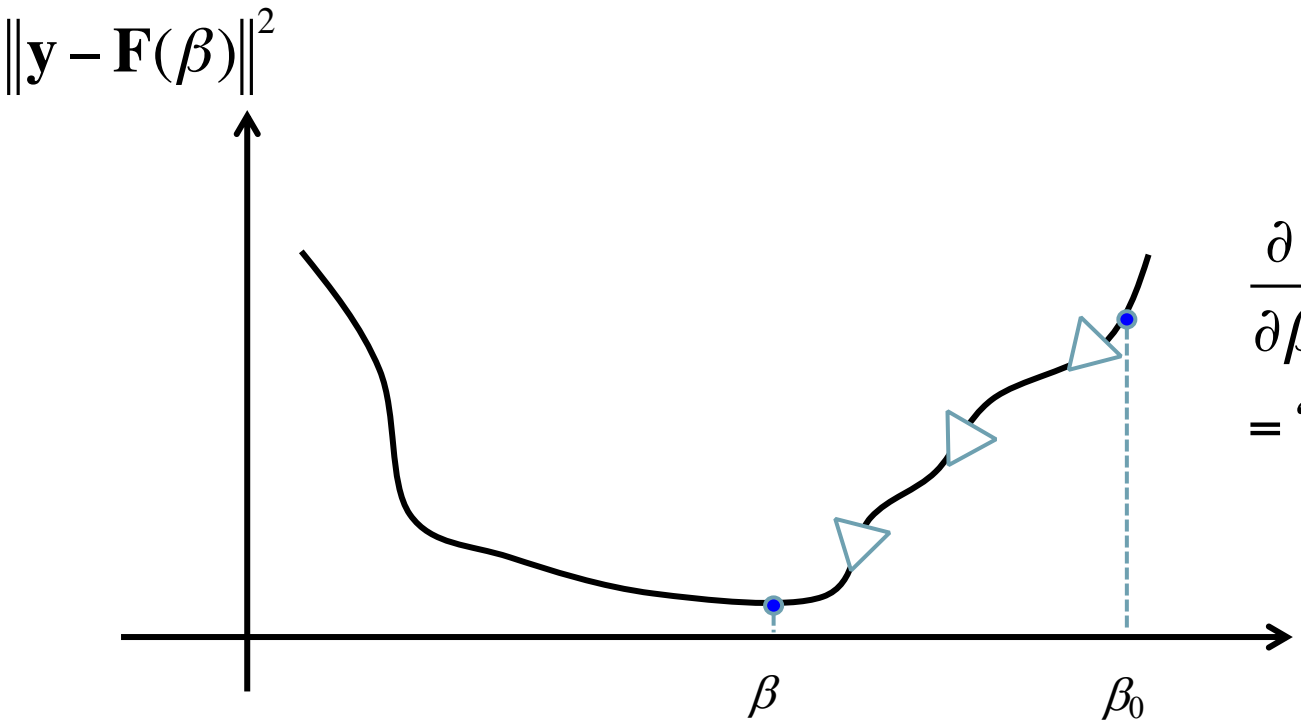
$$J(x,\omega) = \frac{\varpi}{4\pi} \int_{s^2} p(x, \omega \cdot \omega') I(x,\omega') d\omega'$$

↑ "Ancillary" integral RTE

Iterative multi-angle/multi-pixel algorithm

β_0 → $\beta = \underset{\beta}{\operatorname{argmin}} \left\| \mathbf{y} - \mathbf{F}(\beta) \right\|^2$ →

$$\begin{cases} \mathbf{F}(\beta) = I[\beta, J(\beta)] \ldots \text{"formal" solution} \\ J(\beta) = \mathrm{SHDOM}(\beta) \ldots \text{using Picard iteration} \end{cases}$$



$$\frac{\partial}{\partial \beta} \mathbf{F}(\beta, \mathrm{SHDOM}(\beta))$$

$= ???$

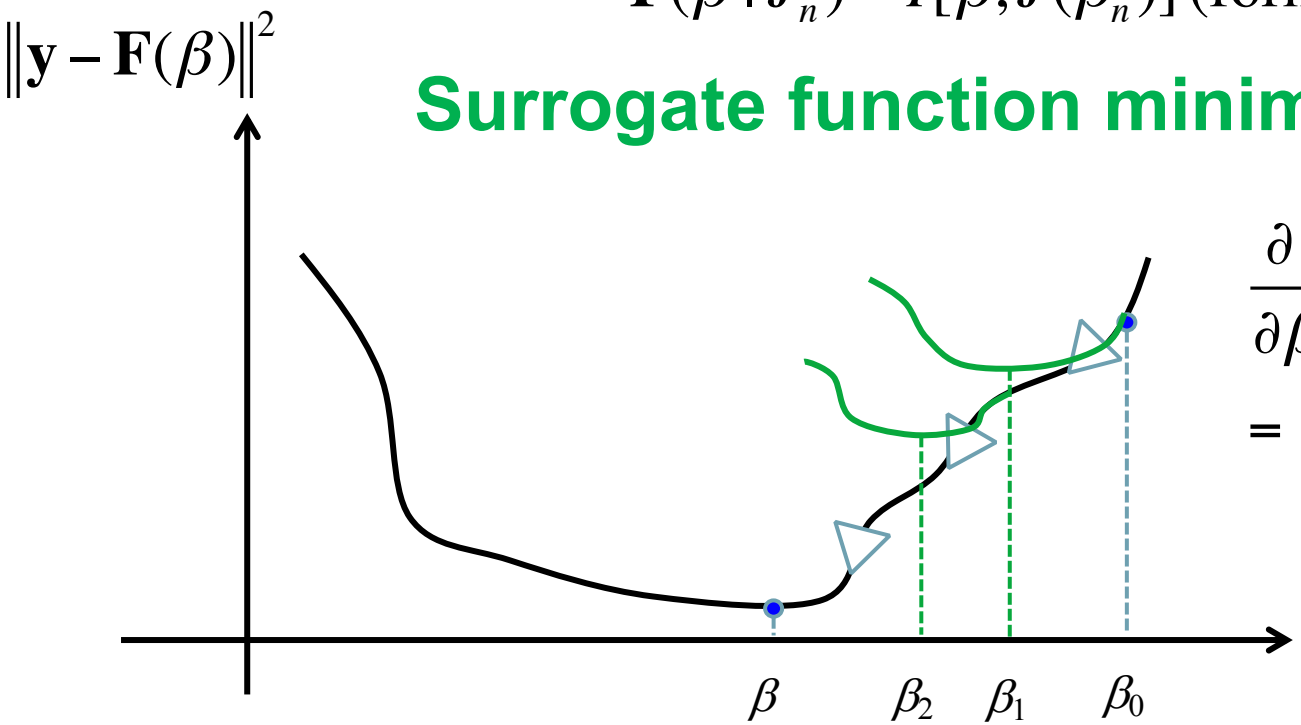
Iterative multi-angle/multi-pixel algorithm

$$\beta_0 \longrightarrow \beta = \underset{\beta}{\operatorname{argmin}} \left\| \mathbf{y} - \mathbf{F}(\beta) \right\|^2 \longrightarrow$$

$$\beta_{n+1} = \underset{\beta}{\operatorname{argmin}} \left\| \mathbf{y} - \mathbf{F}(\beta \mid J_n) \right\|^2$$

$$\mathbf{F}(\beta \mid J_n) = I[\beta, J(\beta_n)] \text{ (formal solution)}$$

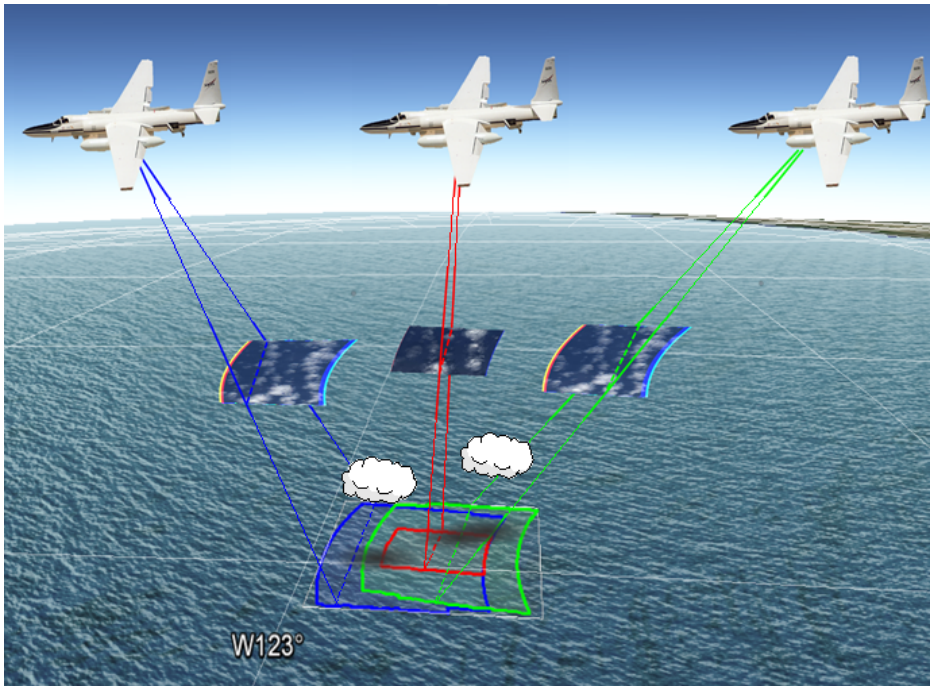
Surrogate function minimization

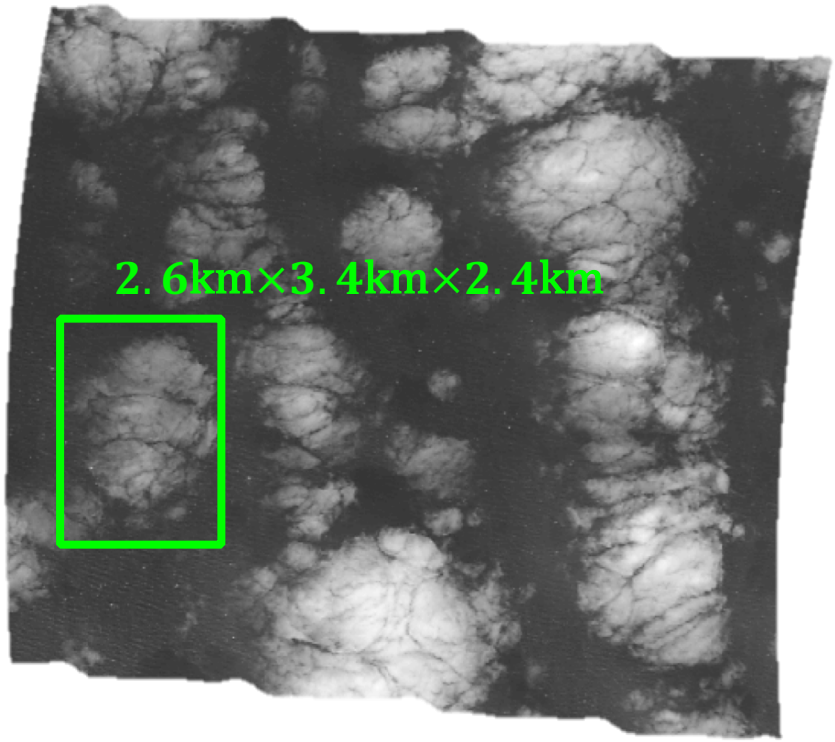


$$\frac{\partial}{\partial \beta} \mathbf{F}(\beta \mid J_n)$$

$= \checkmark$

AirMSPI Data

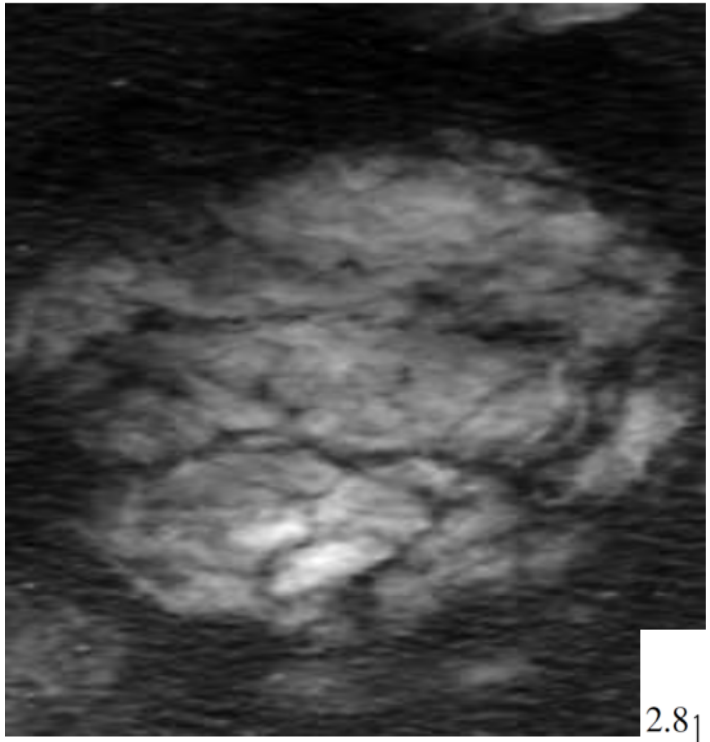




- 9 view angles: ±66.0°, ±58.9°, ±47.7°, ±29.0°, and 0°
- Pixel resolution: 10 m
- Extinction grid: 86,688 unknowns (at 60 m resolution)

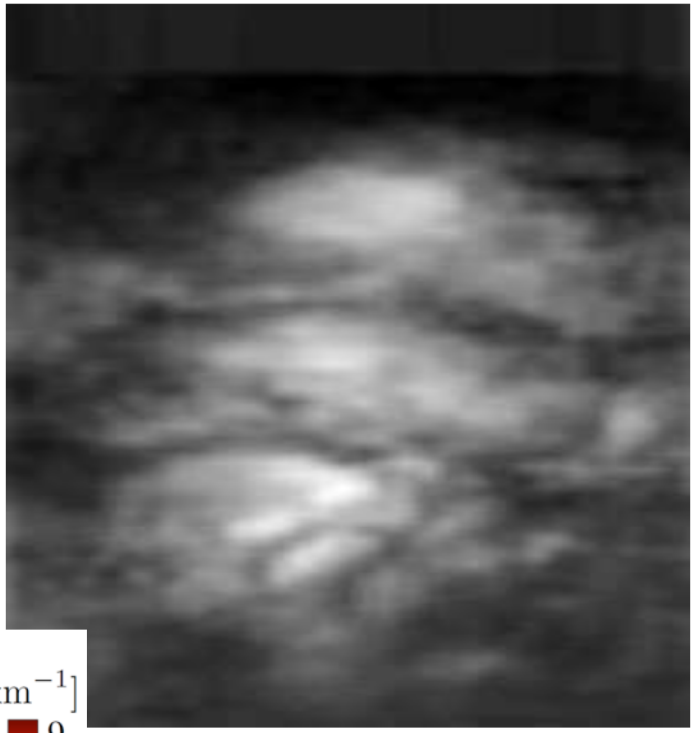
Radiance Domain Comparison

AirMSPI's nadir

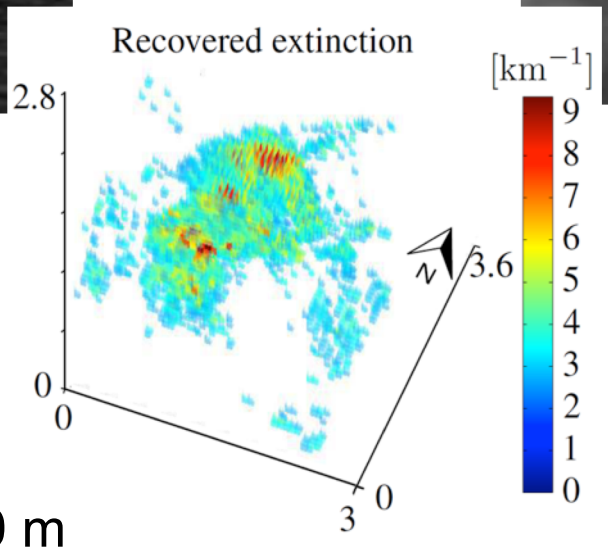


10 m resolution

SHDOM rendered nadir



60 m resolution



- Cloud base at ~1.5 km
- Mean-free-path of ~100 m

Summary/Outlook

- **Two physics-based methods of pulling 3D structure out of 2D remote sensing data in VNIR spectrum**
  - di-oxygen spectroscopy
  - cloud optical tomography
- **<u>To do</u> in *O_2 DOAS exploitation***
  - Trade studies of spectral resolution vs bi-spectral/multi-angle
  - Demo cloud optical thickness recovery at $\tau \rightarrow \infty$ (eg, in $<ct^3>$)
- **<u>To do</u> in *3D cloud reconstruction***
  - Enhance cloud microphysics sensitivity: SWIR and/or polarization
  - Go from airborne (small pixels/clouds) sensors to space-based ones (large pixels and/or clouds): "hidden zone" issue
    - speed-up forward problem
    - inform inverse problem

© 2019 California Institute of Technology.
Government sponsorship acknowledged.