Introduction to Imaging Spectroscopy

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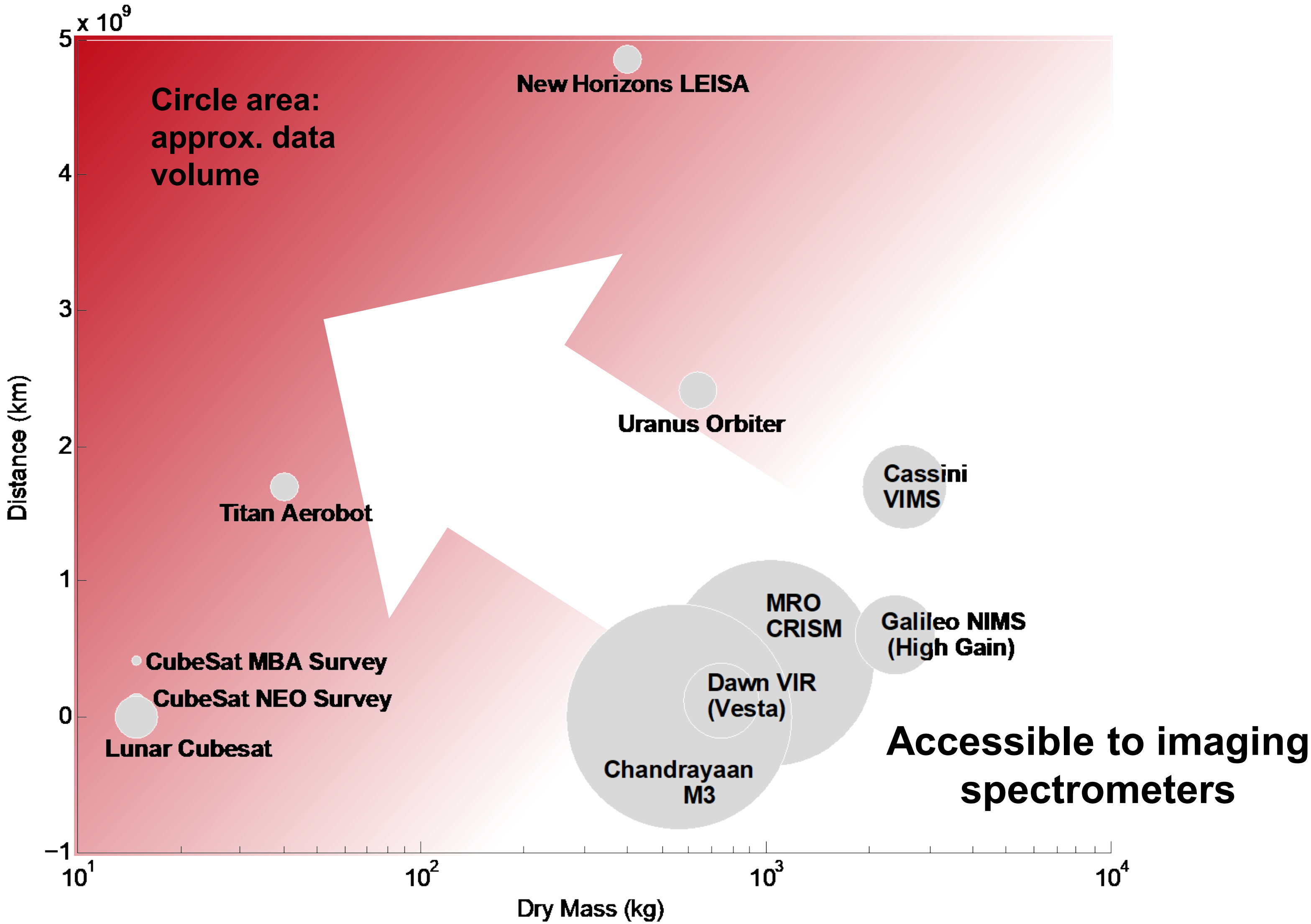
California Institute of Technology

Agenda

Imaging spectroscopy measurement and instruments
Example missions, phenomena and results for Earth and Planetary exploration
Algorithms: easy and hard, monolithic and parallelizable, stochastic and probabilistic

The nebulae promise: Increase the *effective science yield* for a given bandwidth limit



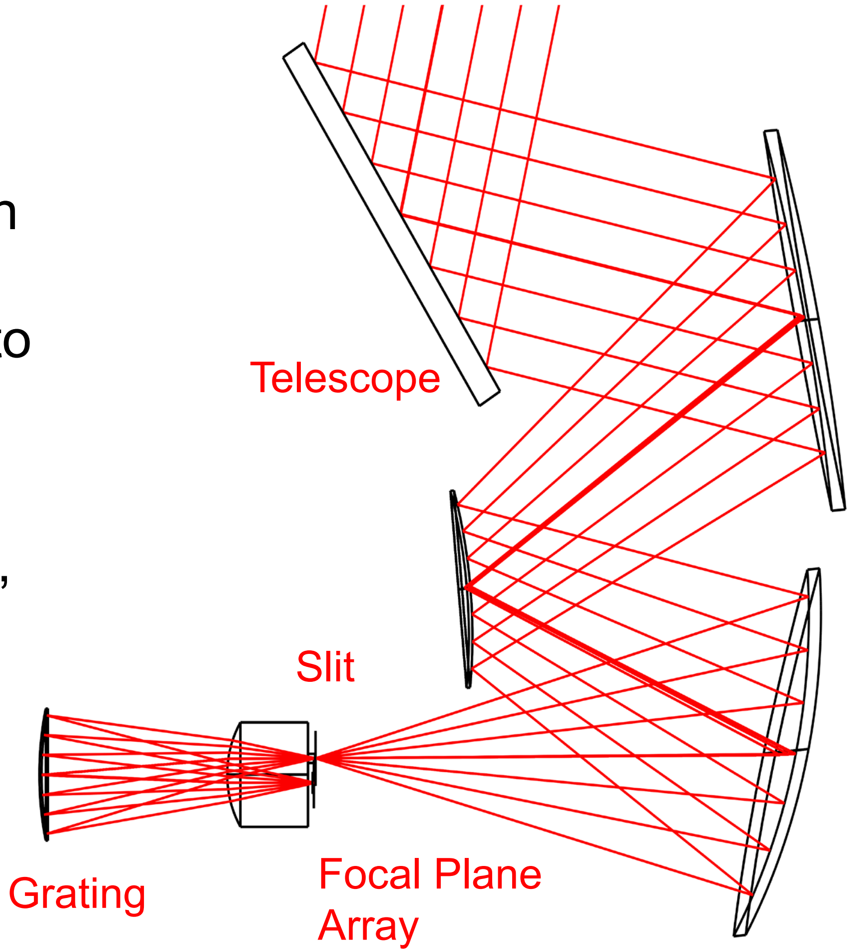
Remote science has stringent requirements

High accuracy: e.g. sub-percent surface reflectance

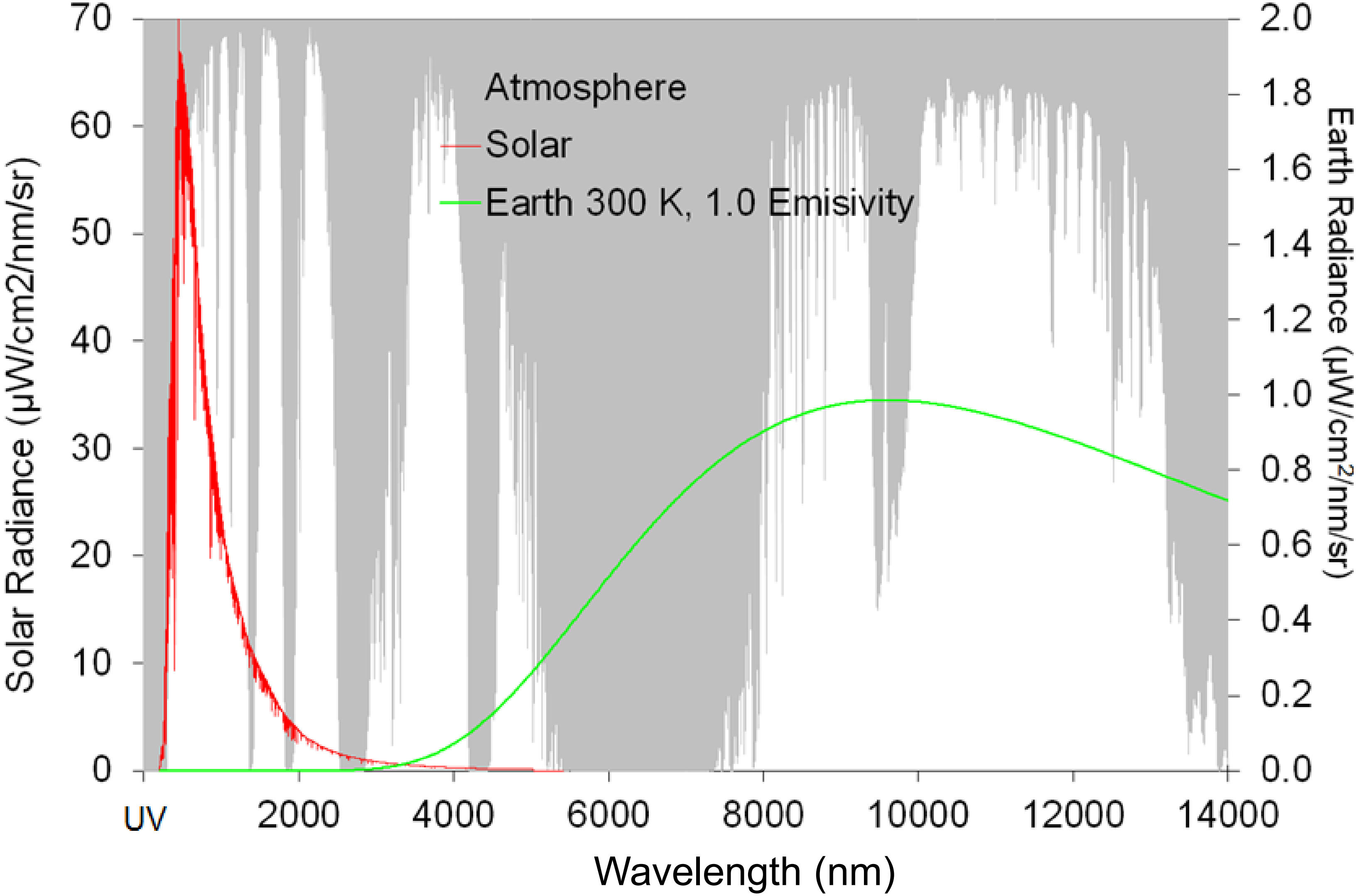
Quantitative physical interpretability: Output reported in physical units of quantities measurable *in situ*, and traceable to rigorous physical models

Principled uncertainty propagation: Respect input noise, report confidence intervals

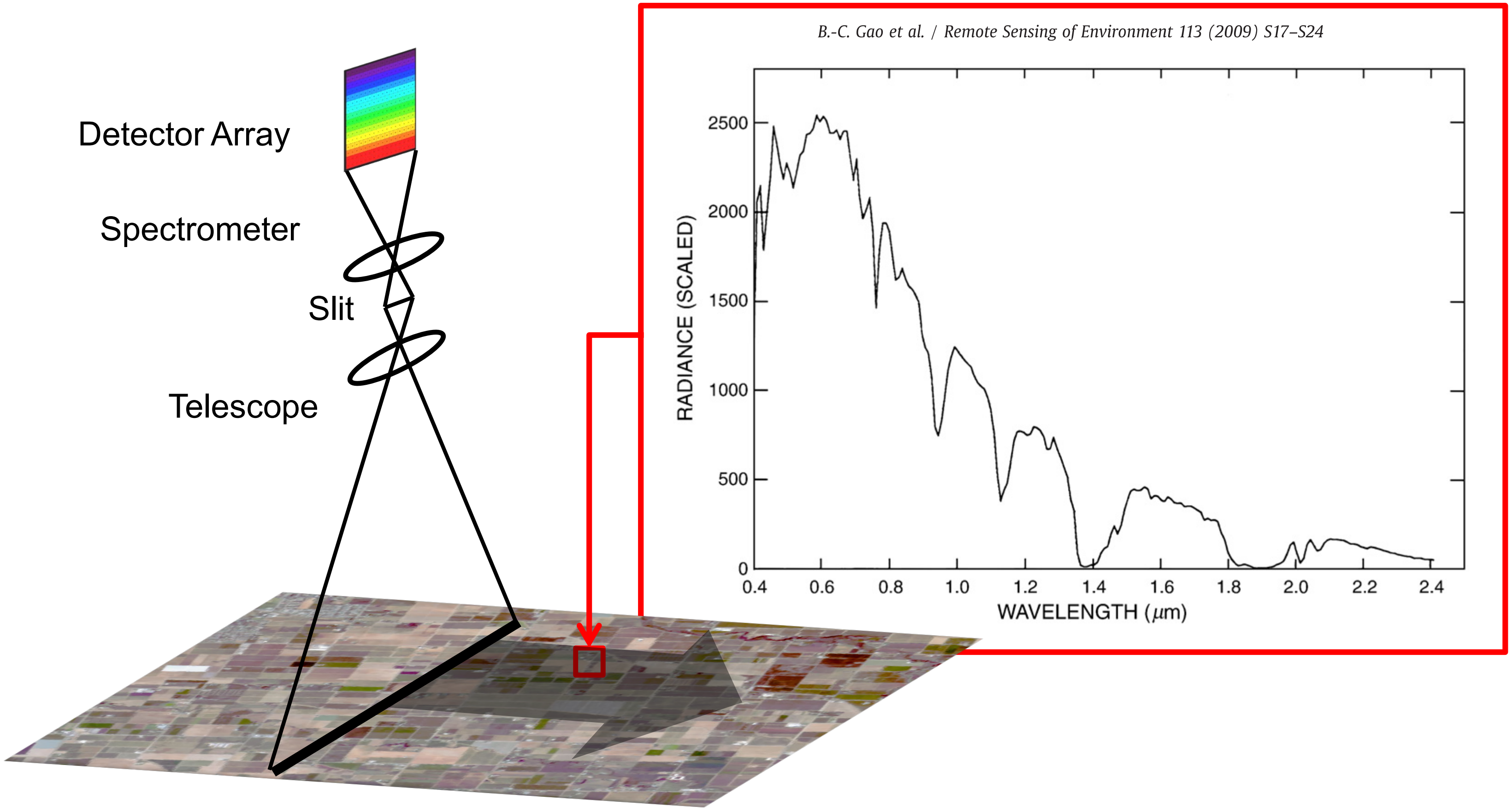
Generalizability: should apply across different new locales, new spatiotemporal sampling



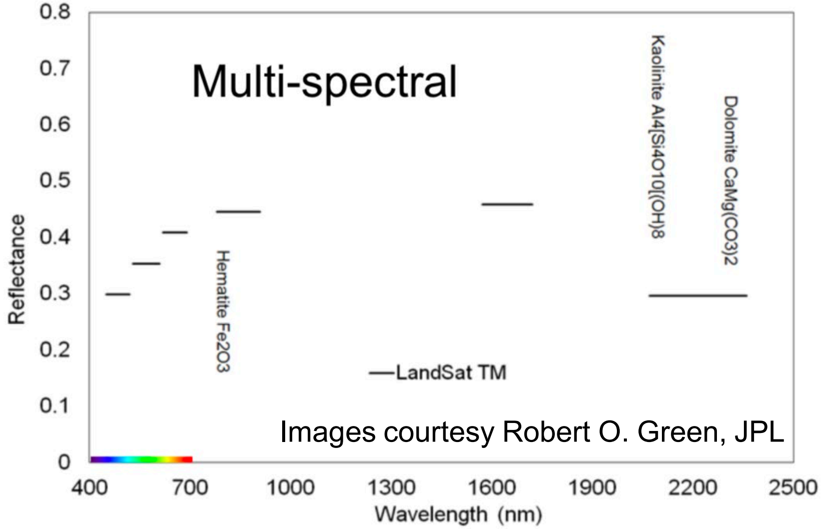
Dramatis Persone

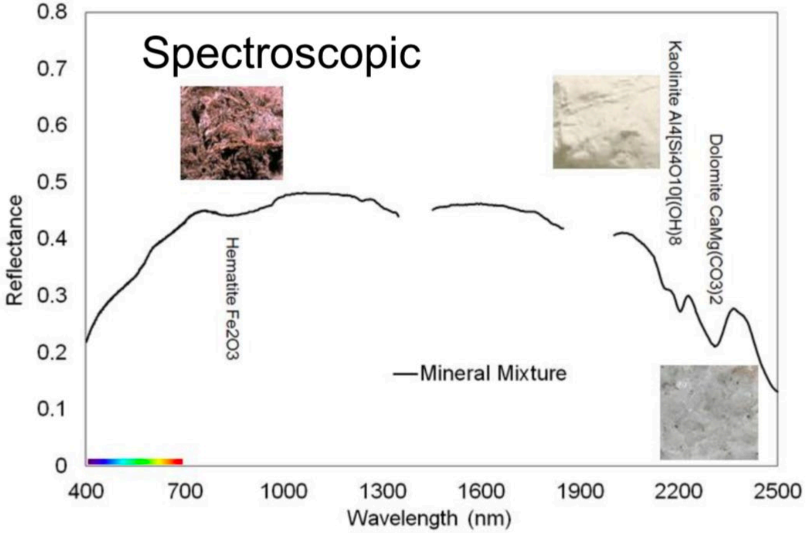


Measurement process – 100s of parallel spectrometers



Imaging spectroscopy vs. multiband analysis





Multiband	Imaging Spectroscopy
Typically built with optical filters	Uses dispersive elements (e.g. gratings)
1-10s of bands	100s of channels
Image-space (morphological) analyses	Spectroscopy using each pixel independently
Band math, thresholds, trees	Feature fitting and shape matching
Often mathematically underdetermined	Often mathematically overdetermined
Analyses are often qualitative	Quantitative measurement with uncertainties
Empirical modeling	Empirical or physics-based modeling

Imaging spectroscopy at JPL

1982

1986


1989
1997

2000

1998

2005


2009

2008

First Imaging Spectrometer AIS flights in 1982

AVIRIS imaging spectrometer >1000 refereed journal articles

NIMS imaging spectrometer to Jupiter

VIMS imaging spectrometer to Saturn

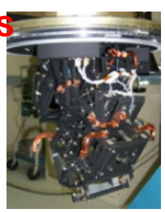
MICAS Miniature Integrated Camera and Imaging Spectrometer to Comet

Hyperion-Earth, CRISM-Mars and ARTEMIS-Earth imaging spectrometers (gratings, designs, calibration, science)

NASA Moon Mineralogy Mapper (M3)

> 7 Airborne/Rover-type Imaging Spectrometer operating at cryogenic temperature and in a vacuum (2005-2015)

24 Months

MaRS 2005

24 Months

24 Months

CAO 2010


< 18 Months

MSS 2011


AVIRIS-NG 2012


PRISM 2012


UCIS 2013


ESWIRS 2014


MISE 2015


CWIS 2016

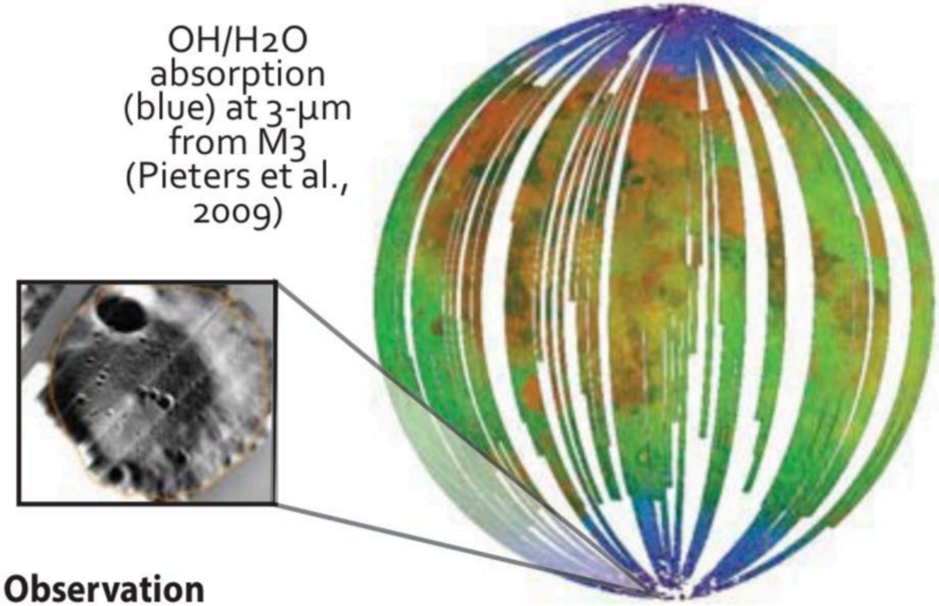

VS-Dyson 2017

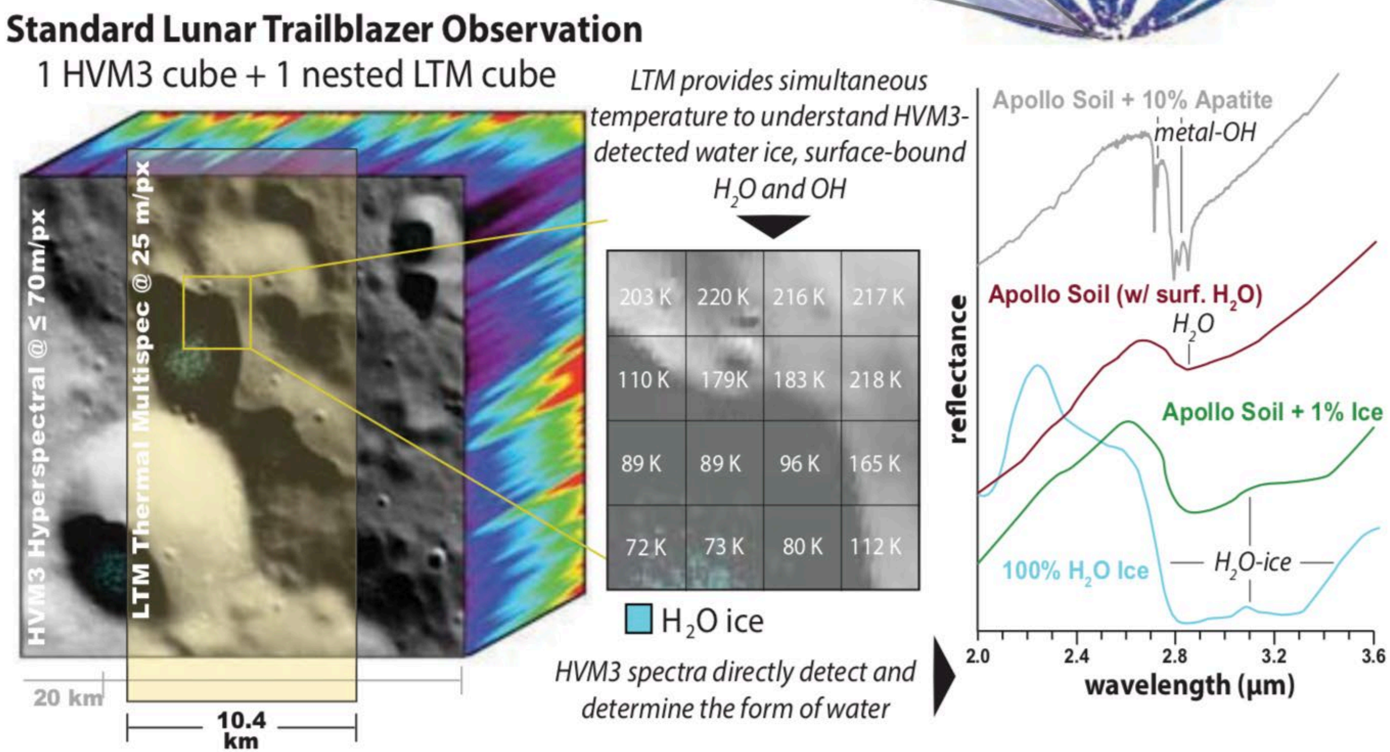

Lunar Trailblazer Mission

PI: Bethany Ehlmann, Caltech

Faustini crater PSR from terrain-scattered light (Cisnaros et al., 2016)

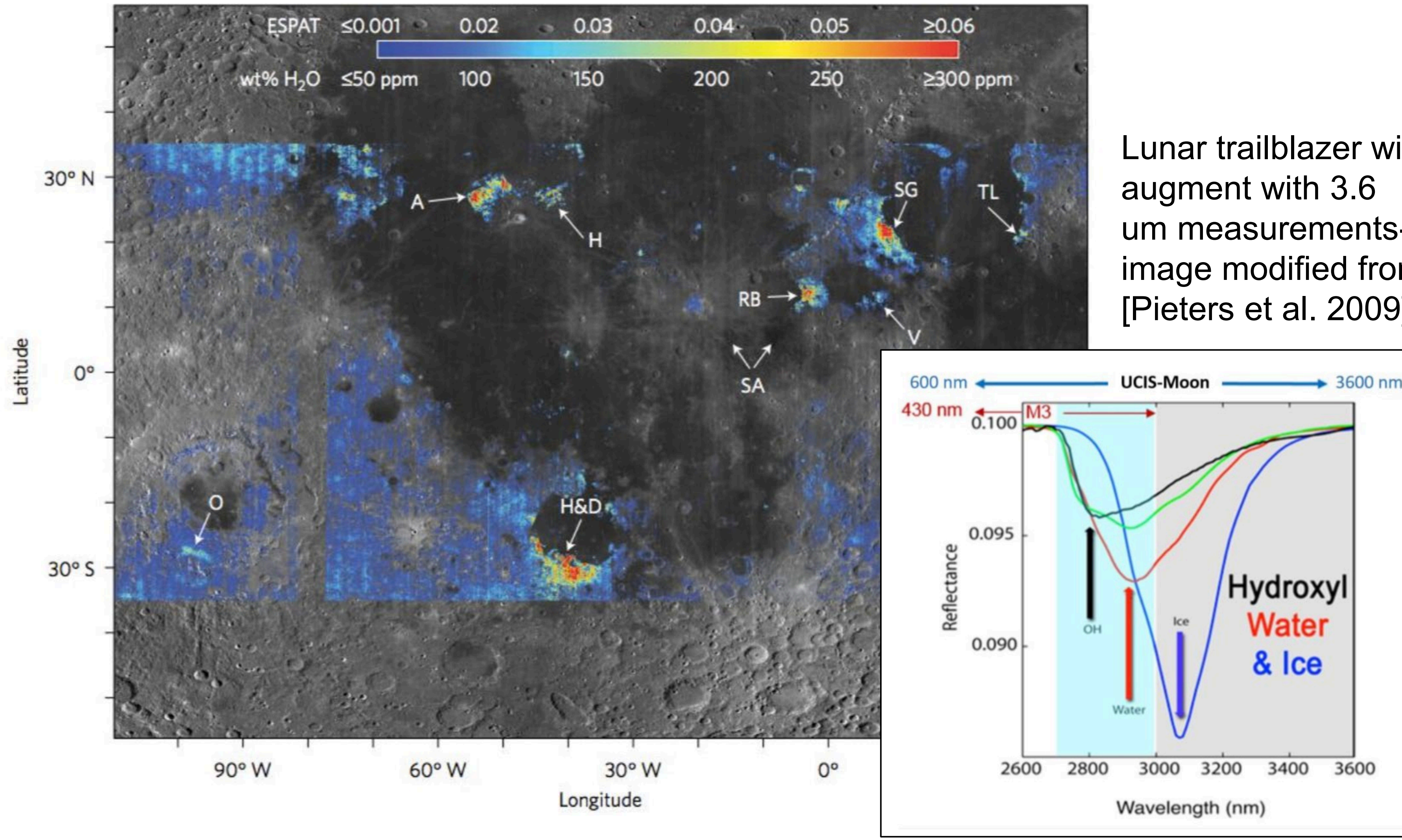
OH/H2O absorption (blue) at 3-µm from M3 (Pieters et al., 2009)





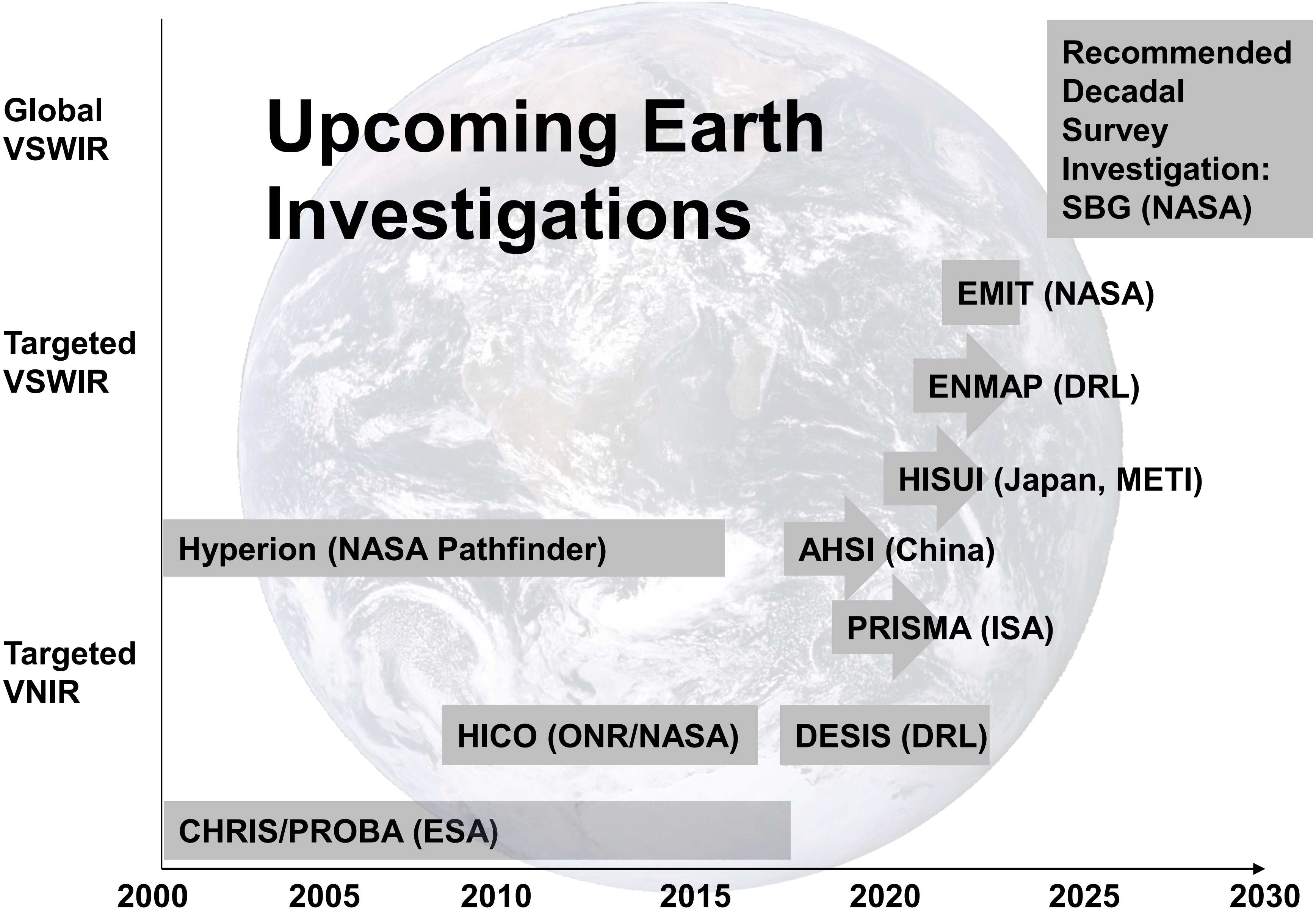
Map of lunar water from 85 degree latitude

From [Milliken and Li, 2017]

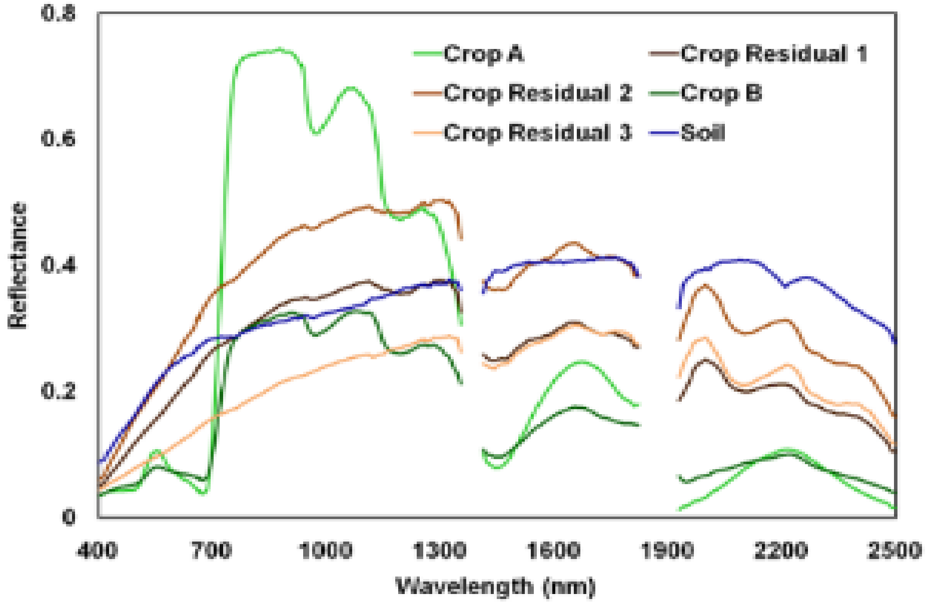


Lunar trailblazer will augment with 3.6 um measurements- image modified from [Pieters et al. 2009]

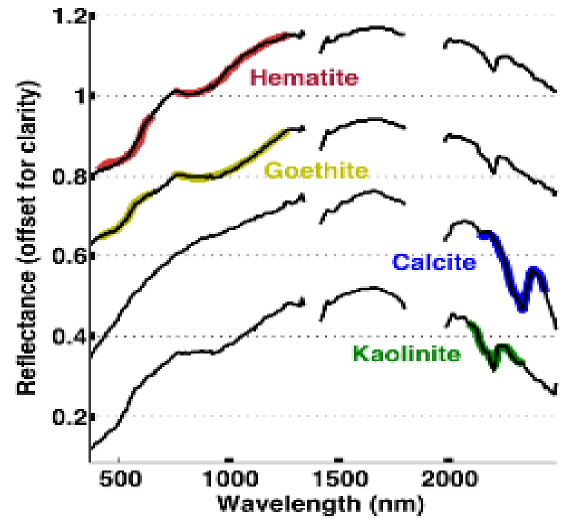
Upcoming Earth Investigations



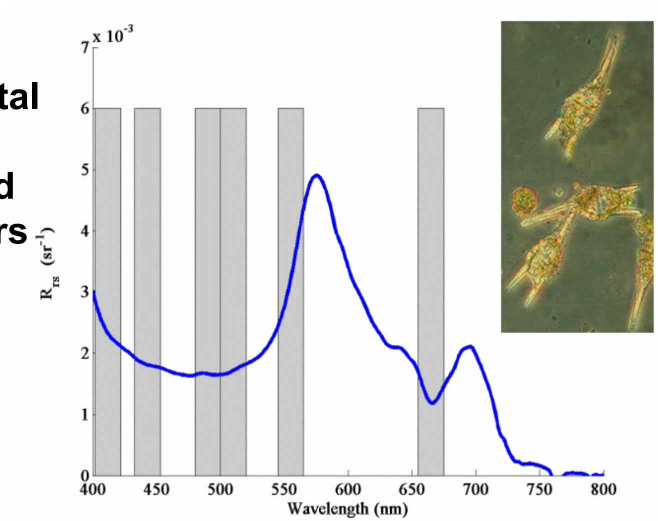
Agriculture and Terrestrial Ecosystems



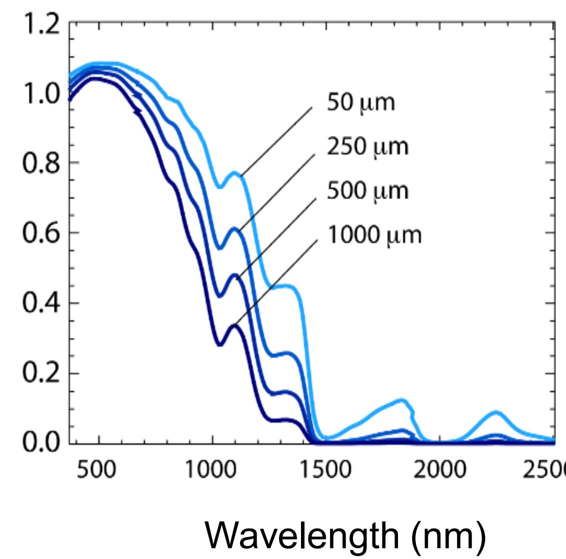
Geology, Soils, Surface Composition



Coastal and Inland Waters



Snow and Ice



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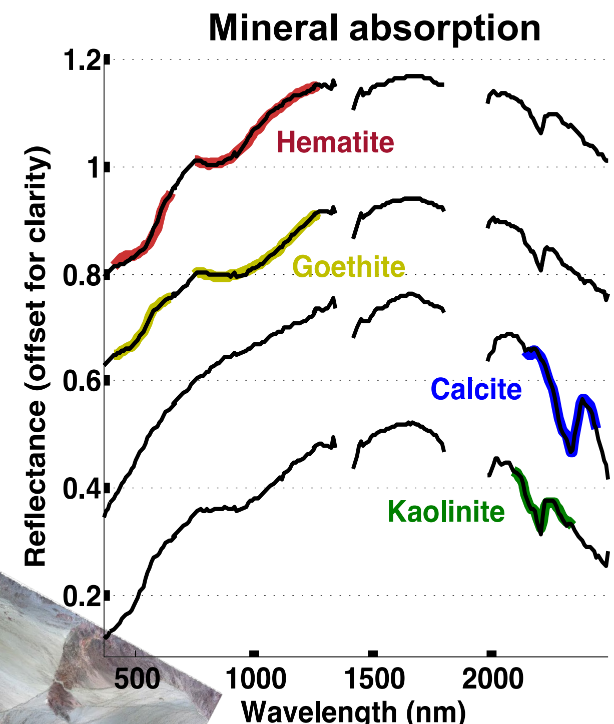
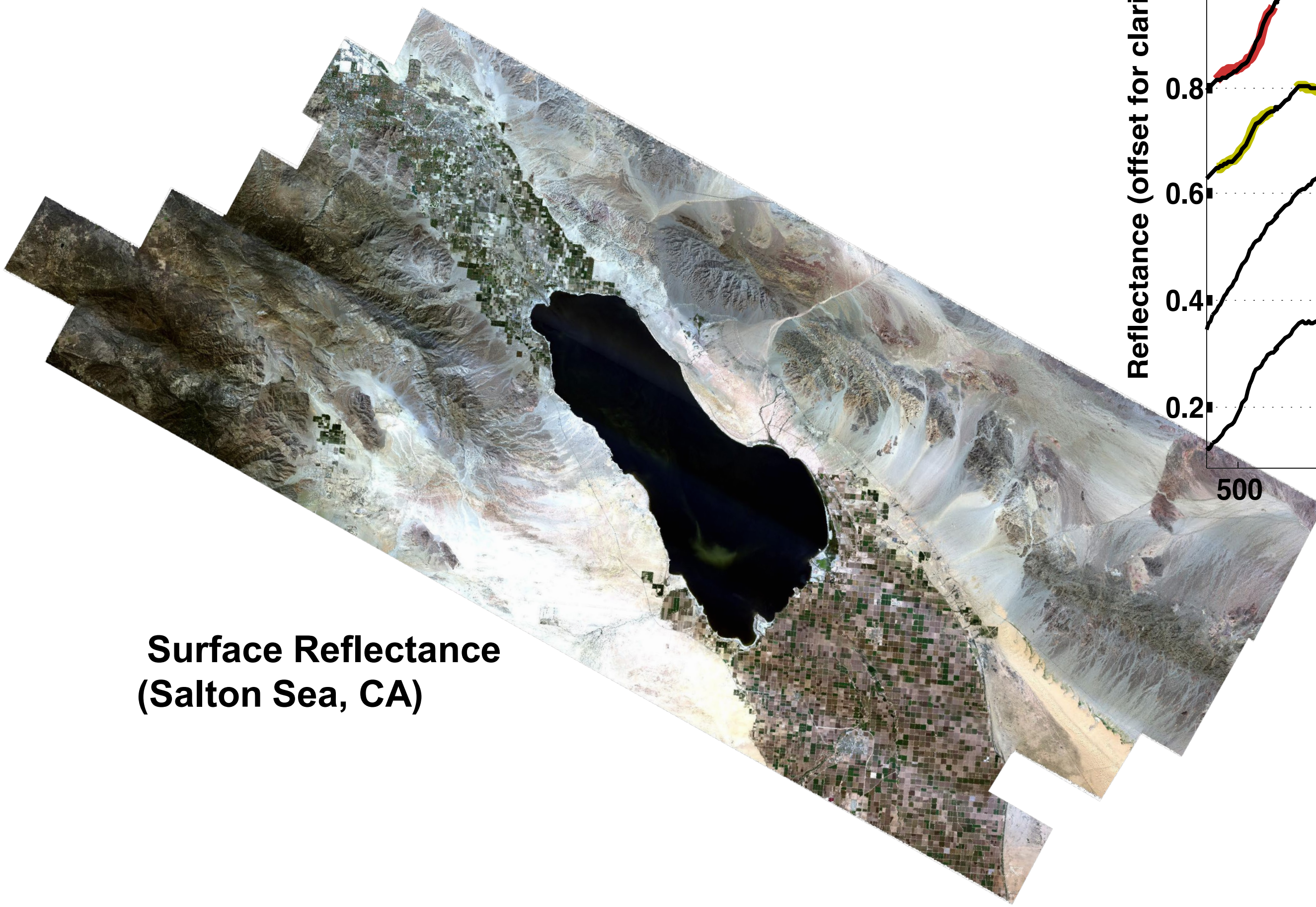
Example: Geologic Mapping via absorption fitting



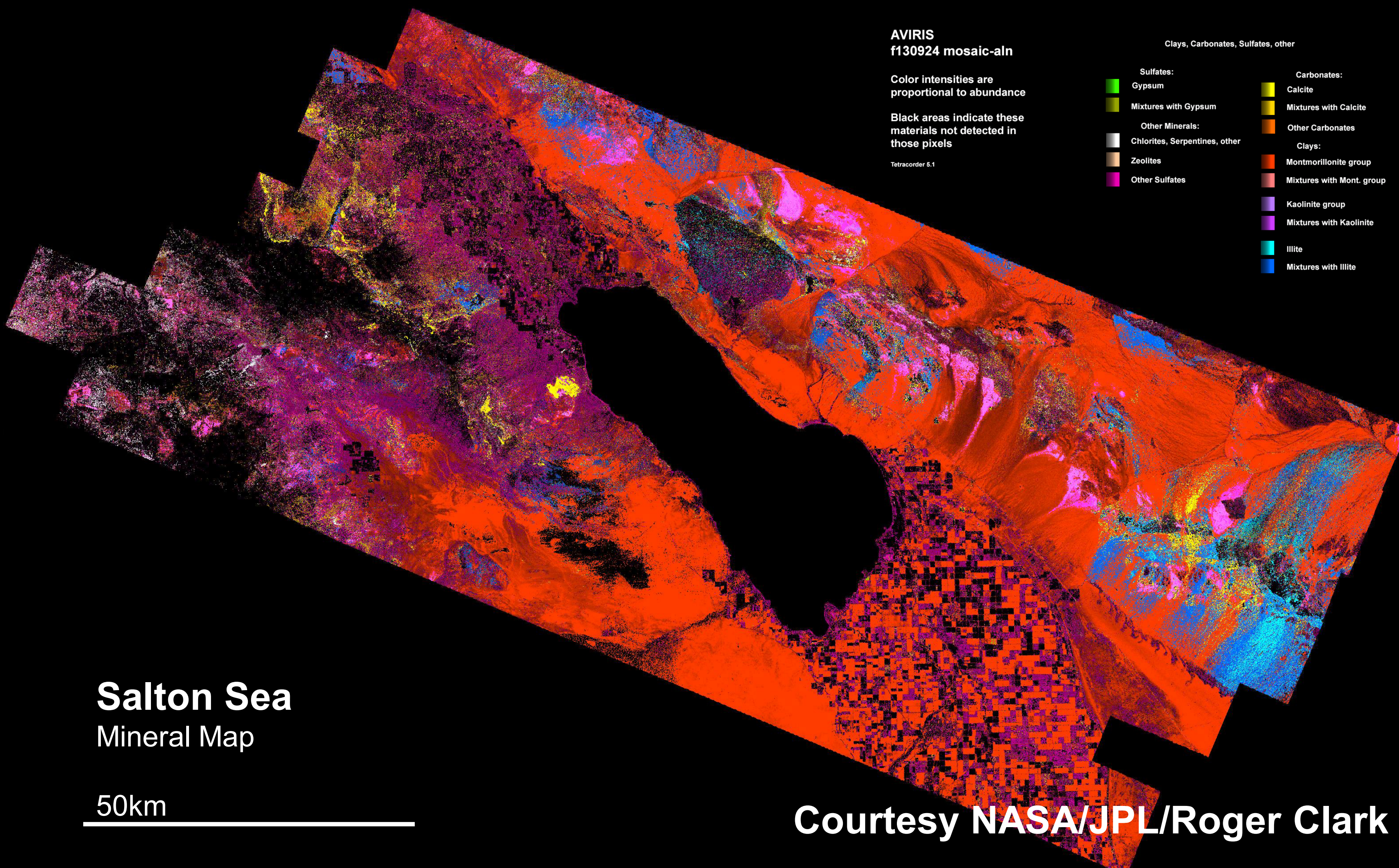


Surface Reflectance
(Salton Sea, CA)

Salton Sea, CA (AVIRIS instrument)

Courtesy NASA/JPL/Roger Clark

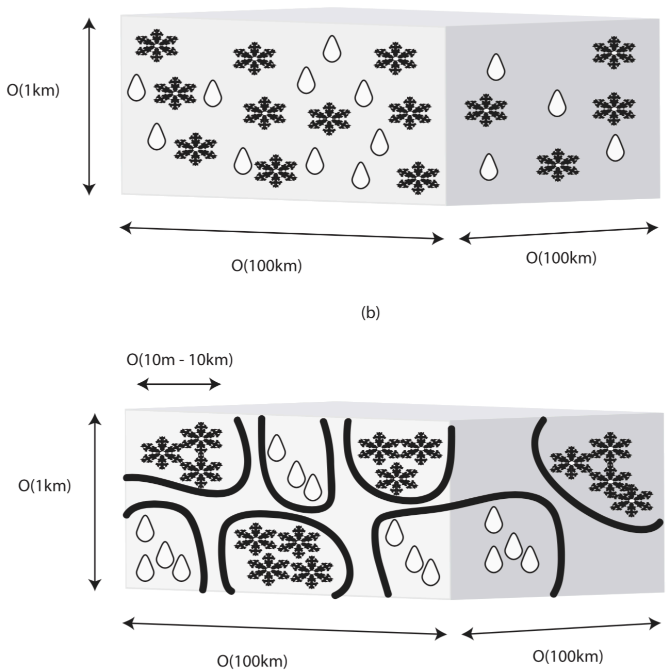
Salton Sea, CA (AVIRIS instrument)



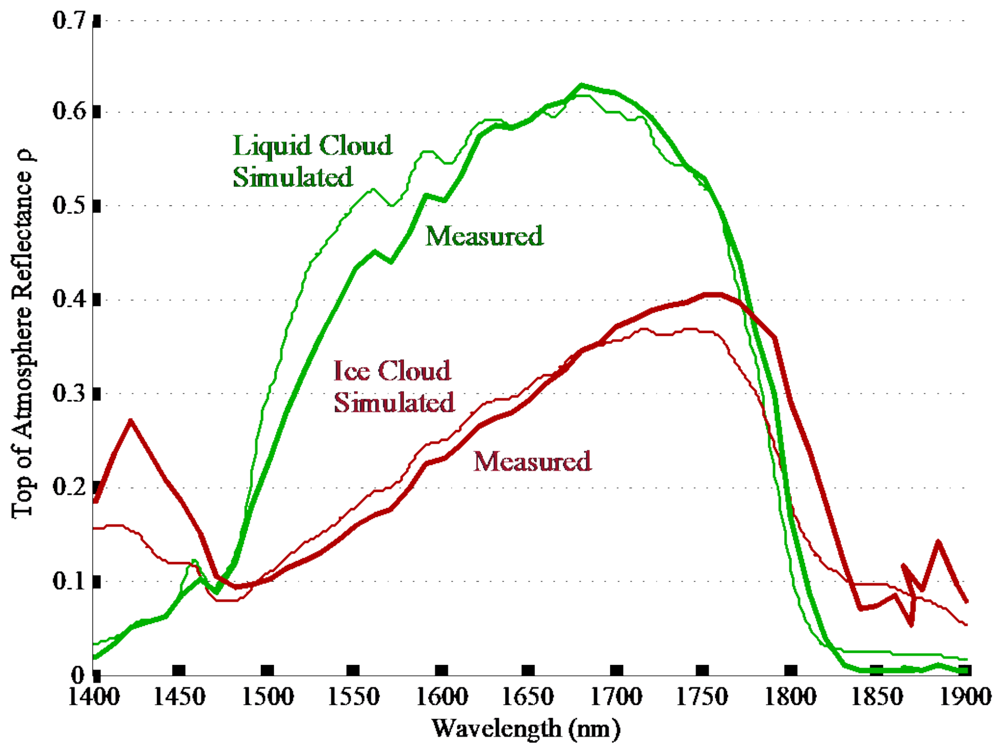
Courtesy NASA/JPL/Roger Clark

Cloud optical properties at high spatial resolution

Important for sub-gridsquare GCM parameterizations and glaciation rates of mixed clouds

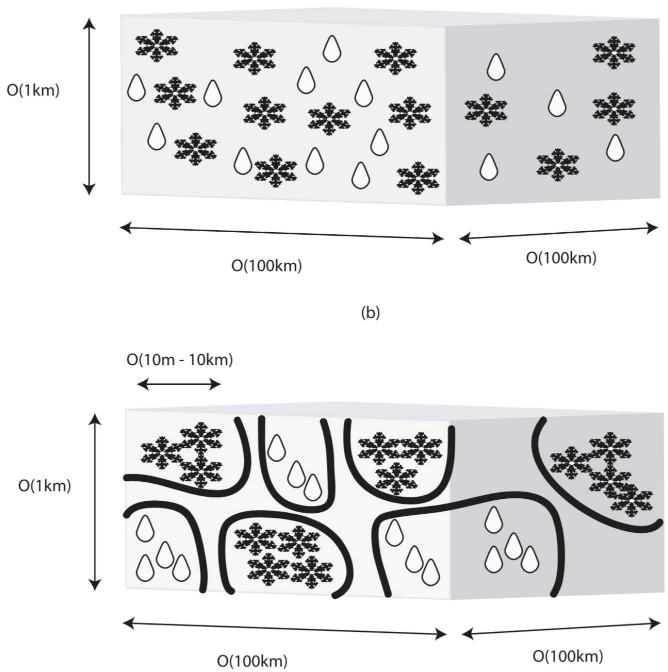


Tan and Storelvmo, Journal of the Atmospheric Sciences, 2016

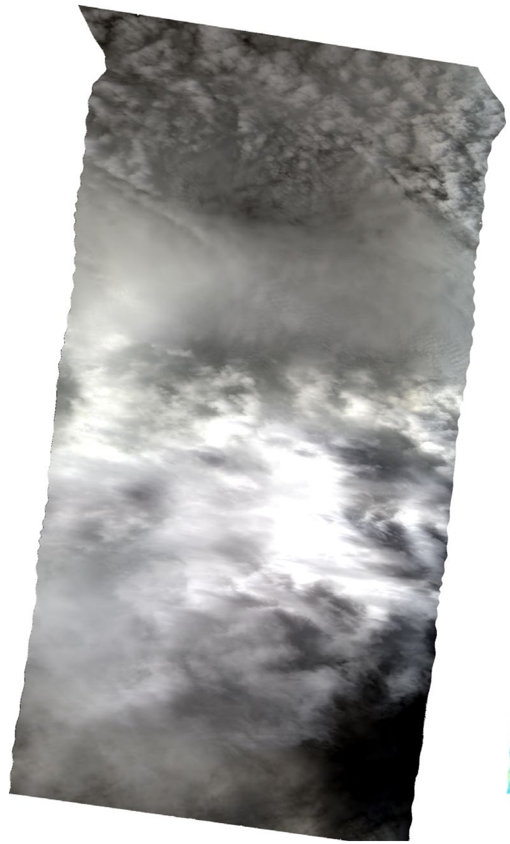


Cloud optical properties at high spatial resolution

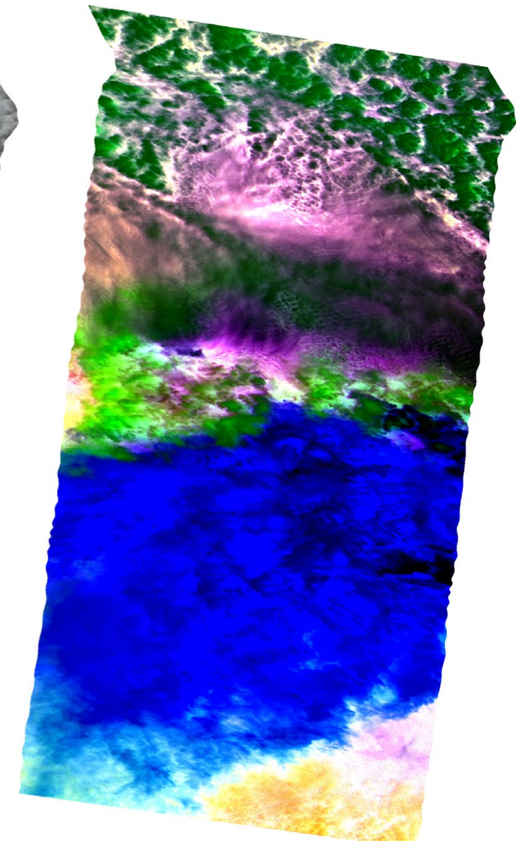
[Thompson et al., JGR 2016]



Tan and Storelvmo, Journal of the Atmospheric Sciences, 2016

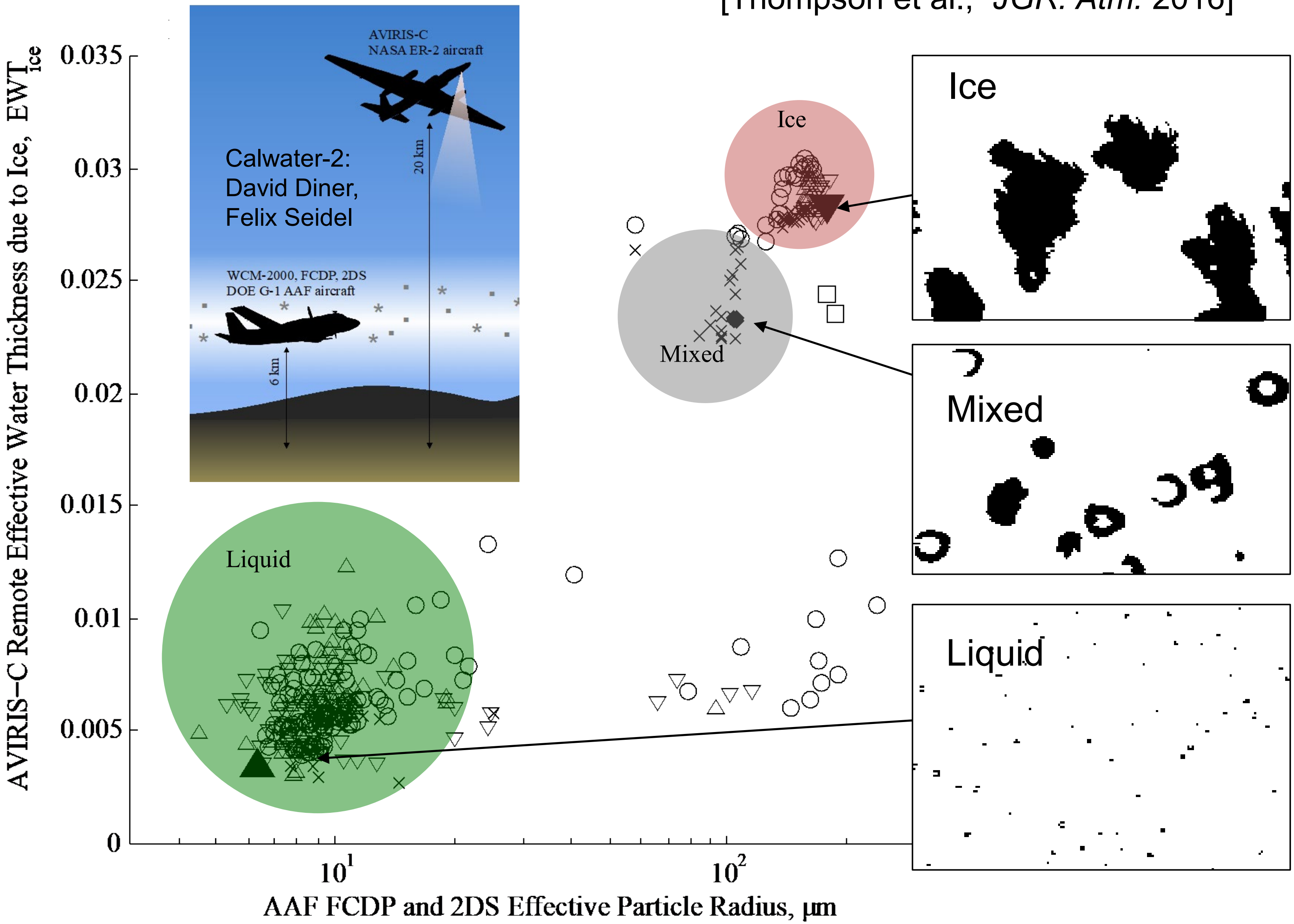


RGB Image

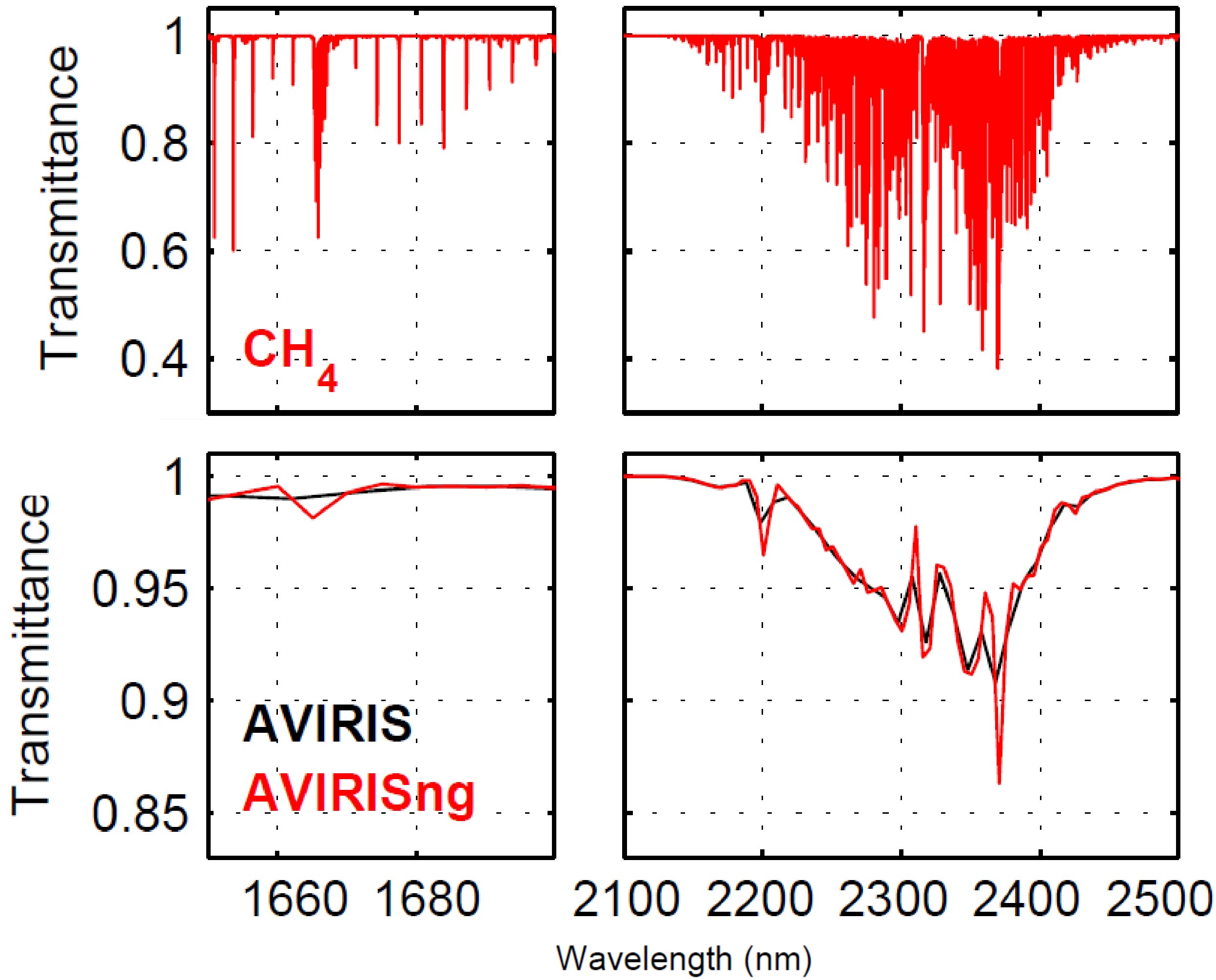


Ice Liquid
Vapor

[Thompson et al., *JGR. Atm.* 2016]

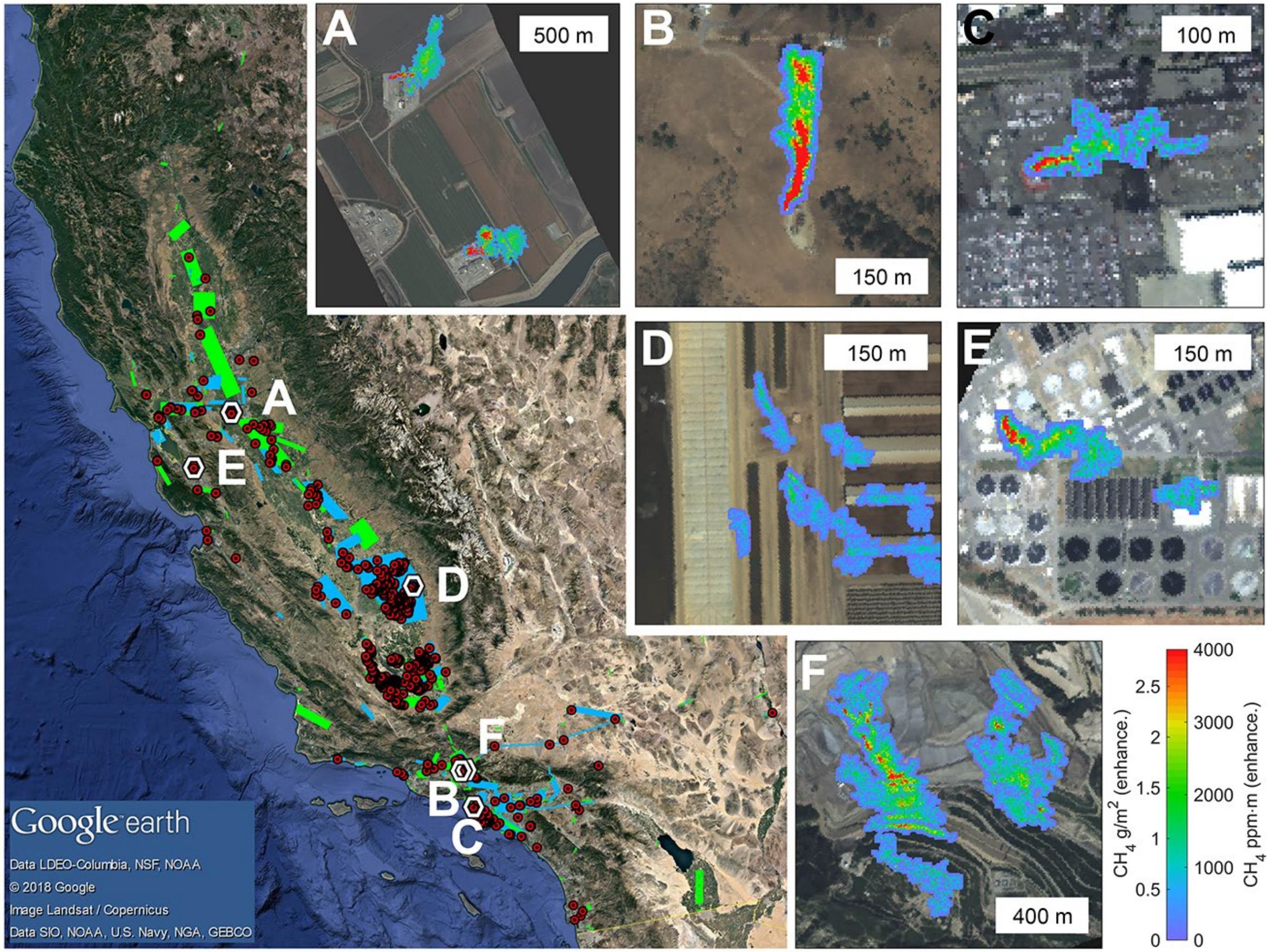


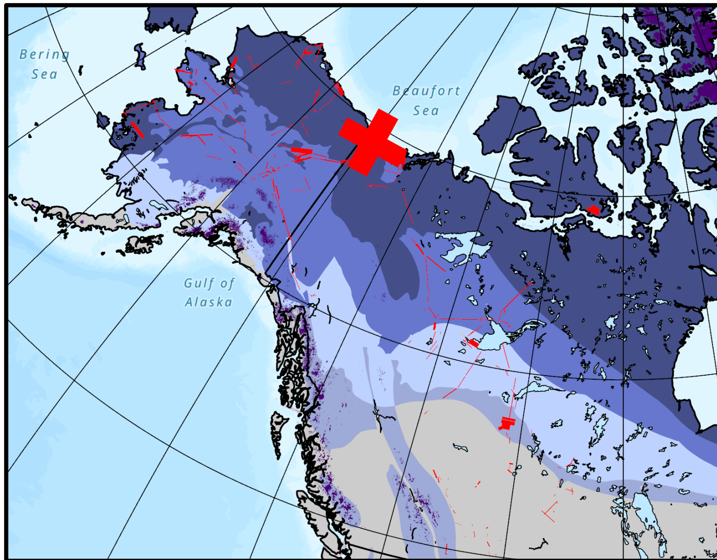
Localized greenhouse sources

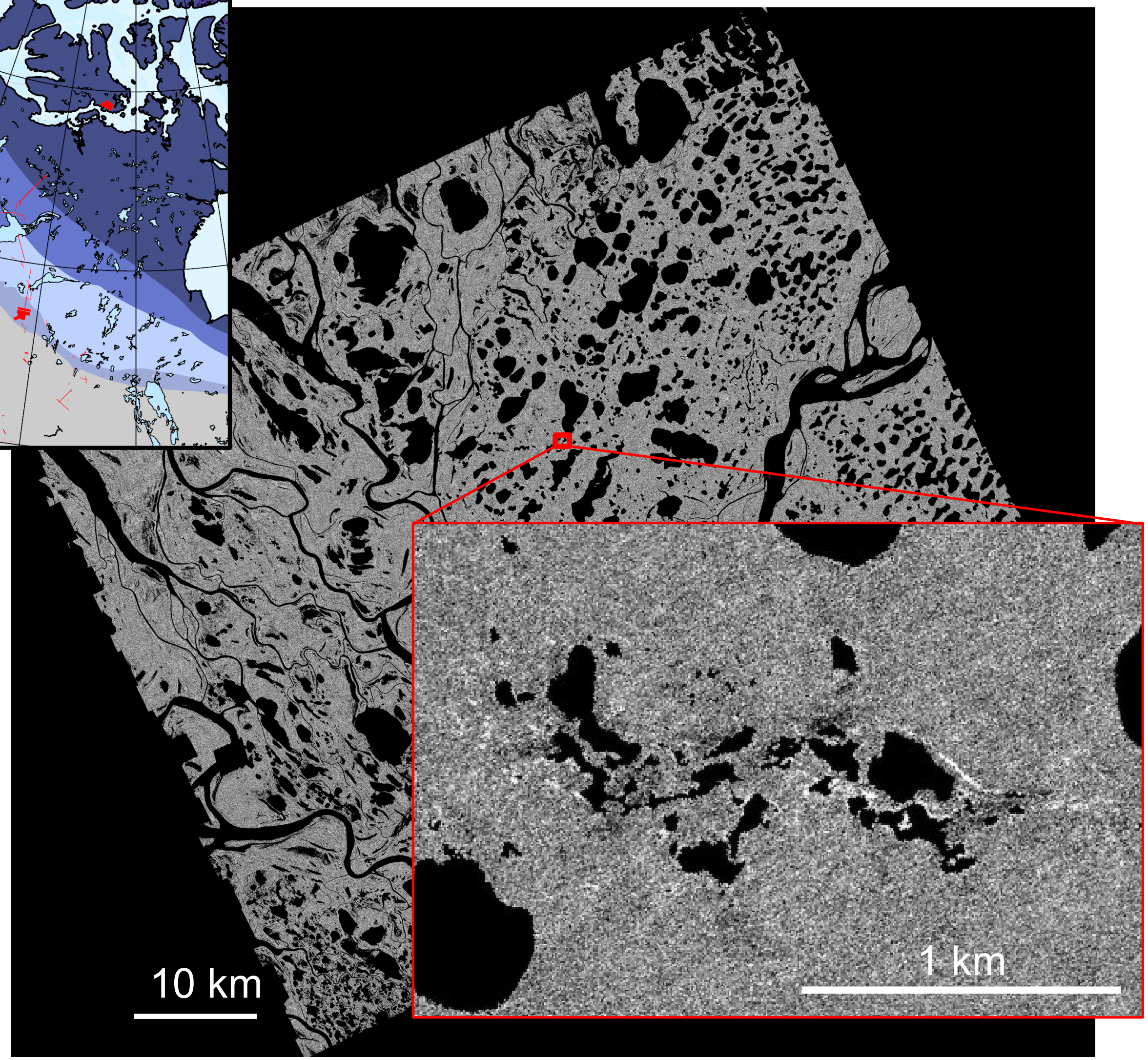


CH_4 in California

[Duren et al. *Nature,* in press); Thorpe et al., 2016; Thompson et al. 2015 & 2016]





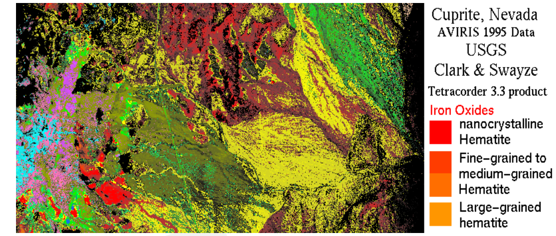


Natural CH_4 emissions in the Arctic

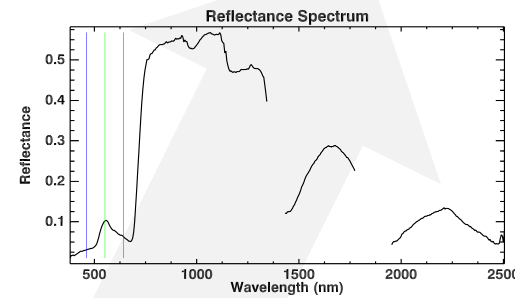
Elder, Thompson, et al.
[in preparation]

Functional elements of surface analyses

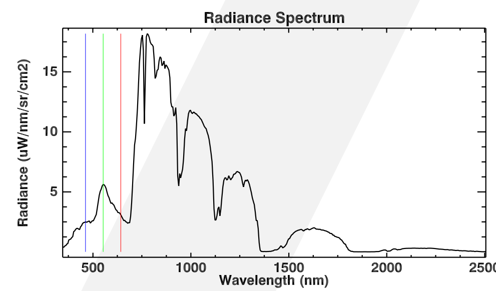
L3: Maps of Geophysical Variables



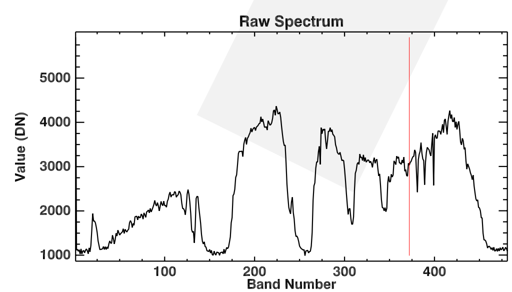
L2: Lambertian Reflectance (VSWIR) Emissivity/Temp (TIR)



L1: Orthorectified Radiance at sensor mW/nm/cm^2/sr

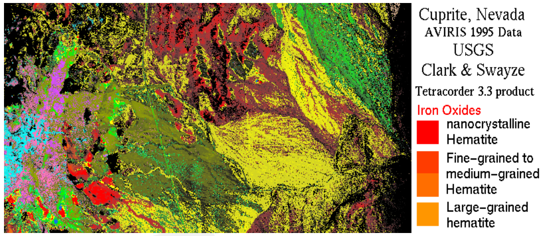


L0: Raw Digital Numbers

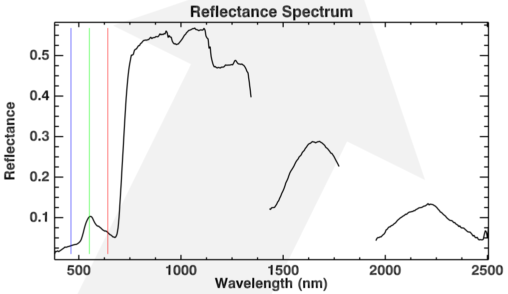


Typical data volumes

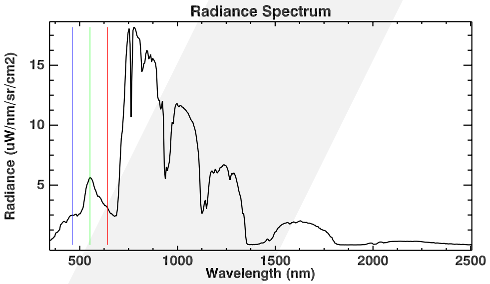
L3: ? GB per acquisition second



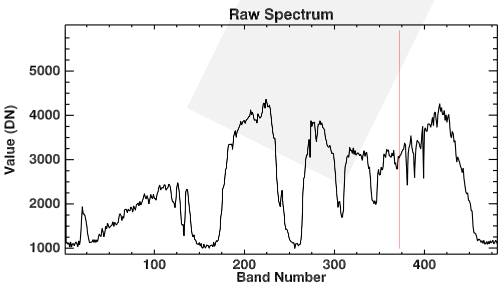
L2: 3 GB per acquisition second



L1: 3 GB per acquisition second



L0: 3 GB per acquisition second



~15 Tb/day acquisition is easily possible

over 50 TB of data per day of uncompressed L0-L2 data

Band arithmetic or dot products (trivial)

Closed form linear algebra (fast)

Iterative nonlinear optimization (slower)

***Possible external dependencies**

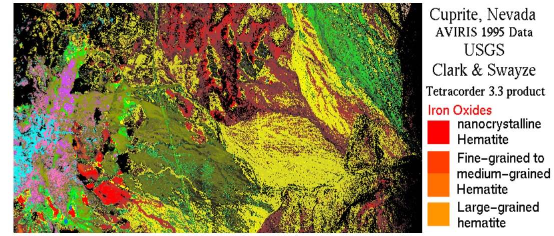
Fit reflectance signatures

Band ratios

Least squares

Matched filter

M.A.P model inversion



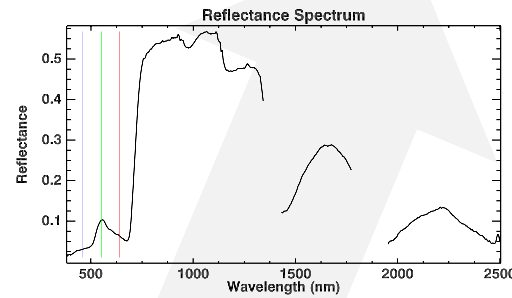
Calculate surface signal

I/F division (standard)

Topographic corrections*

M.A.P. model inversion*

Iterative thermal estimation*



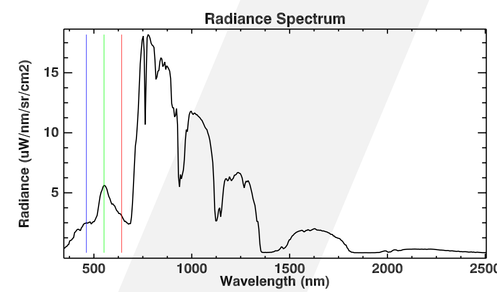
Calibration

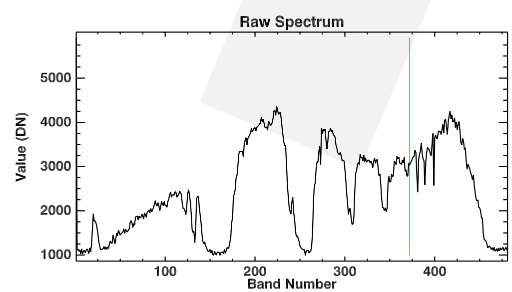
Radiometric calibration*

PSF Corrections

Radiation correction

Bad pixel inference





Compression

Lossless 4x in real time

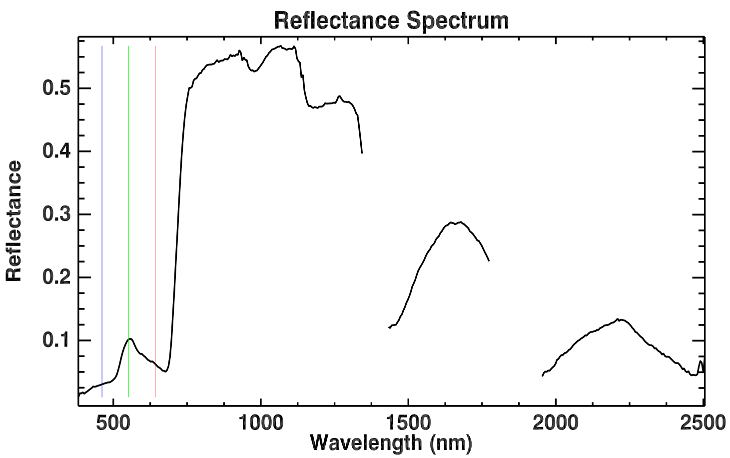
Algorithms

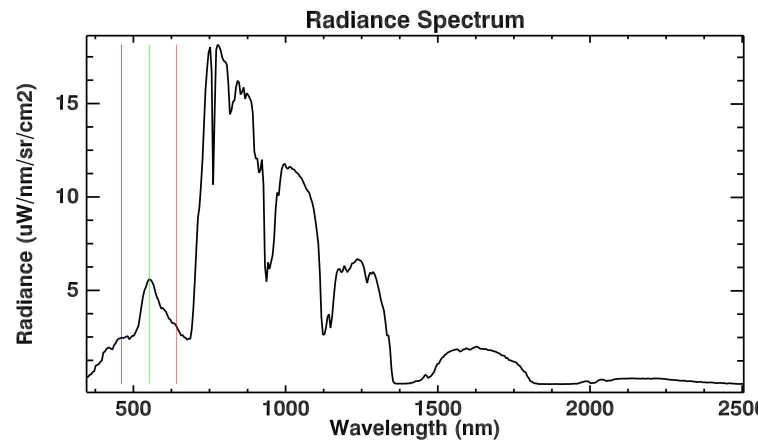
Iterative model inversion methods

[Thompson et al., *Remote Sensing of Environment* 2018, 2019a, 2019b]

1. Predict radiance

$$\mathbf{y} = \mathbf{F}(\mathbf{x}) + \epsilon$$





2. Optimize state vector

$$\underbrace{\chi^2(\mathbf{x})}_{\text{Cost}} = \underbrace{(\mathbf{F}(\mathbf{x}) - \mathbf{y})^{\mathrm{T}}\, \mathbf{S}_{\epsilon}^{-1}\, (\mathbf{F}(\mathbf{x}) - \mathbf{y})}_{\text{Model match to measurement}} + \underbrace{(\mathbf{x} - \mathbf{x}_{\mathrm{a}})^{\mathrm{T}}\, \mathbf{S}_{\mathrm{a}}^{-1}\, (\mathbf{x} - \mathbf{x}_{\mathrm{a}})}_{\text{Bayesian prior}}$$

Parallelizability

Global scale

- L4+ Planetary Maps and Global Models at low res

Multiple scenes, one domain

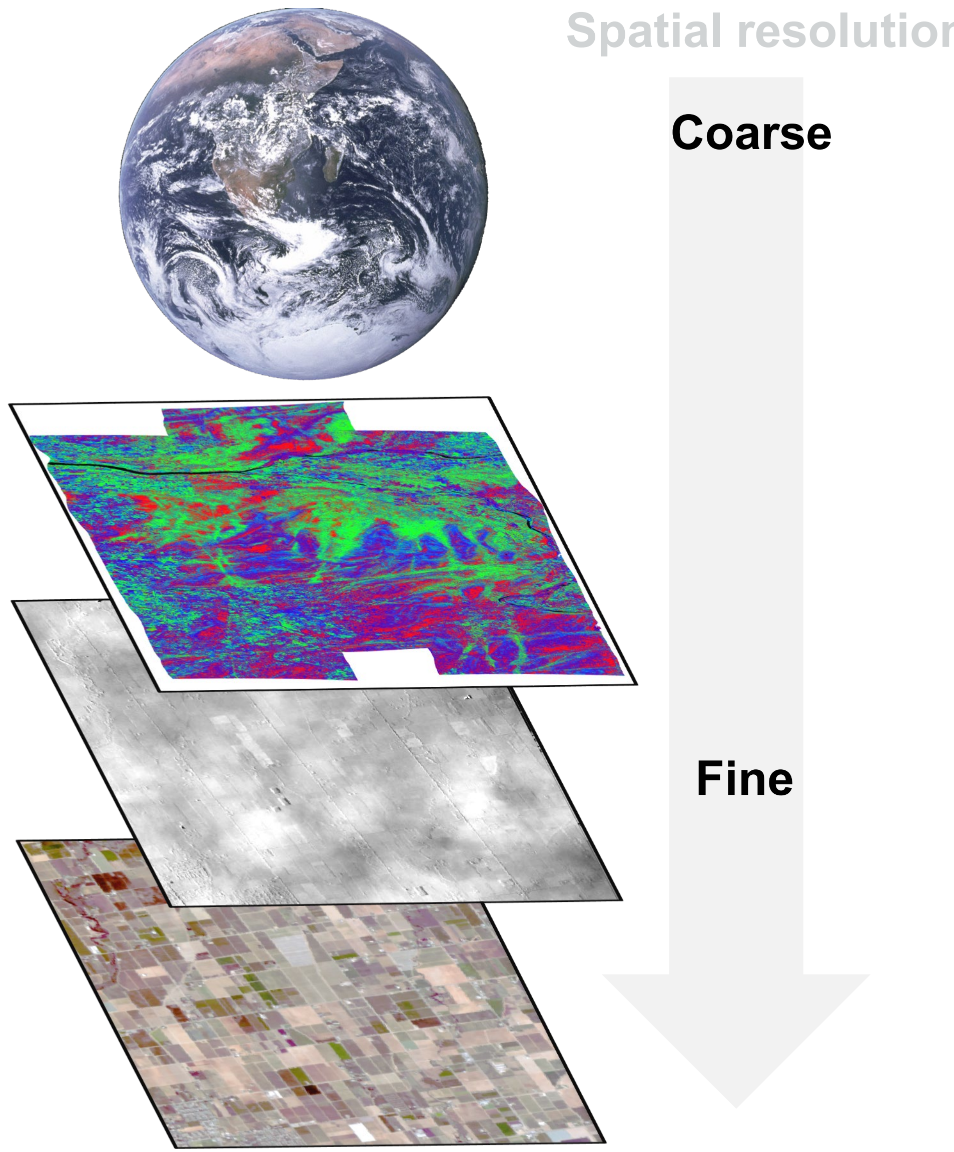
- Region-wide Analyses
- Time series
- Possibly lower spatial resolution

Multiple spectra, one scene

- Region of interest analysis
- Some atmospheric studies

Independent spectra or aggregated spectra

- ALL standard products



AVIRIS-C RGB and H_2O field from [Thompson et al., *Surveys in Geophys.* 2019]

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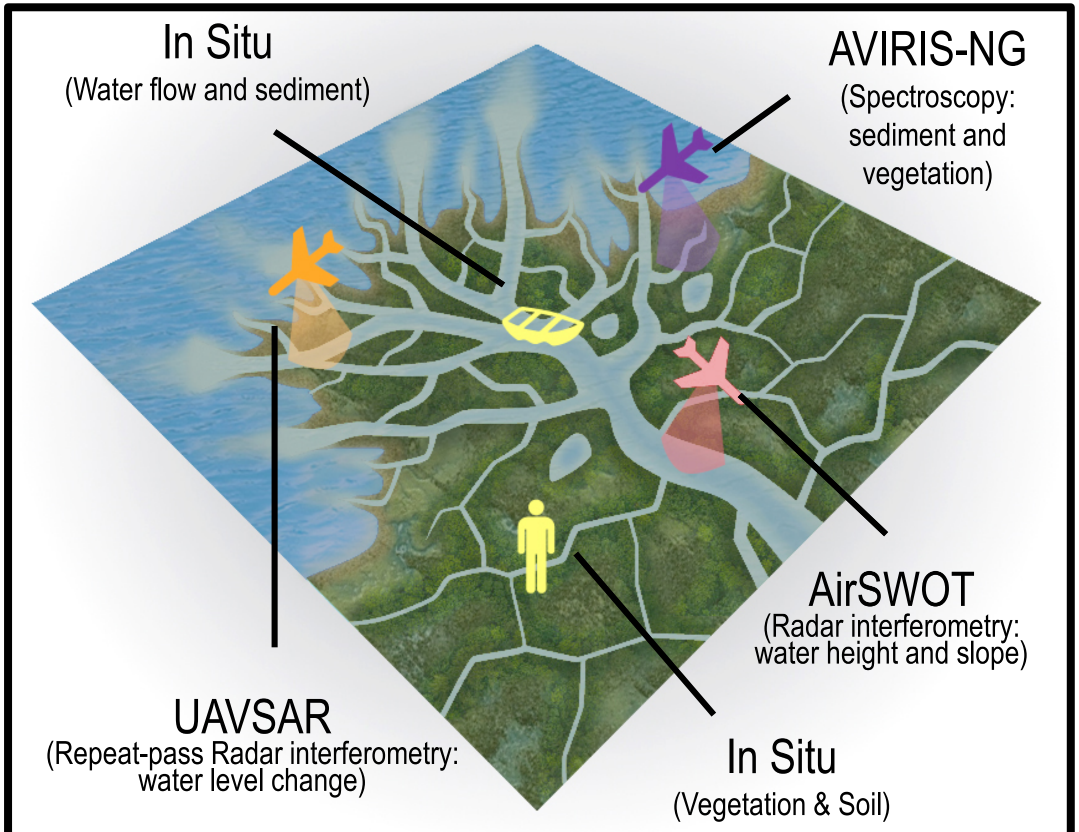
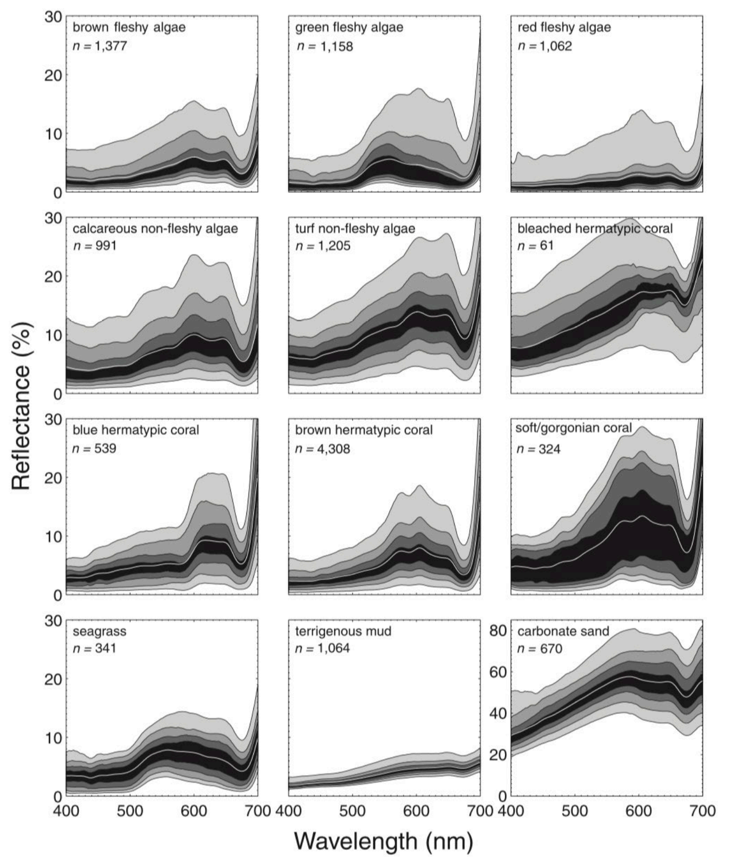
Delta-X EV-S mission PI: Marc Simard

Urgency: If ignored, Relative Sea Level Rise (RSLR) will very soon have devastating consequences on the livelihood of the half billion people that live in these low-lying coastal regions. Nearly all the world's major river deltas are threatened along with the services they provide: flood protection, carbon sequestration, biodiversity and food supply.

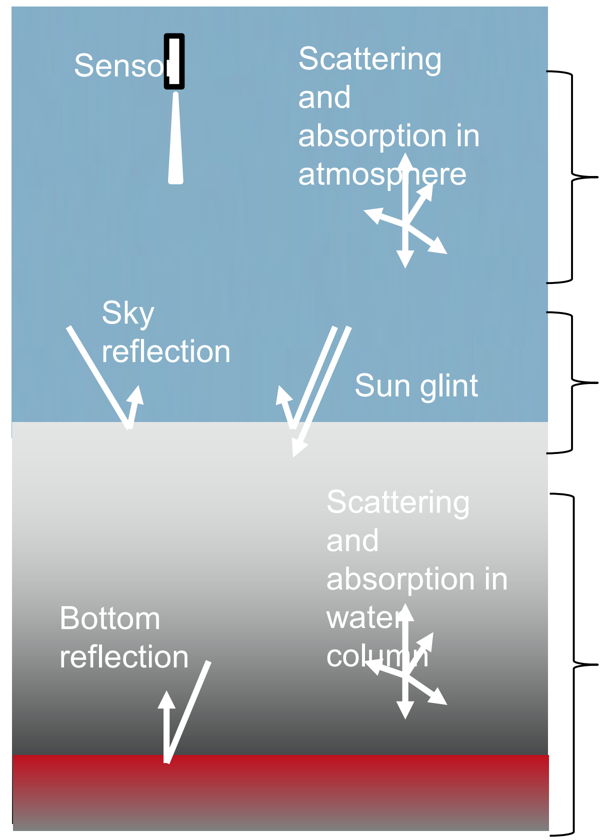


Delta-X Science Question: Will river deltas completely drown, or some parts of these deltas accumulate sufficient sediments and produce enough plants to keep pace with RSLR ?

NASA's CORAL Mission



Hochberg et al., *Remote Sensing of Environment* 2003



Step 1
Aerosol optical depth τ
Aerosol type ζ
Water leaving reflectance R_{rs}

Step 2
Glint-corrected Rrs_0

Step 3
Backscatter b_b
Attenuation K_d
Depth H
Benthic reflectance R_b

Thompson et al., *Remote Sensing of Environment* 2017

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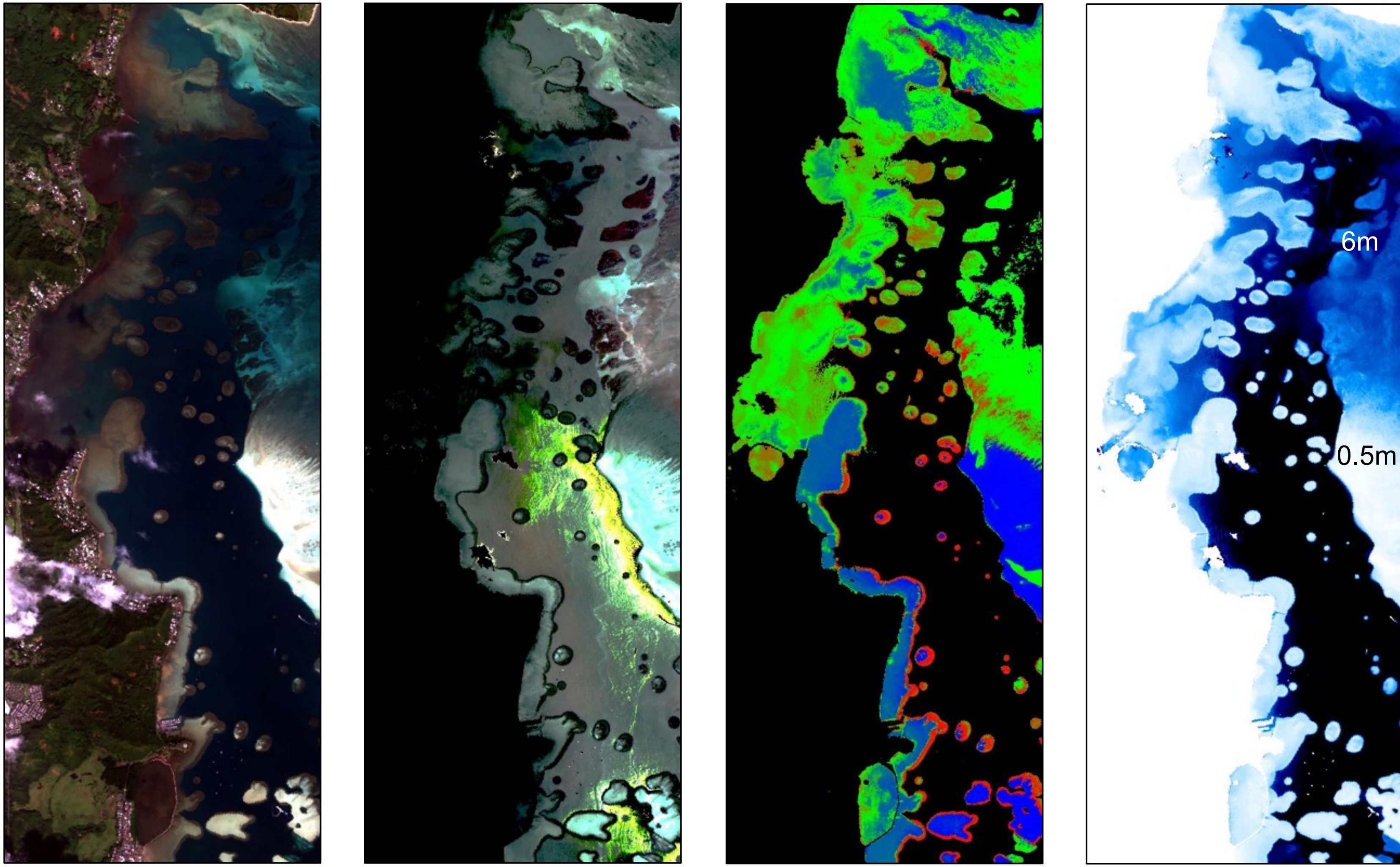
Water-leaving Reflectance | **Rb** | **Benthic Cover** | **Depth**



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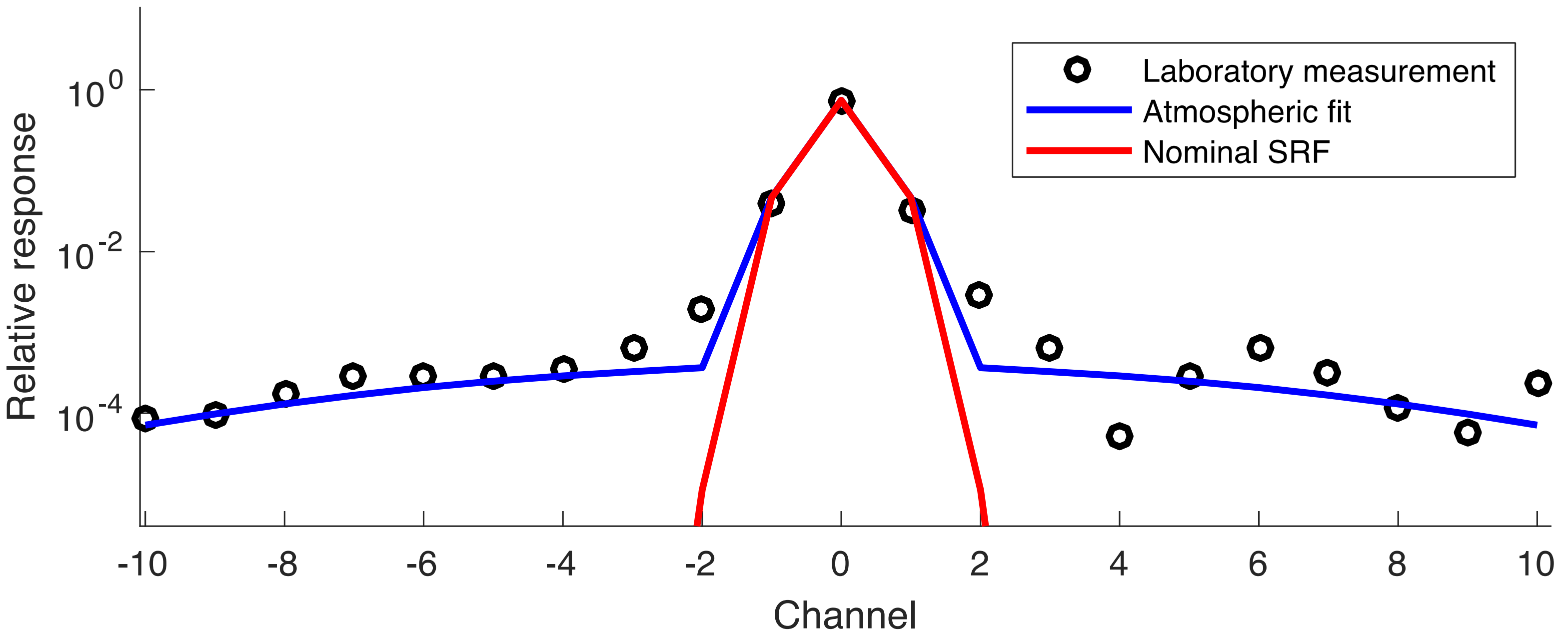
Agenda

- **Overview and upcoming missions**
- **Deep Dive 1:** Instrument characterization
- **Deep Dive 2:** CH_4 leaks, other greenhouse point sources
- **Deep Dive 3:** Optimal Estimation for surface/atmosphere retrievals

PSF Characterization

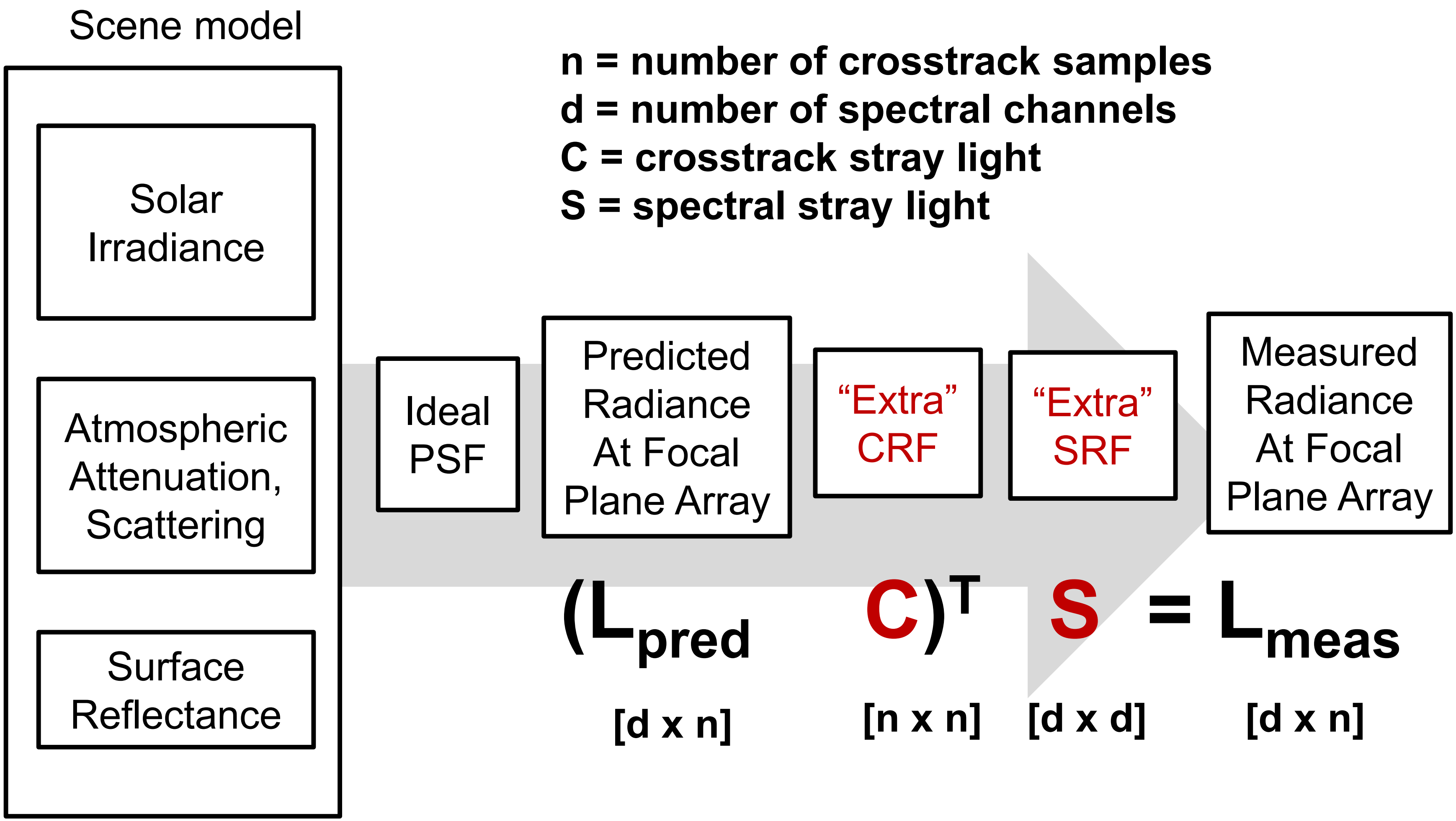
Subtle tails of the Focal Plane point spread function can:

- Disrupt fine atmospheric structure
- Create unwanted spatial blur



Measurement model

n = number of crosstrack samples
d = number of spectral channels
C = crosstrack stray light
S = spectral stray light



$$(L_{pred} \; C)^T \; S = L_{meas}$$

[d x n] **[n x n]** **[d x d]** **[d x n]**

Method

1. Find well-constrained properties of scenes' true radiance
2. Posit the functional forms of the CRF and SRF
3. Optimize free parameters to match observations via:

$$(L_{pred} \quad C)^T \quad S = L_{meas}$$

$$[d \times n] \quad [n \times n] \quad [d \times d] \quad [d \times n]$$

4. Correct future data using the following linear transformation:

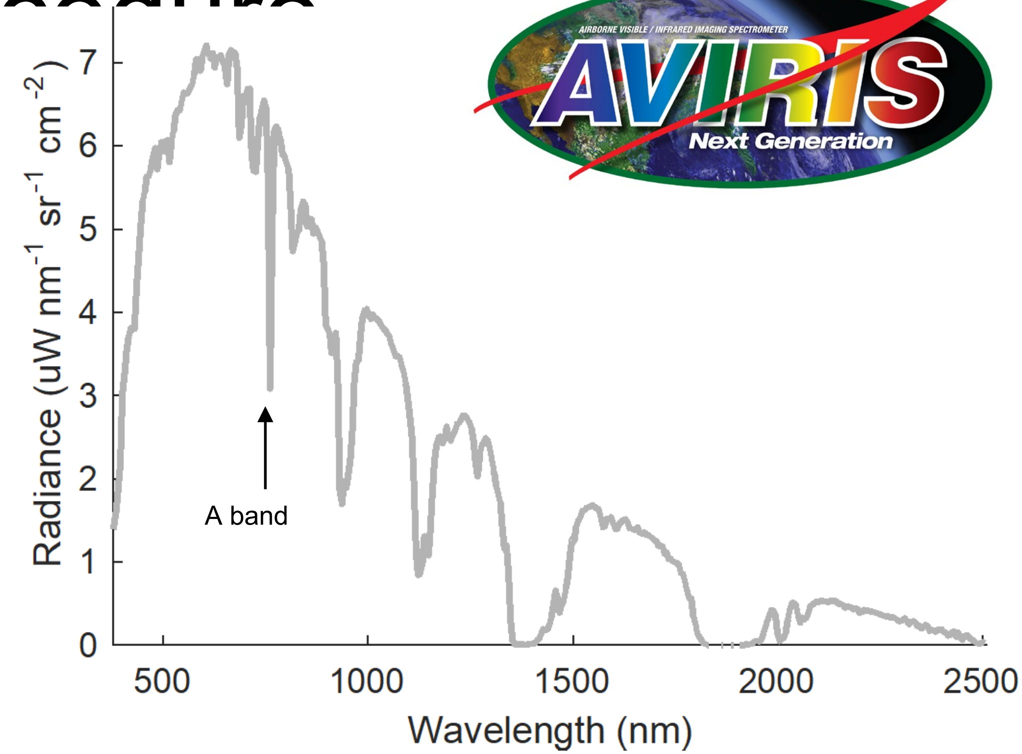
$$L_{corr} = ((C^T)^+ \, ((S^T)^+ \, L_{meas}{}^T)^T)^T$$

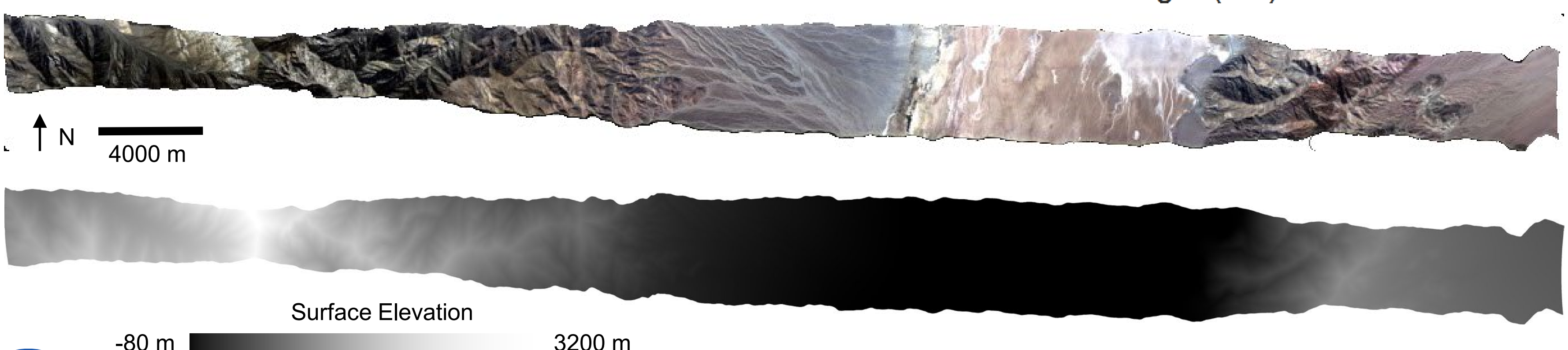
Here, $^+$ represents the Moore-Penrose inverse, e.g.

$$C^+ = (C^T C)^{-1} C^T \qquad C^+C = I$$

Procedure

- Exploit the predictable shape of the O_2 A band
- Find a haze-free day to constrain path radiance
- Calculate “true” A band based on elevation and sensor altitude
- Dataset: Death Valley transect, a large elevation gradient





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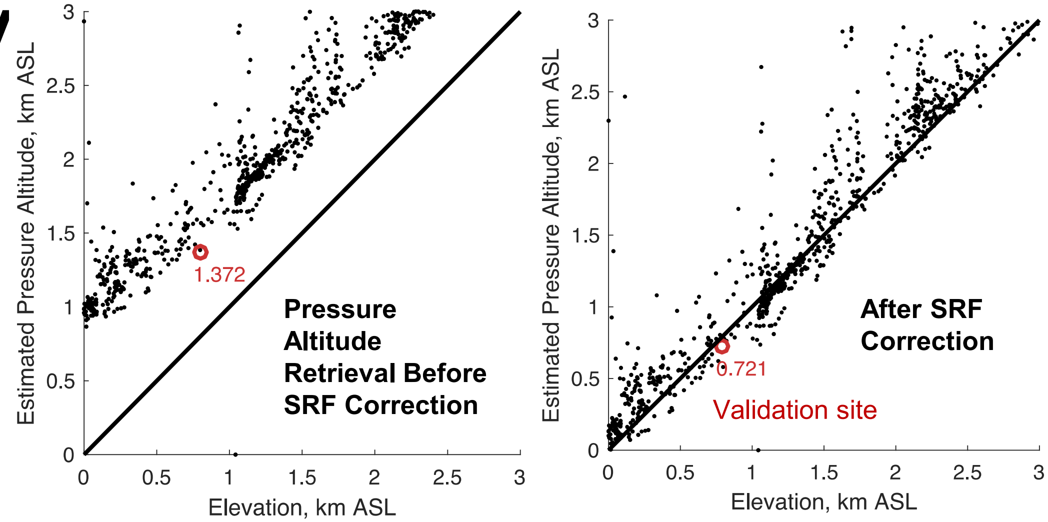
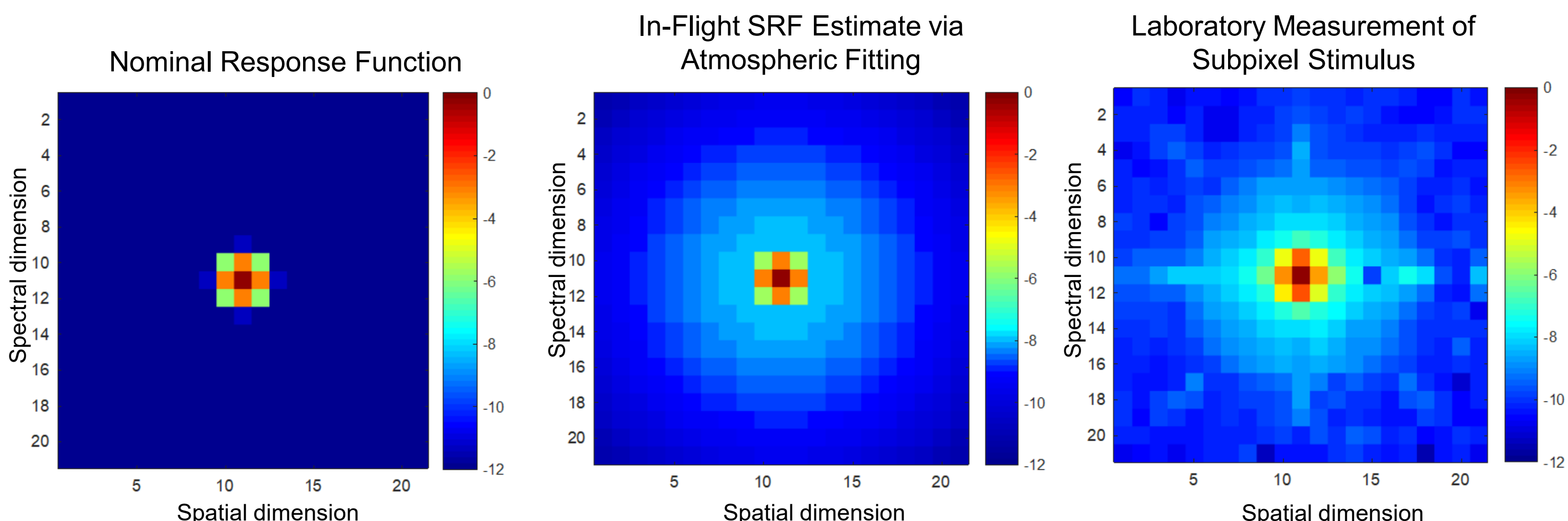
V

Methods include:

- Comparisons vs. lab measurements
- Pressure altitude predictions vs. DEMs
- Surface reflectance fidelity



Results from *Thompson et al., RSE 2018*



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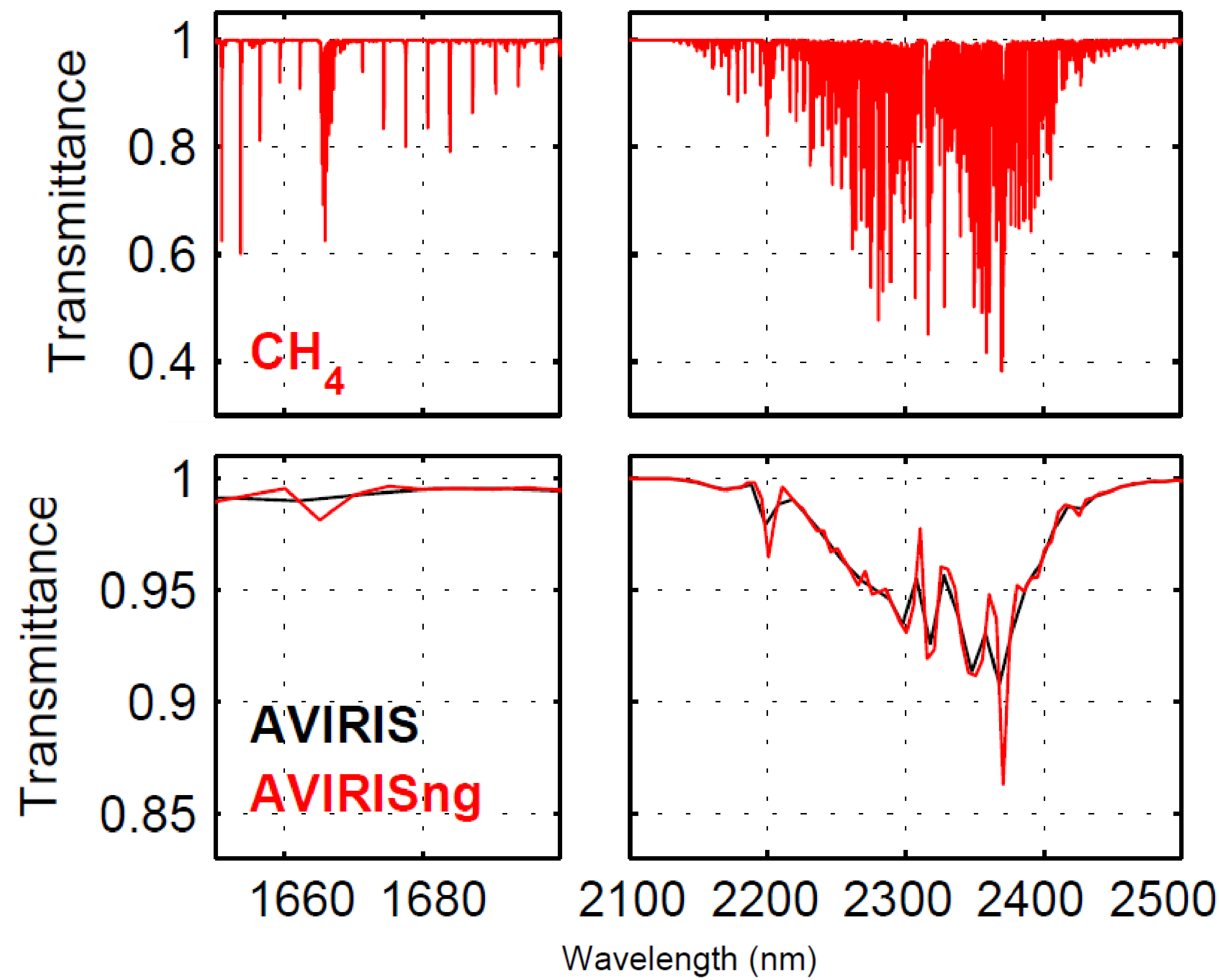
Localized greenhouse sources



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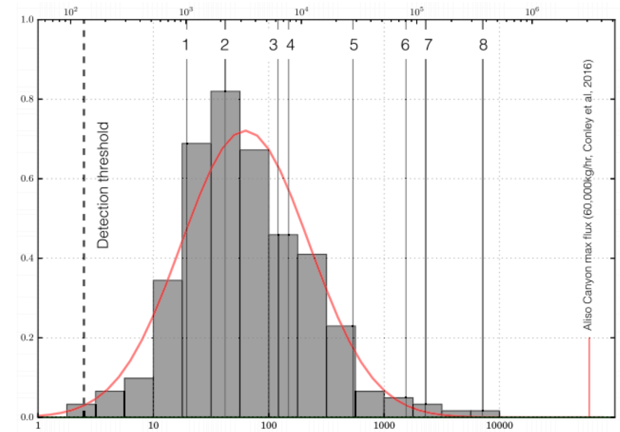
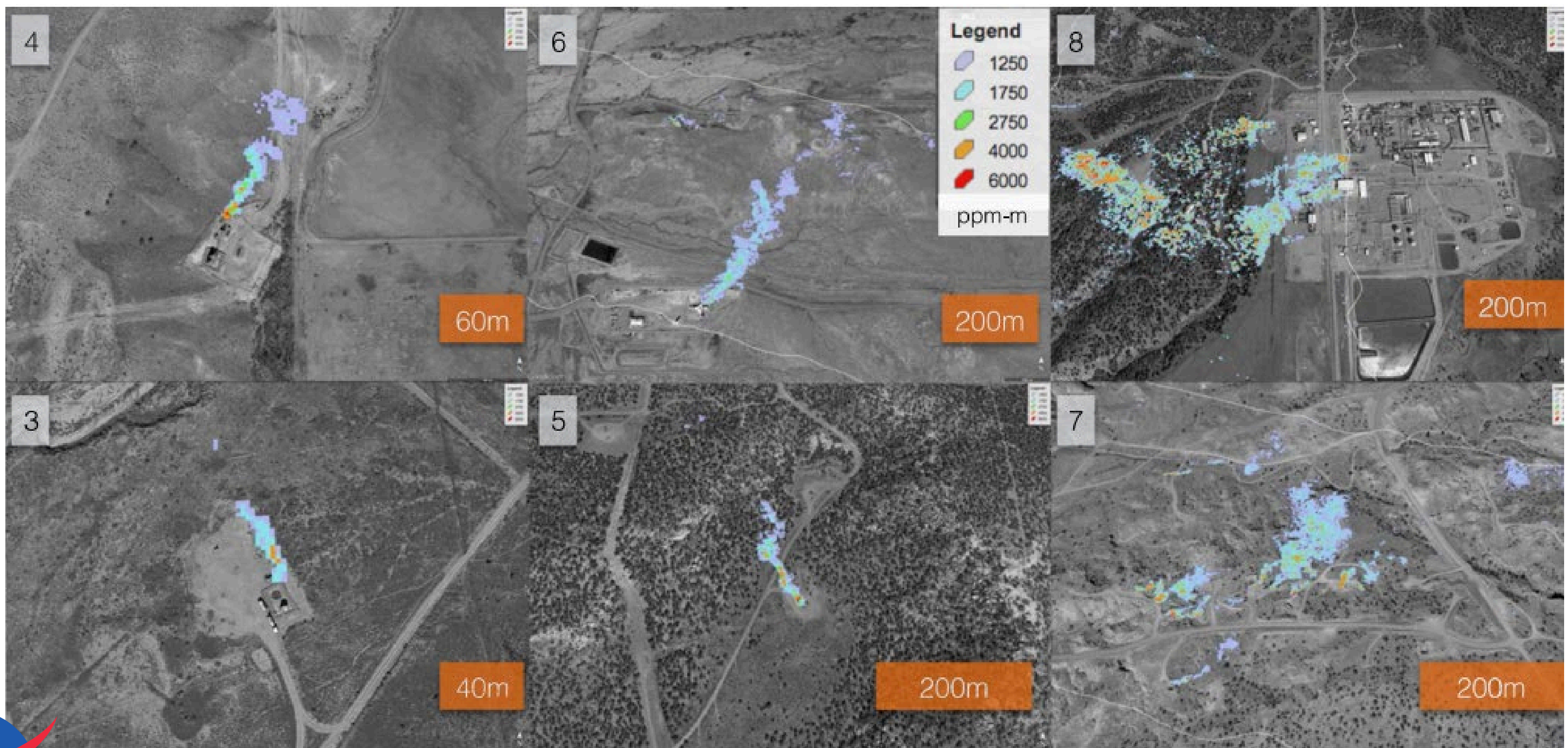
Fugitive CH_4 emissions at Four Corners, NM

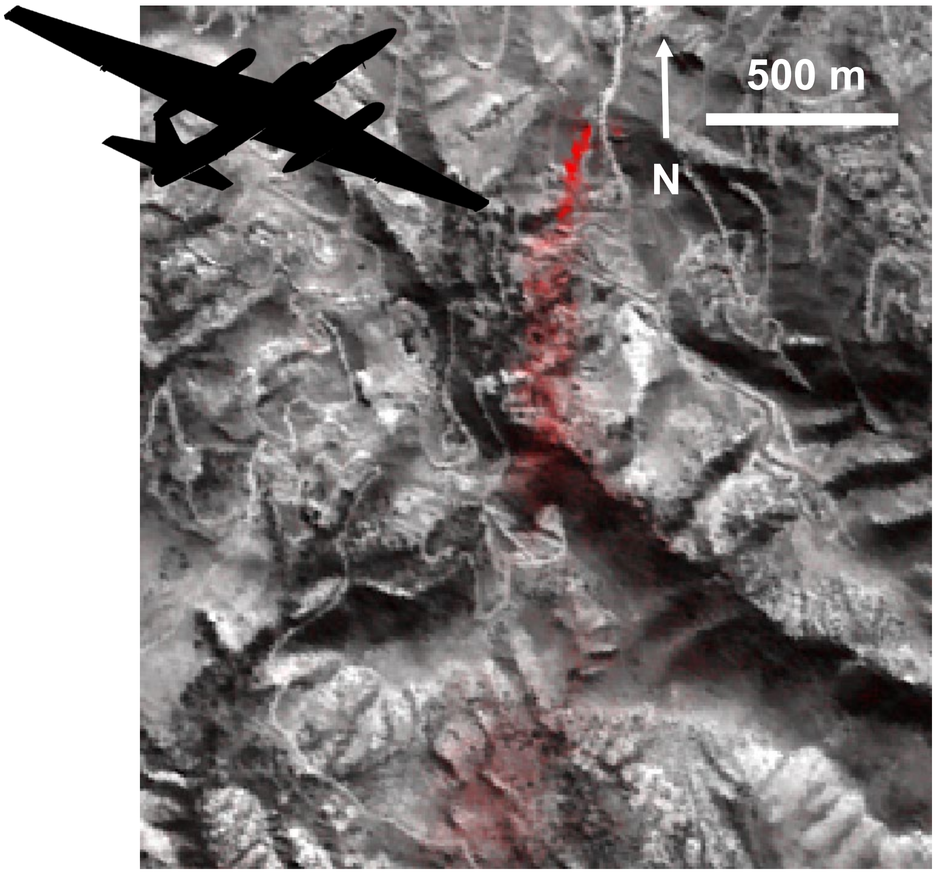
Frankenberg, Thorpe, Thompson et al., PNAS 2016



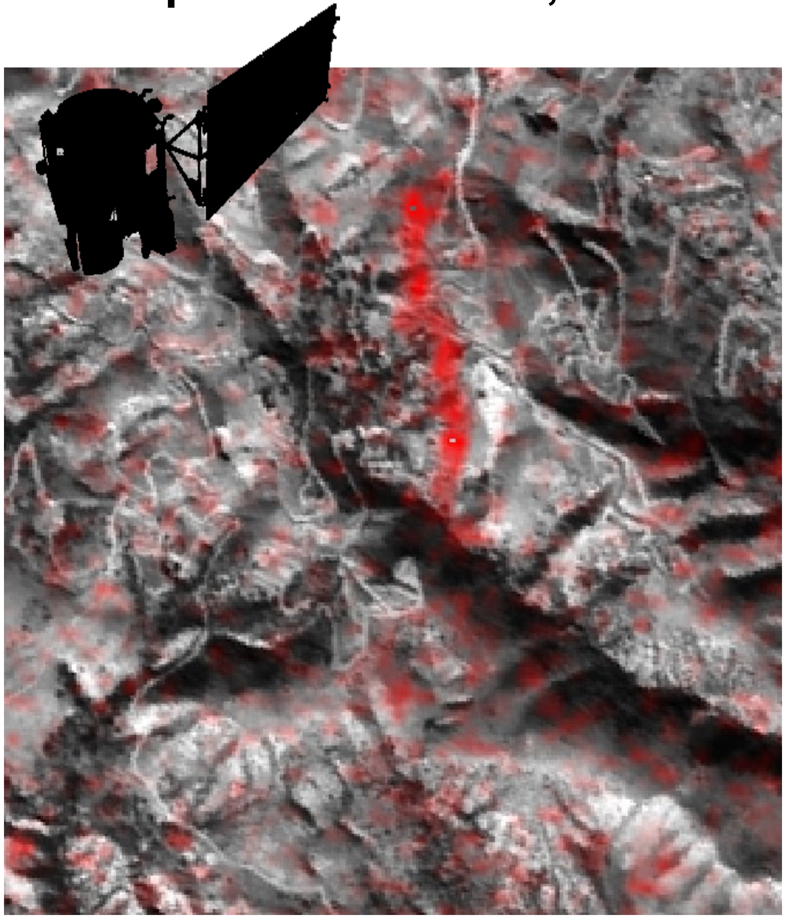


Aliso canyon gas storage leak

ER-2 at 6.6 km altitude, 1/12/2016



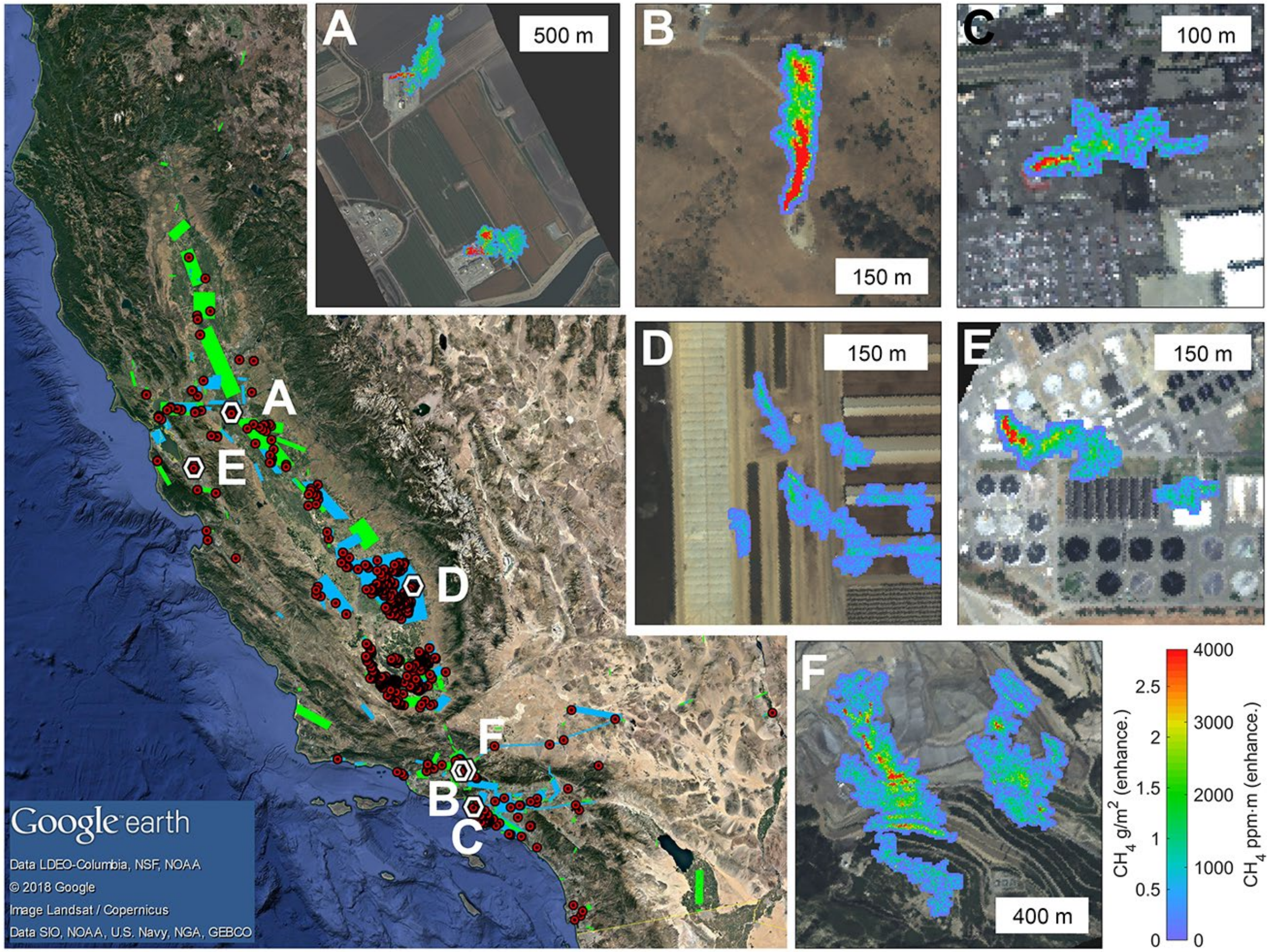
EO-1 Spacecraft at LEO, 1/1/2016

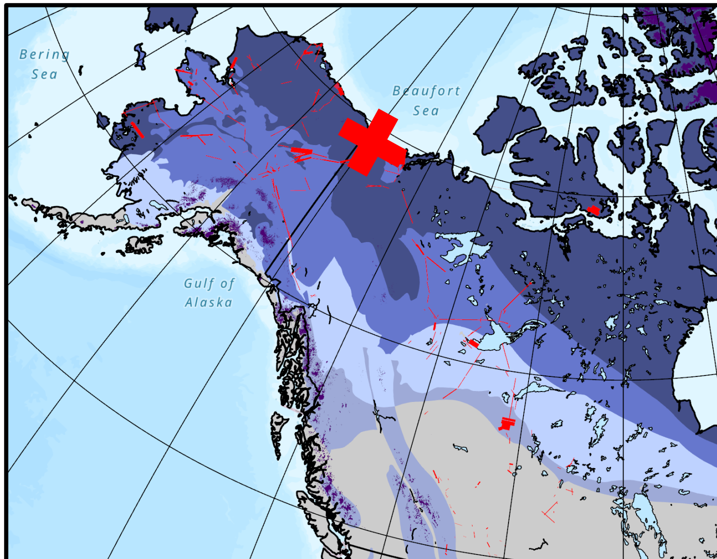


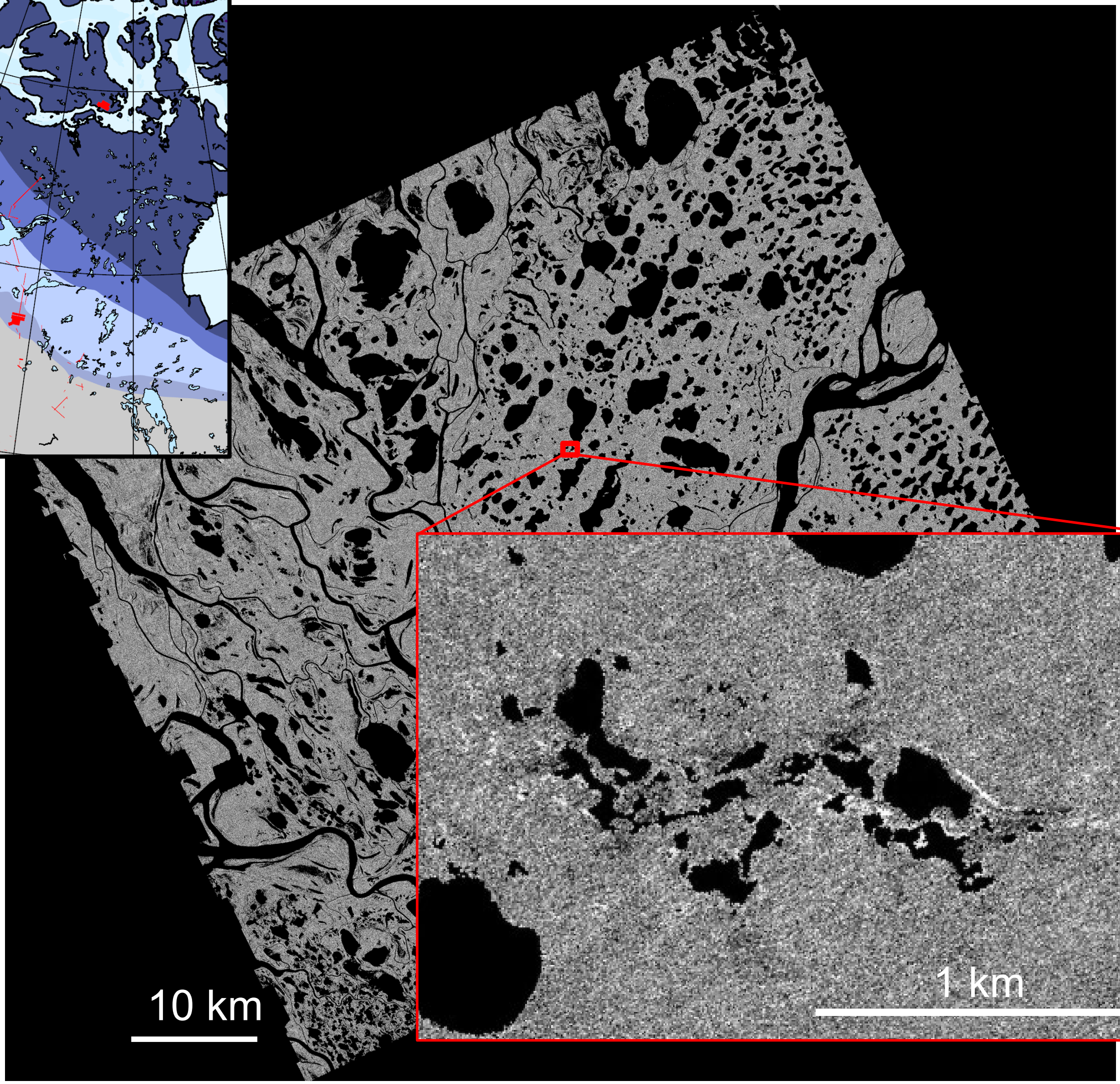
Thompson et al., *Geophys. Res. Lett.* (2016)

CH_4 in California

Duren et al. (in review), Thorpe et al. (2016), Thompson et al. (2015)





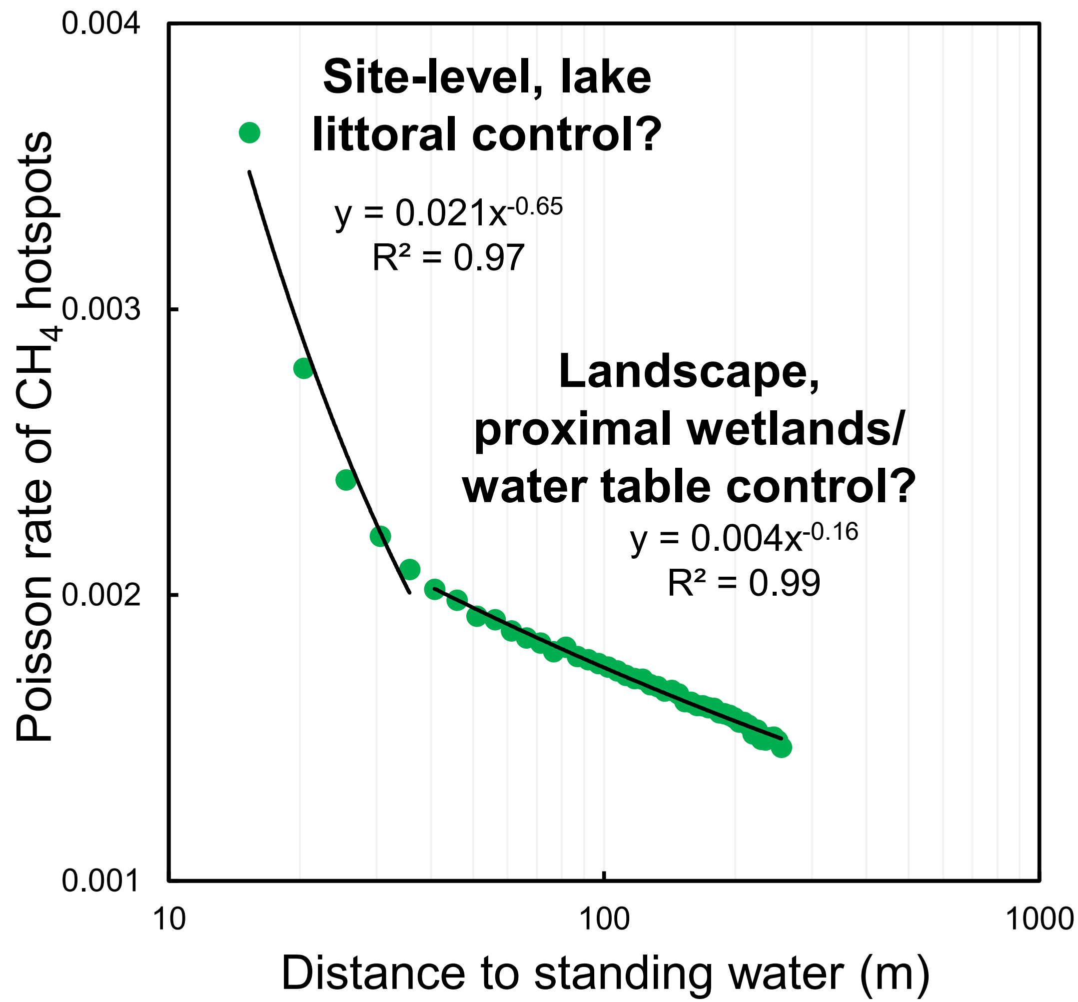


Statistical surface controls

Elder, Thompson, et al.
(in review)

Arctic-wide statistics reveal a two component power law

Elder, Thompson, et al. (manuscript in preparation)
Analysis of AVIRIS-NG data from the ABoVE campaign



Algorithms for CH_4 detection

The matched filter aims to detect a perturbing signal **t** against a background distribution defined by a mean vector and covariance matrix, μ, Σ

For a radiance vector **x** it discriminates two hypotheses:

$$H_0 : \mathbf{x} \sim \underbrace{\mathcal{N}(\mu, \Sigma)}_{\text{(pure background)}} \qquad H_1 : \mathbf{x} \sim \underbrace{\mathcal{N}(\mu + \alpha\mathbf{t}, \Sigma)}_{\text{(background plus target)}}$$

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Algorithms for CH_4 detection

The matched filter is written:

$$\hat{\alpha}(\mathbf{x}) \quad = \quad \frac{(\mathbf{x}-\mu)^T\Sigma^{-1}\mathbf{t}}{\mathbf{t}^T\Sigma^{-1}\mathbf{t}}$$

For interpretability, the target signature **t** is defined as the change in radiance caused by an additional unit absorption of CH_4 above background.

$$\mathbf{t} = \frac{\partial \mathbf{x}}{\partial \ell} \quad = \quad -\mu e^{-\kappa\ell}\kappa = -\mu\kappa$$

Absorption path length

Absorption coefficient

Challenge #1: Multi-modality

The background distribution is seldom uniform. This can lead to undesirable “clutter” effects and reduction of sensitivity in general.

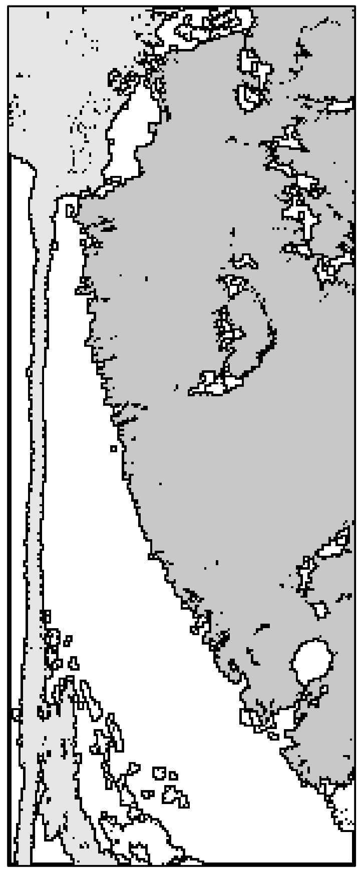
Sources of nonuniformity include:

- Variability in surface substrate materials
- Structured instrument effects, e.g. calibrations for pushbroom spectrometers.

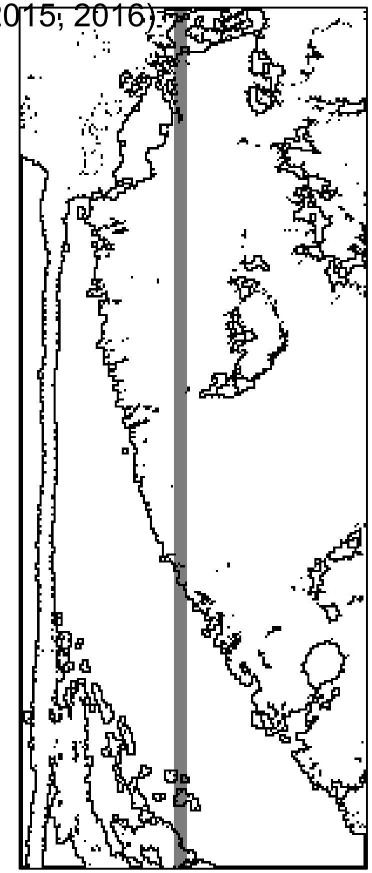
Multi-modal covariance options

Original data cube

Partition spatially
(Funk et al., 2001)



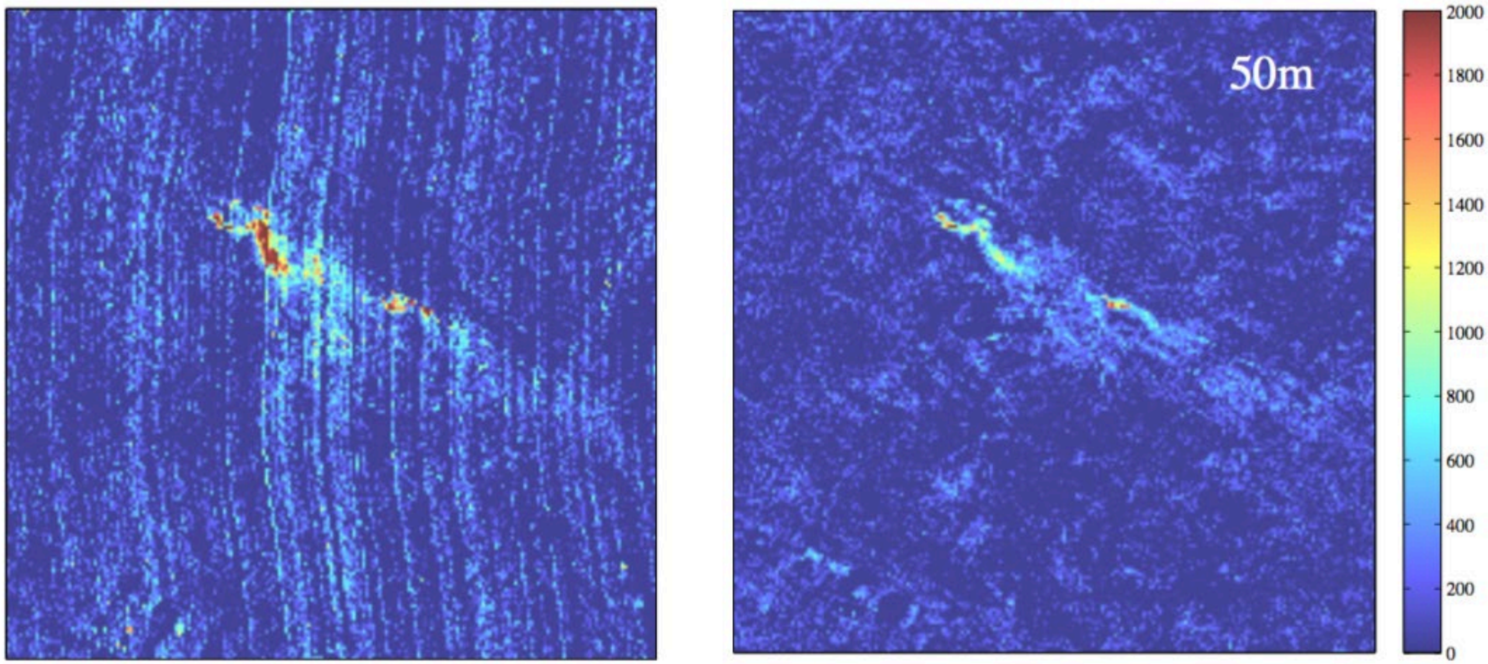
Pushbroom column
partitioning (Thompson et al.,
2015; 2016)



Combined pushbroom
and spatial partitioning

Multi-modal covariance estimates

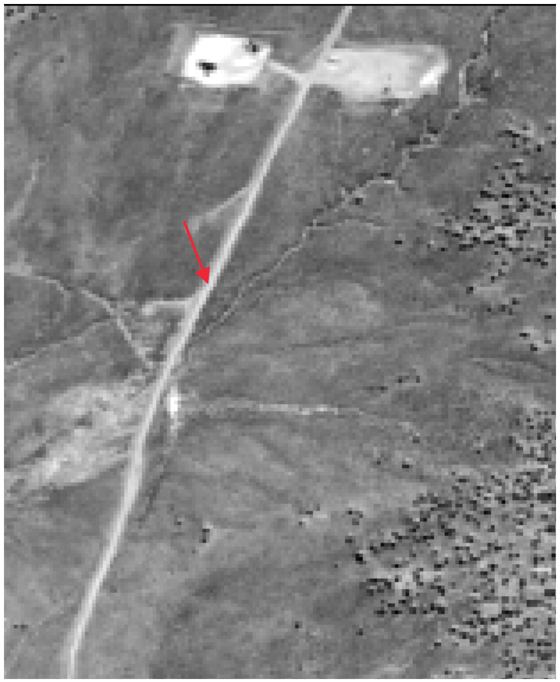
Partitioning that accounts for instrument effects can mitigate deviations from calibration model assumptions



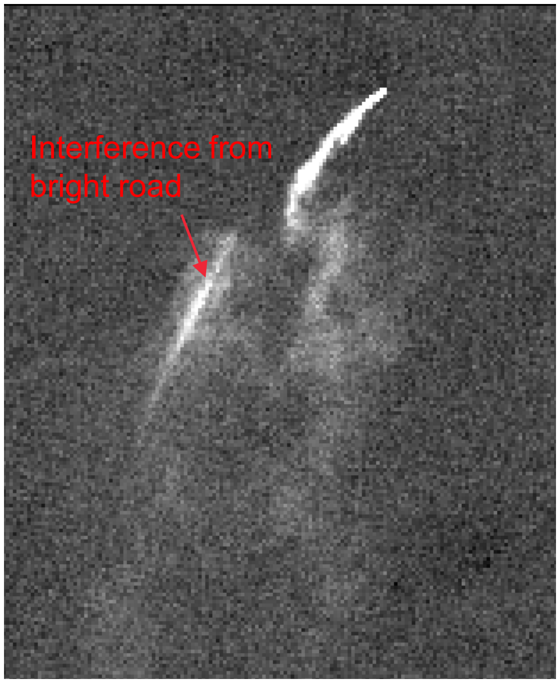
Greenhouse gas point source retrievals improved by columnwise covariance estimattion (Thompson et al., 2015)

Multi-modal covariance estimates

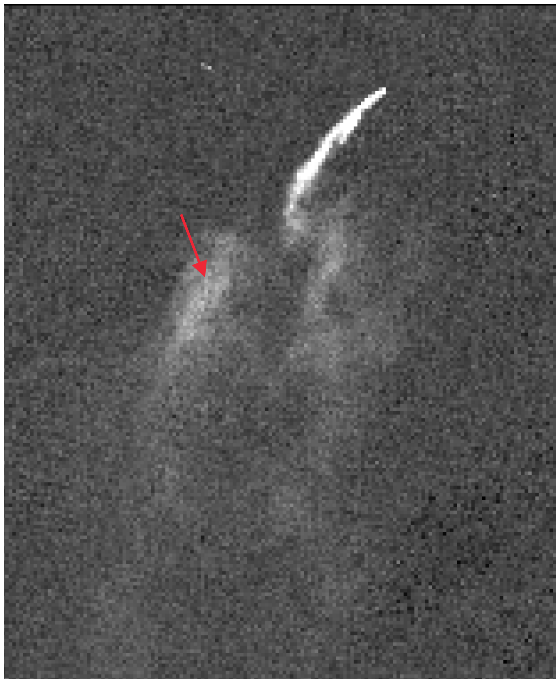
Coupling k-means background clustering with the column-wise MF provides improved robustness to background changes



AVIRIS-NG
Four Corners 2015



Column-wise
Matched Filter (MF)



Column-wise MF with multi-modal background model

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Challenge #2: Sample sizes

- As the number of partitions increases, it becomes increasingly difficult to estimate the covariance matrix reliably.
- This is also an issue for small flightlines.
- Poor covariance estimation reduces sensitivity.

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Approach

Shrinkage estimation regularizes the sample covariance matrix, shifting it toward a stable prior (such as a diagonal covariance matrix).

$$R_\alpha = (1-\alpha)S + \alpha T$$

Regularized covariance estimate

Weighting factor

Sample covariance

Shrinkage target

We adopt a method from Theiler et al. (Proc. SPIE, 2012) to select the optimal weighting using a closed form for cross-validation error

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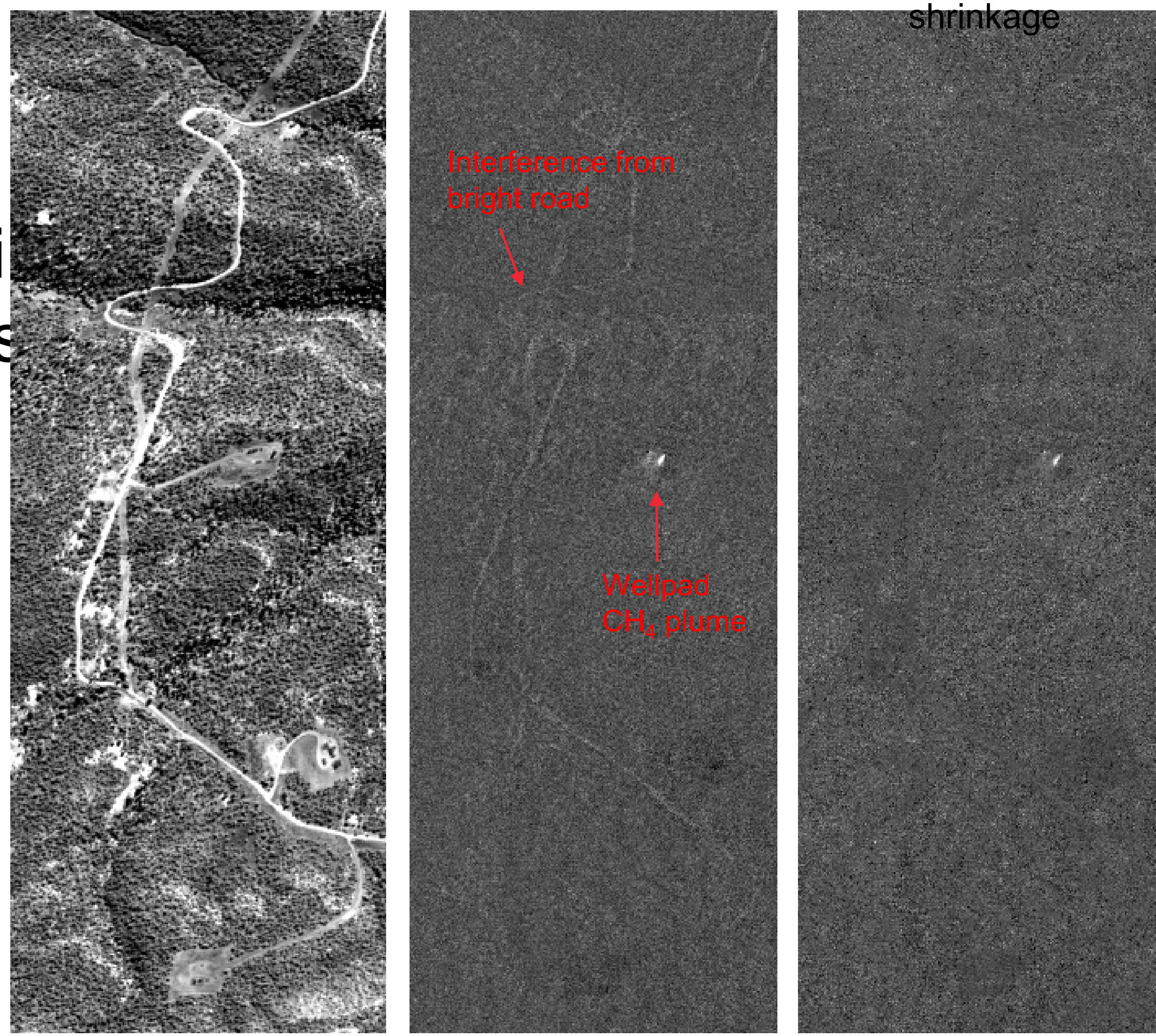
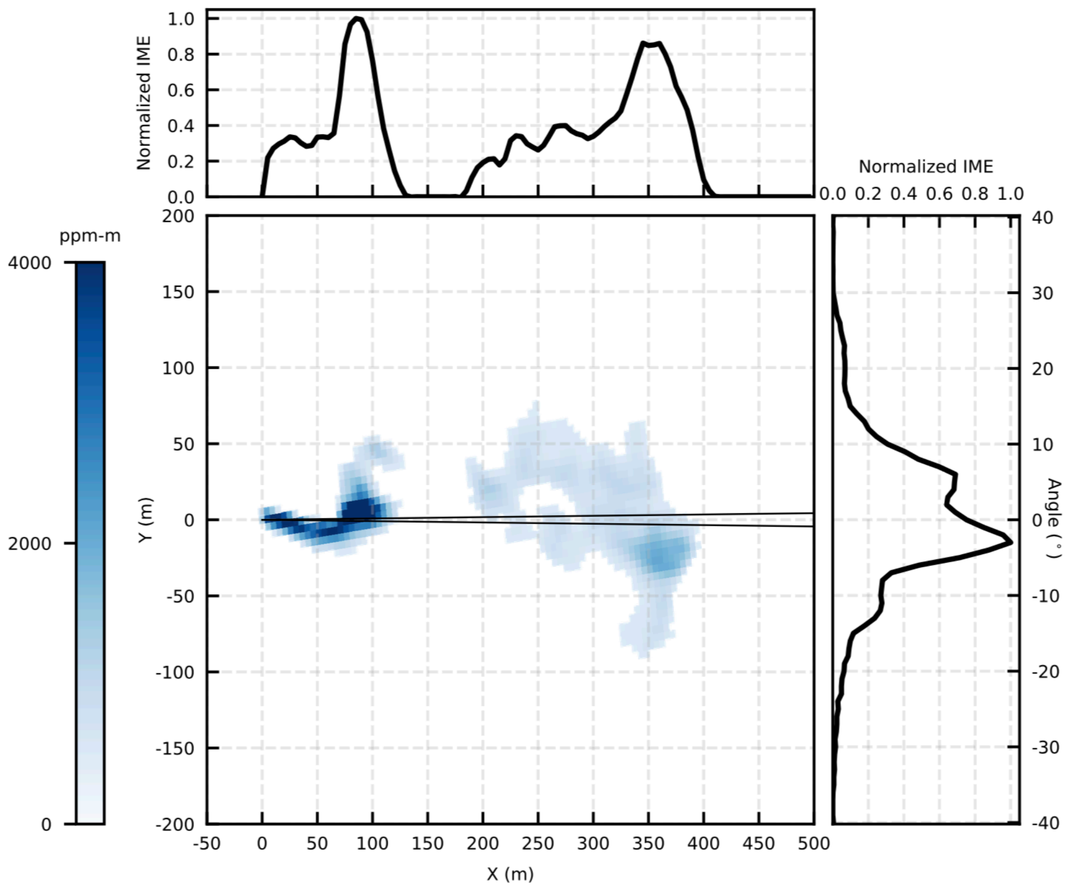
Reliable covariance estimation usi few samples

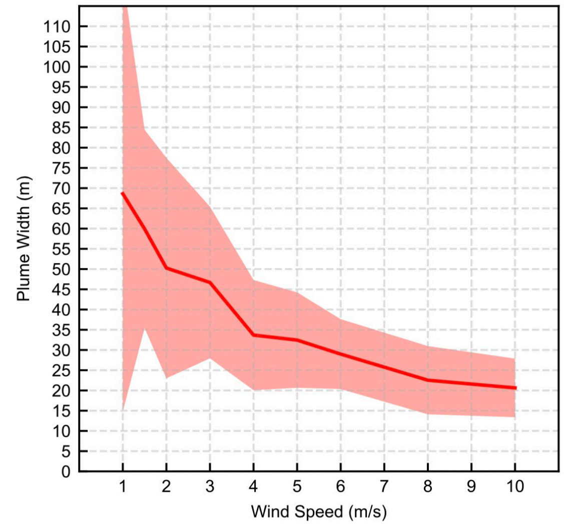
Methods such as shrinkage estimators (Theilier, SPIE 2012) enable a more accurate covariance estimate, further suppressing background clutter for models based on few samples.

AVIRIS-NG Four Corners 2015 | Column-wise Matched Filter (MF) | Column-wise MF with covariance shrinkage



Remote wind speed estimation





Large Eddy Simulations reveal a stochastic relationship between plume shape and windspeed, enabling flux estimates (Jongaramrungruang et al., in prep.)

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Agenda

- **Overview and upcoming missions**
- **Deep Dive 1:** Instrument characterization
- **Deep Dive 2:** CH_4 leaks, other greenhouse point sources
- **Deep Dive 3:** Optimal Estimation for surface/atmosphere retrievals

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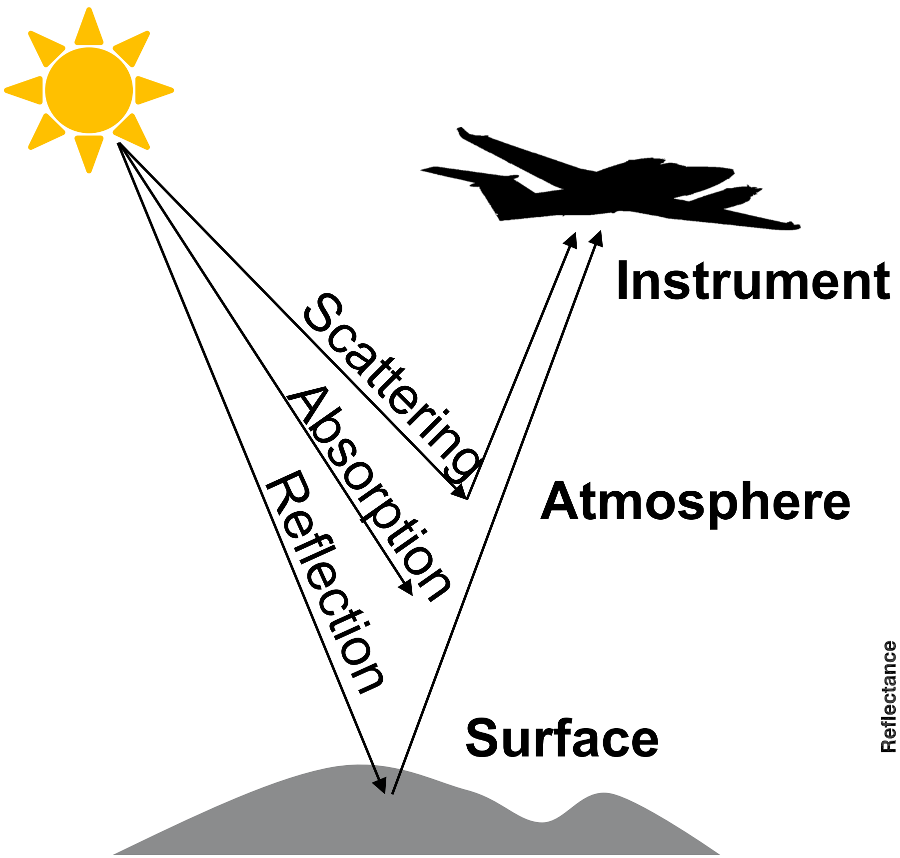
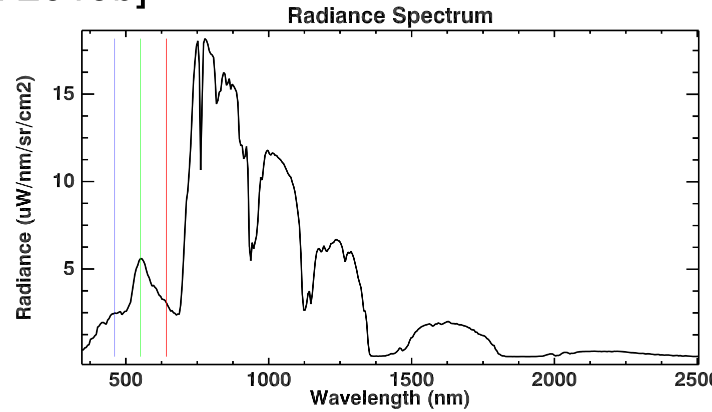
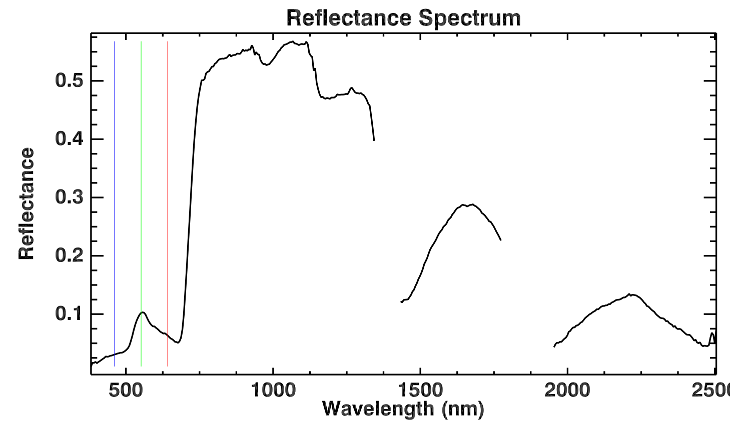
From radiance to reflectance

[Thompson et al., RSE 2015; Thompson et al., RSE 2018, Thompson et al., RSE 2019a, Thompson et al., RSE 2019b]







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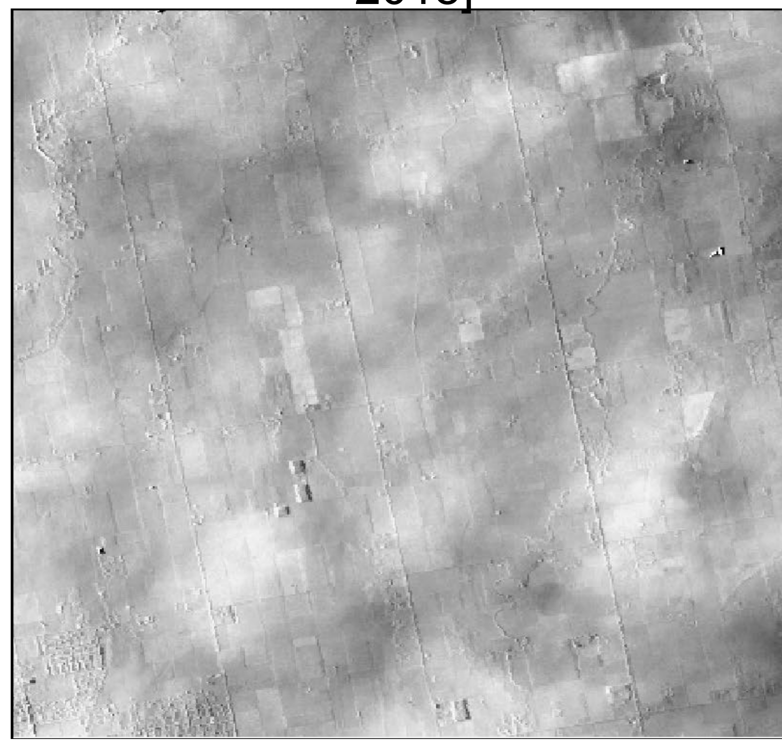
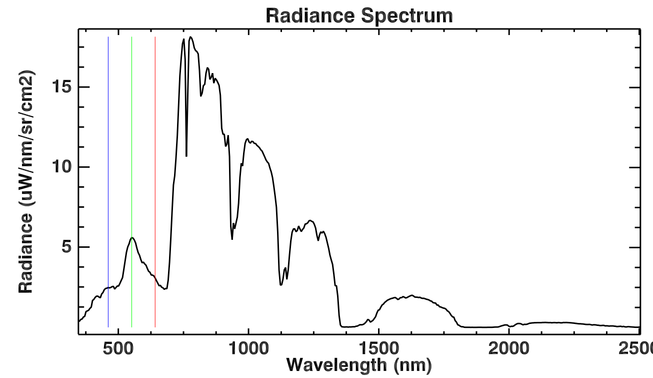
“AVIRIS Classic” imaging spectrometer, visible wavelengths

Retrieved Water vapor [Thompson et al., *Surv. Geohysics,* 2018]

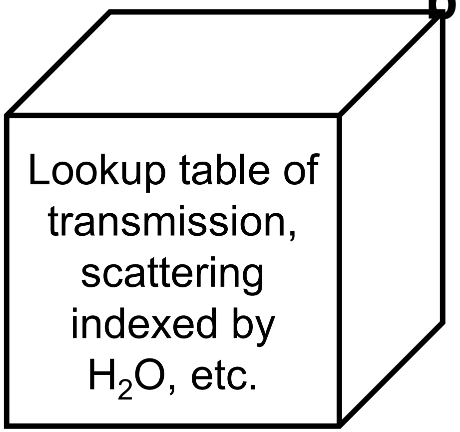


Conventional atmospheric correction: A sequential process

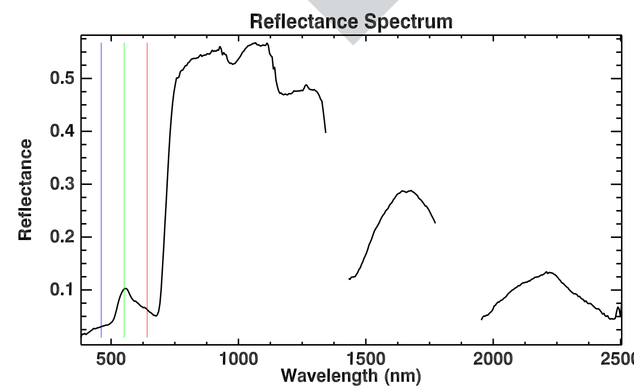


2. Estimate atmosphere (typically by band ratios)

$$\overbrace{\rho^*_{obs}}^{\text{measurement}} = \rho_a + \frac{T\overbrace{\rho_s}^{\text{reflectance}}}{1 - S\rho_s}$$

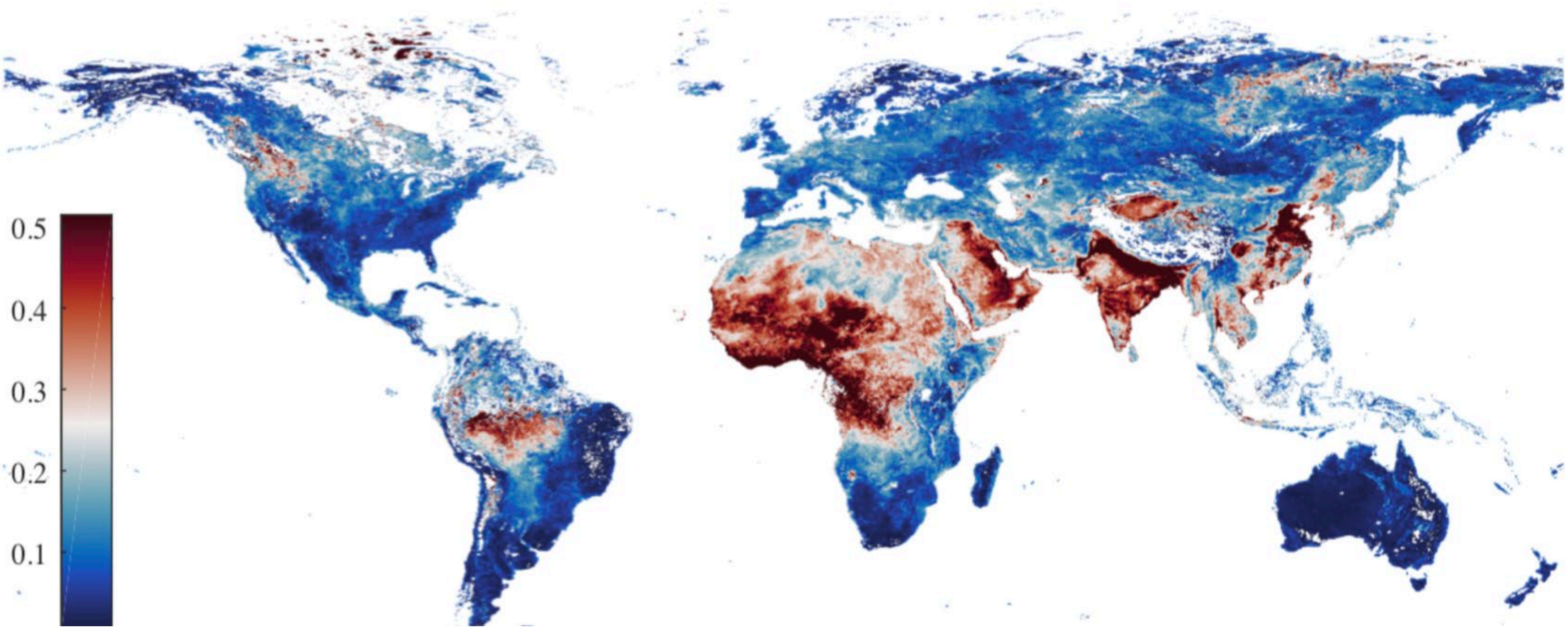


3. Algebraic Inversion



1. In advance, do RTM calculations

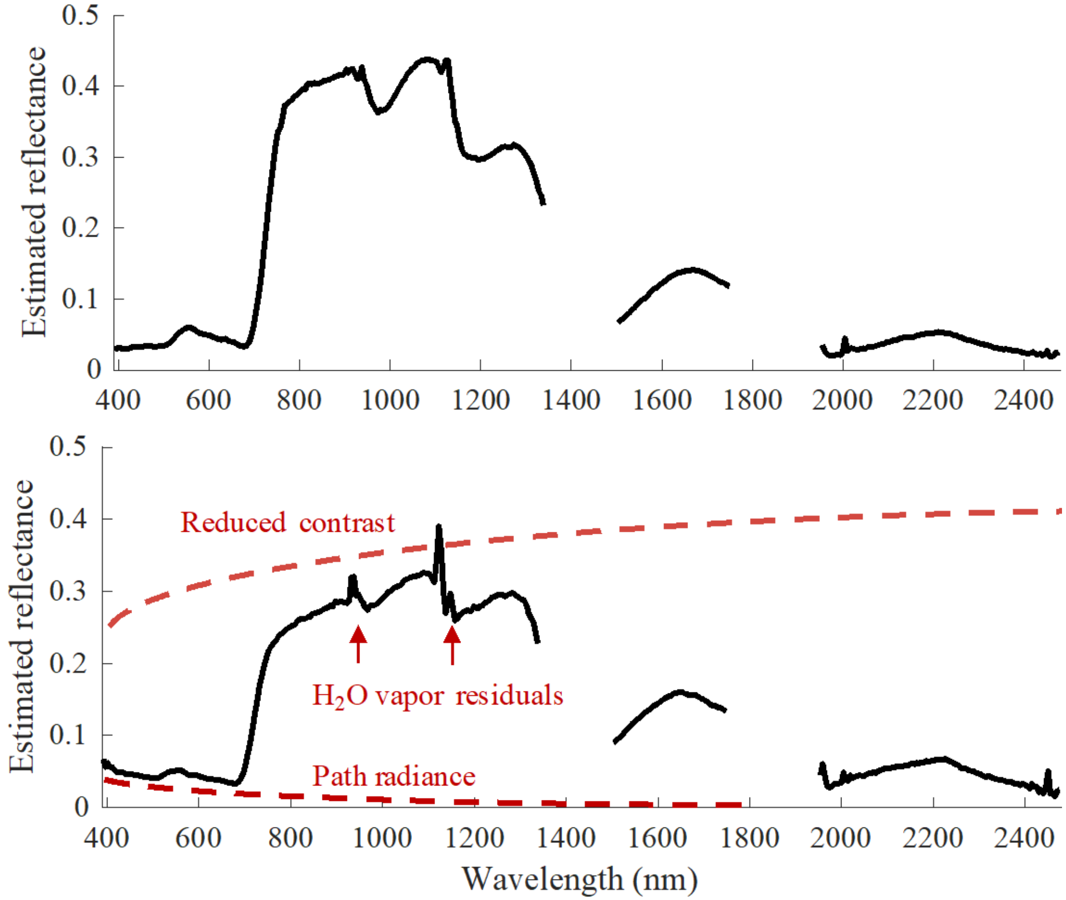
Global spectroscopy missions are an atmospheric correction challenge



Annual average AOD

Thompson et al., (in review)

Global spectroscopy missions are an atmospheric correction challenge



Thompson et al., (in review)

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Optimal Estimation Theory [Rodgers 2000]: Simultaneous estimation of surface and atmosphere

- **A true spectroscopic retrieval that** can exploit information distributed across the spectrum, helping to disentangle surface and atmosphere
- **A rigorous probabilistic formulation** incorporates prior knowledge via Bayes' rule
- **Comprehensive uncertainty estimates** can inform downstream analyses and global maps
- **Flexible state vectors** that might be more robust for difficult observing conditions
- **Elegant, conceptually simple 1-step estimation**

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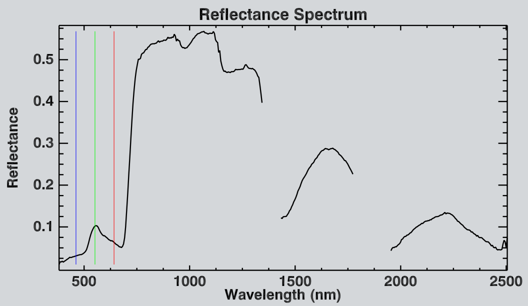
The "forward problem"

State vector

$$\mathbf{x} \in \mathbb{R}^N$$

$$\mathbf{x} = \begin{bmatrix} \text{Surface parameters} \\ \ldots \\ \text{Atmosphere parameters} \\ \ldots \\ \text{Instrument parameters} \\ \ldots \end{bmatrix}$$



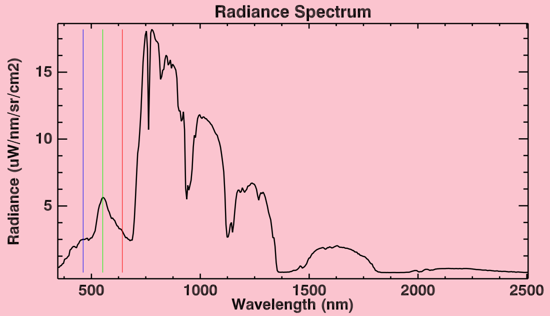
Forward model

$$F(\mathbf{x}) : \mathbb{R}^N \mapsto \mathbb{R}^M$$

Measurement

$$\mathbf{y} \in \mathbb{R}^M$$

$$\mathbf{y} = \begin{bmatrix} \text{Calibrated at-aperture} \\ \text{radiance measurements} \end{bmatrix}$$



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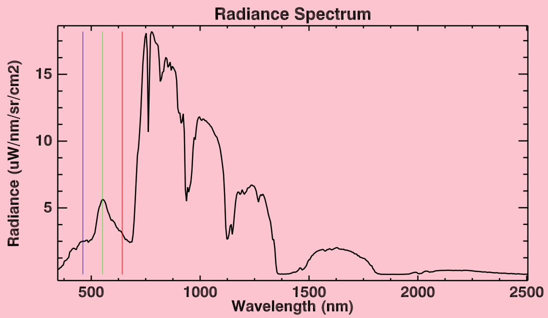
The "inverse problem"

Measurement

$$\mathbf{y} \in \mathbb{R}^M$$

$$\mathbf{y} = \begin{bmatrix} \text{Calibrated at-aperture} \\ \text{radiance measurements} \end{bmatrix}$$



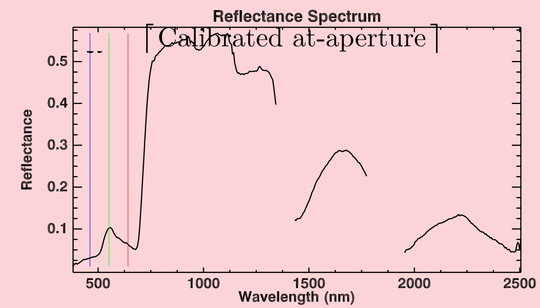
Inversion algorithm

$$R(\mathbf{y}) : \mathbb{R}^M \mapsto \mathbb{R}^N$$

Estimated state vector

$$\hat{\mathbf{x}} \in \mathbb{R}^N$$

$$\hat{\mathbf{x}} = \begin{bmatrix} \text{Estimated} \\ \text{surface parameters} \\ \dots \\ \text{Estimated} \\ \text{atmosphere parameters} \\ \dots \\ \text{Estimated} \\ \text{instrument parameters} \\ \dots \end{bmatrix}$$



Maximum *A Posteriori* solution

$$p(\mathbf{x}|\mathbf{y}) = \frac{p(\mathbf{y}|\mathbf{x})p(\mathbf{x})}{p(\mathbf{y})}$$

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Maximum *A Posteriori* solution

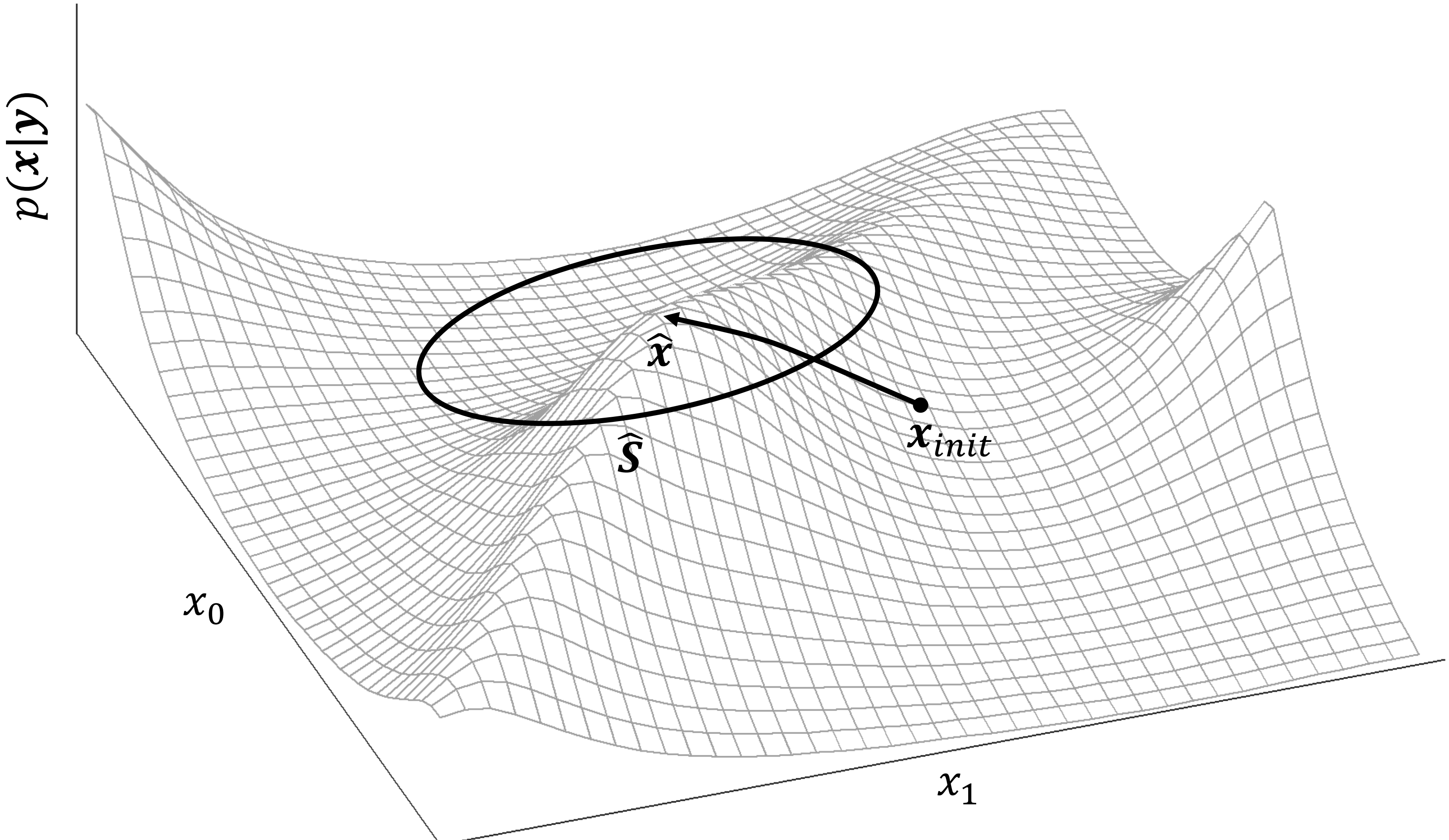
$$p(\mathbf{x}|\mathbf{y}) = \frac{p(\mathbf{y}|\mathbf{x})p(\mathbf{x})}{p(\mathbf{y})}$$

The *Maximum A Posteriori* estimation is equivalent to the optimization:

$$\underbrace{\boldsymbol{\chi}^2(\mathbf{x})}_{\text{Cost}} = \underbrace{(\mathbf{F}(\mathbf{x}) - \mathbf{y})^{\mathbf{T}}\, \mathbf{S}_{\boldsymbol{\epsilon}}^{-1}\, (\mathbf{F}(\mathbf{x}) - \mathbf{y})}_{\text{Model match to measurement}} + \underbrace{(\mathbf{x} - \mathbf{x}_{\mathbf{a}})^{\mathbf{T}}\, \mathbf{S}_{\mathbf{a}}^{-1}\, (\mathbf{x} - \mathbf{x}_{\mathbf{a}})}_{\text{Bayesian prior}}$$

… we can solve it by conjugate gradient descent.

Maximum A Posteriori estimation



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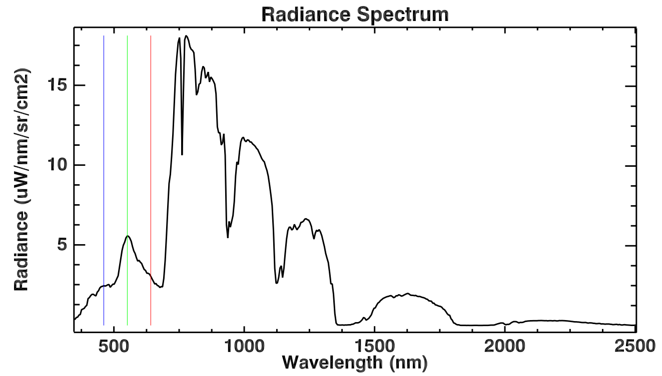

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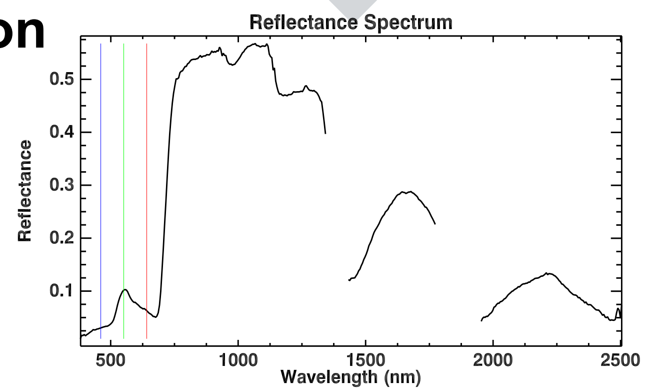
$$\underbrace{\rho^*_{obs}}_{\text{measurement}} = \rho_a + \frac{T\overbrace{\rho_s}^{\text{reflectance}}}{1 - S\rho_s}$$

3. Algebraic Inversion



Lookup table of transmission, scattering indexed by H_2O, etc.

1. In advance, do RTM calculations

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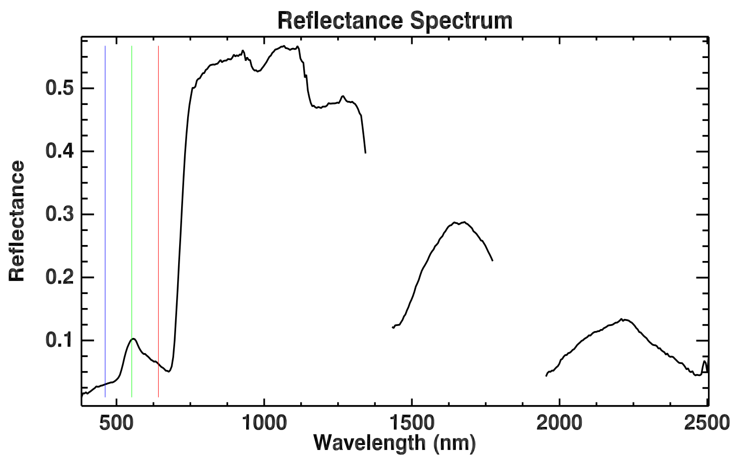
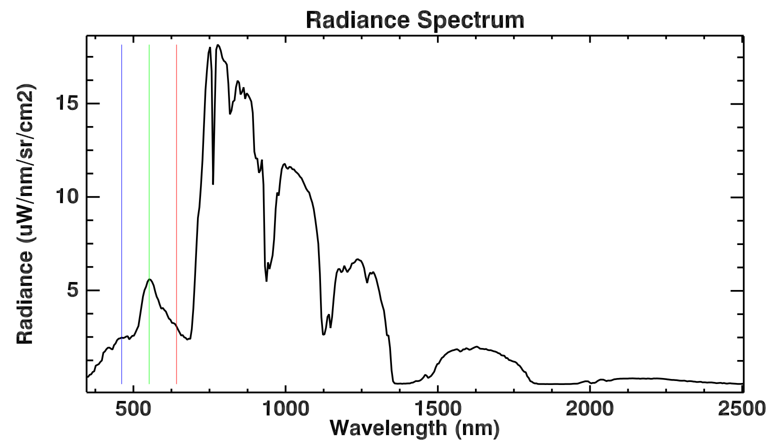
Iterative simultaneous estimation of atmosphere and surface

1. Predict radiance

$$\mathbf{y} = \mathbf{F}(\mathbf{x}) + \epsilon$$





2. Optimize state vector

$$\underbrace{\chi^2(\mathbf{x})}_{\text{Cost}} = \underbrace{(\mathbf{F}(\mathbf{x}) - \mathbf{y})^{\mathrm{T}}\, \mathbf{S}_{\epsilon}^{-1}\, (\mathbf{F}(\mathbf{x}) - \mathbf{y})}_{\text{Model match to measurement}} + \underbrace{(\mathbf{x} - \mathbf{x_a})^{\mathrm{T}}\, \mathbf{S_a}^{-1}\, (\mathbf{x} - \mathbf{x_a})}_{\text{Bayesian prior}}$$

Case study

[Thompson et al.,
Remote Sensing of Environment 2018]

- In-situ AOD via Reagan sunphotometers
- In-situ surface reflectance via ASD Fieldspec

Jet Propulsion Laboratory

Ivanpah Playa

California Institute of Technology

From Thompson et al., RSE 2018.

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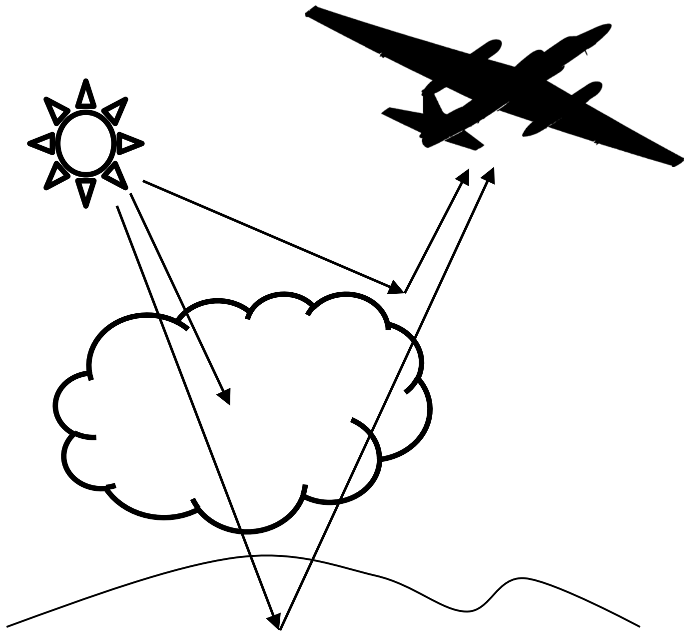

Model components

Pre-defined
Statistical, fit to data
Retrieved in the inversion

Instrument: AVIRIS-NG

- Instrument model with Wavelength- and signal-dependent SNR
- Photon shot & read noise
- Uncorrelated calibration uncertainty
- Systematic calibration / RT uncertainty

Atmosphere: MODTRAN 6.0 RTM

- DISORT MS, Correlated-k
- Rural aerosol model
- broad prior uncertainties
- Unmodeled unknowns, including H_2O absorption coefficients
- H_2O, AOD retrieved

Surface: Multi-component Multivariate Gaussians

- Prior based on universal library, highly regularized to permit accurate retrieval of arbitrary shapes
- Reflectance estimated independently in every channel

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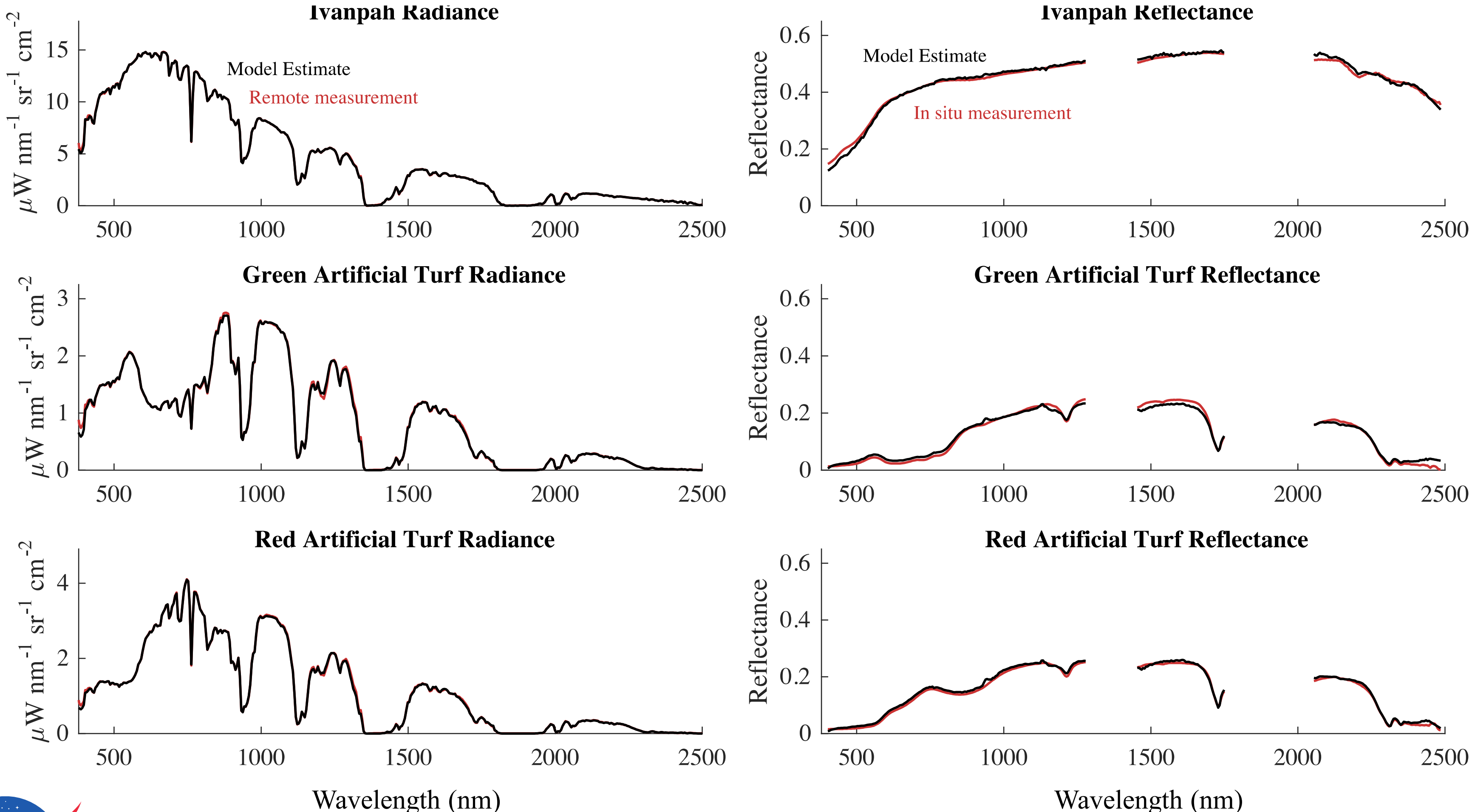
Reflectance estimate vs. in situ

[Thompson et al., *Remote Sensing of Environment* 2018]



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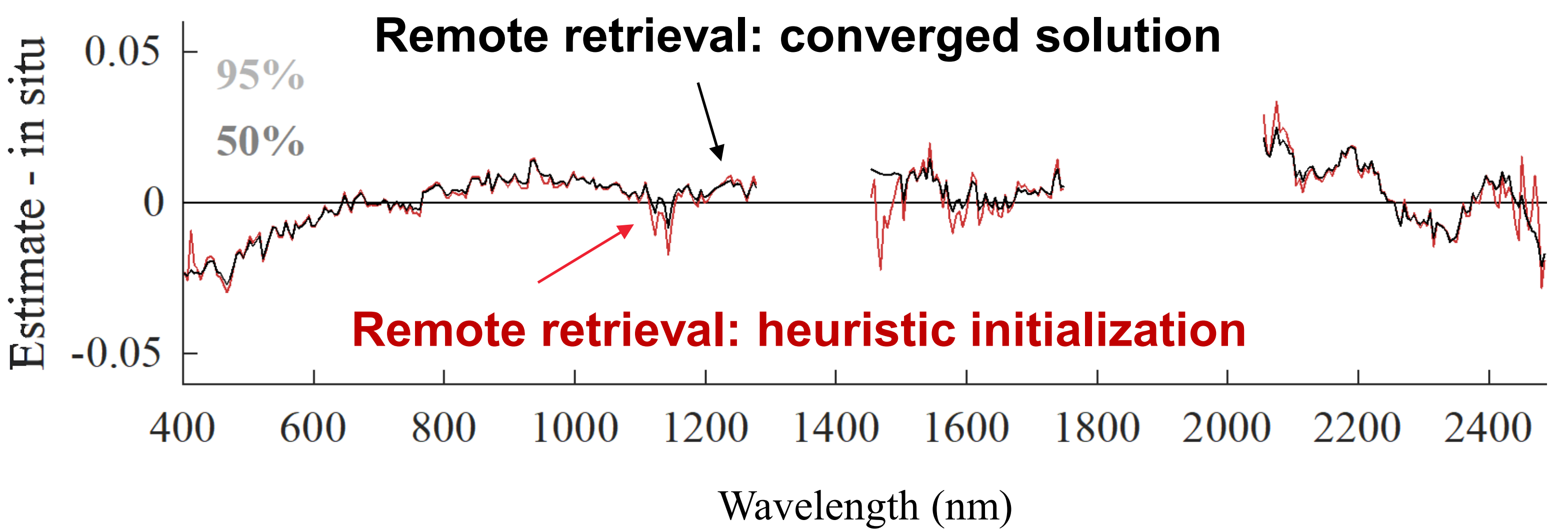
Posterior uncertainty compared to actual discrepancies

[Thompson et al., *Remote Sensing of Environment* 2018]



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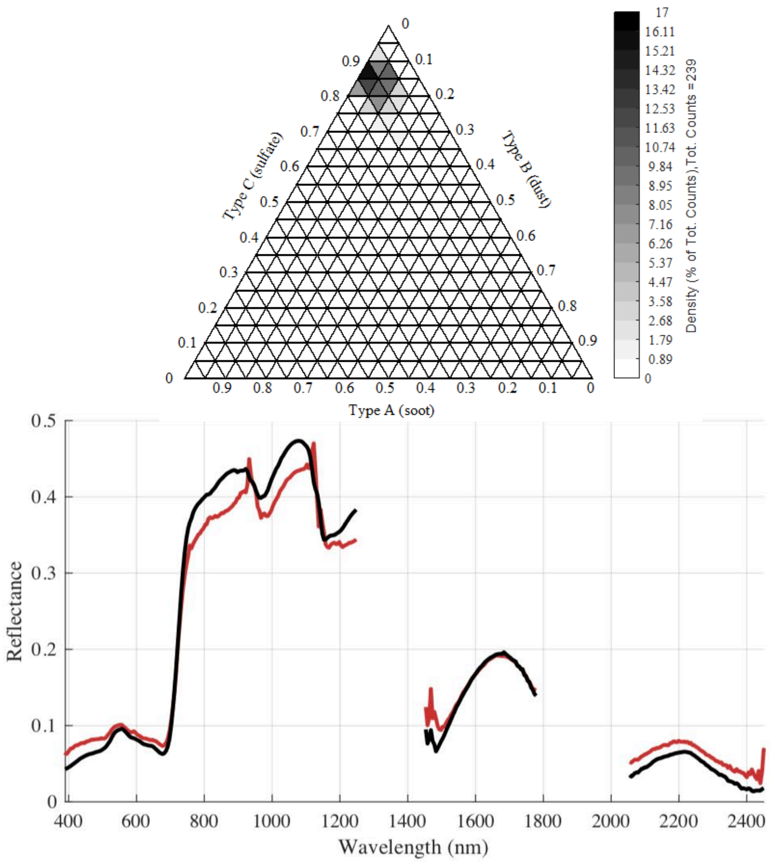
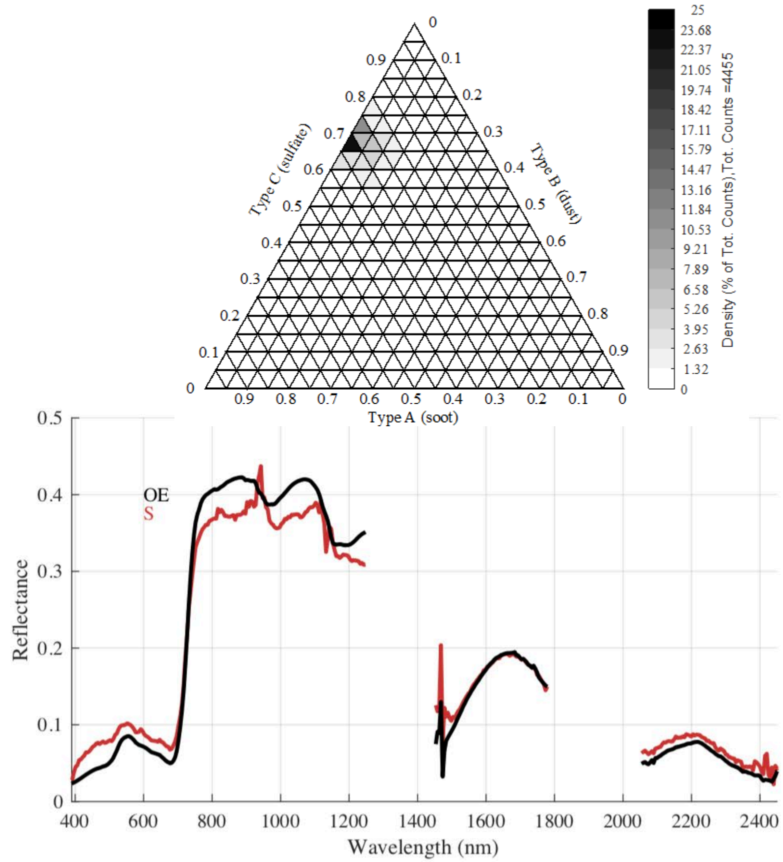
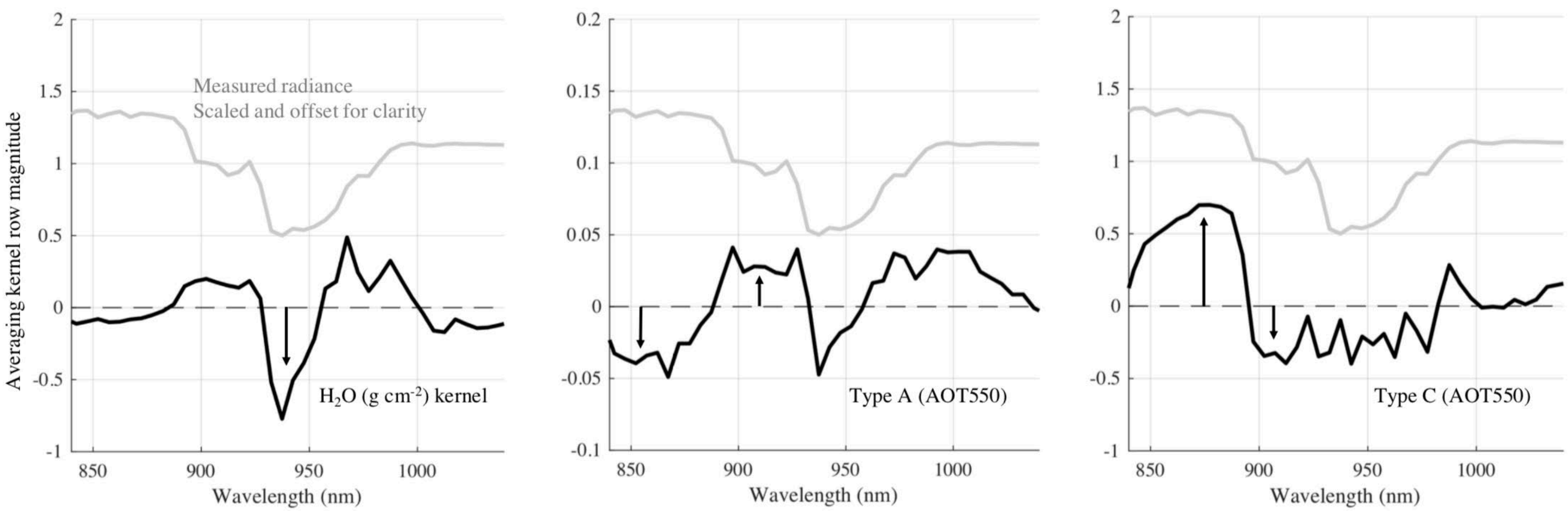
High aerosol loading in India campaign





High aerosol loading in India campaign

“Averaging Kernels” for H_2O, and absorbing and scattering aerosol particles



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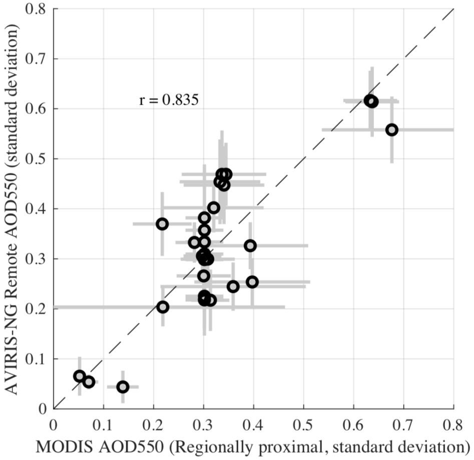
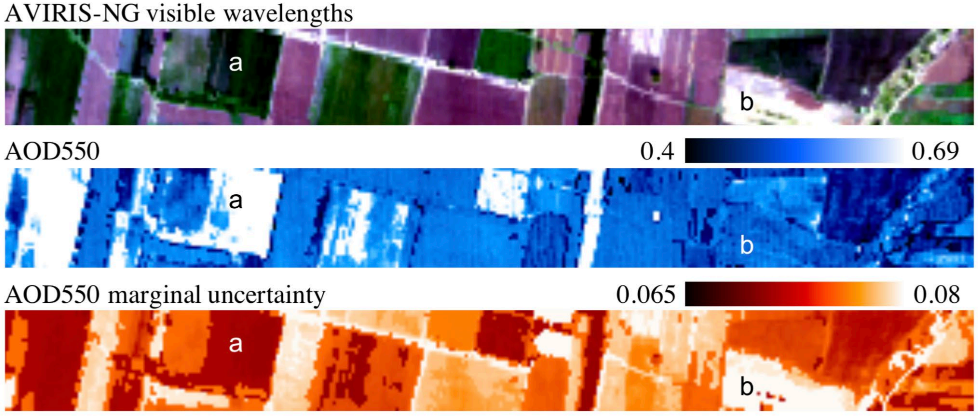
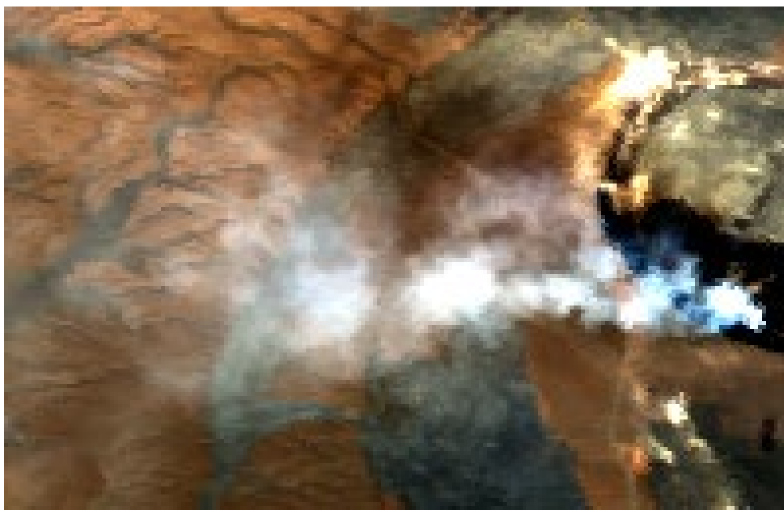
High aerosol loading in India campaign





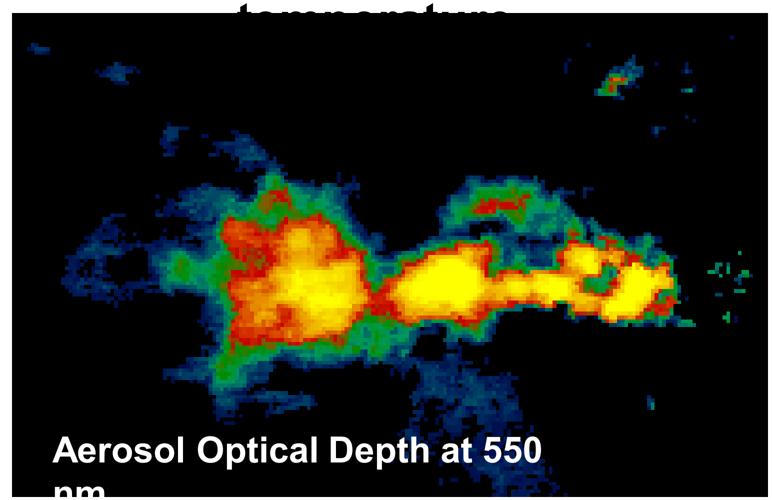
Right: A dataset of 29 flightlines shows uniform improvements in spectral quality metrics vis a vis the AVIRIS-NG standard reflectance product. AOD estimates align with MODIS AOD retrievals from the same day (correlation coefficient r = 0.83).   Left: different surfaces provide varying levels of aerosol information for the retrieval. Green vegetation is particularly well-constrained We use the most confident 5% of retrievals to form the flightline-wide estimate.

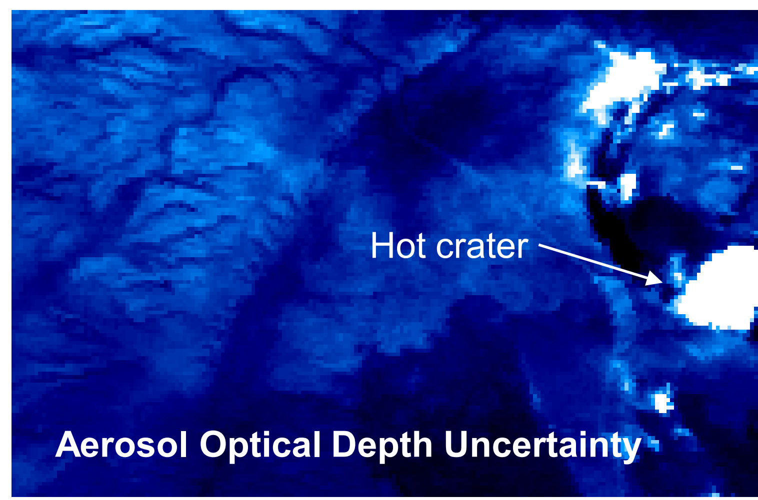
Aerosol mapping examples (Hawaii campaign)



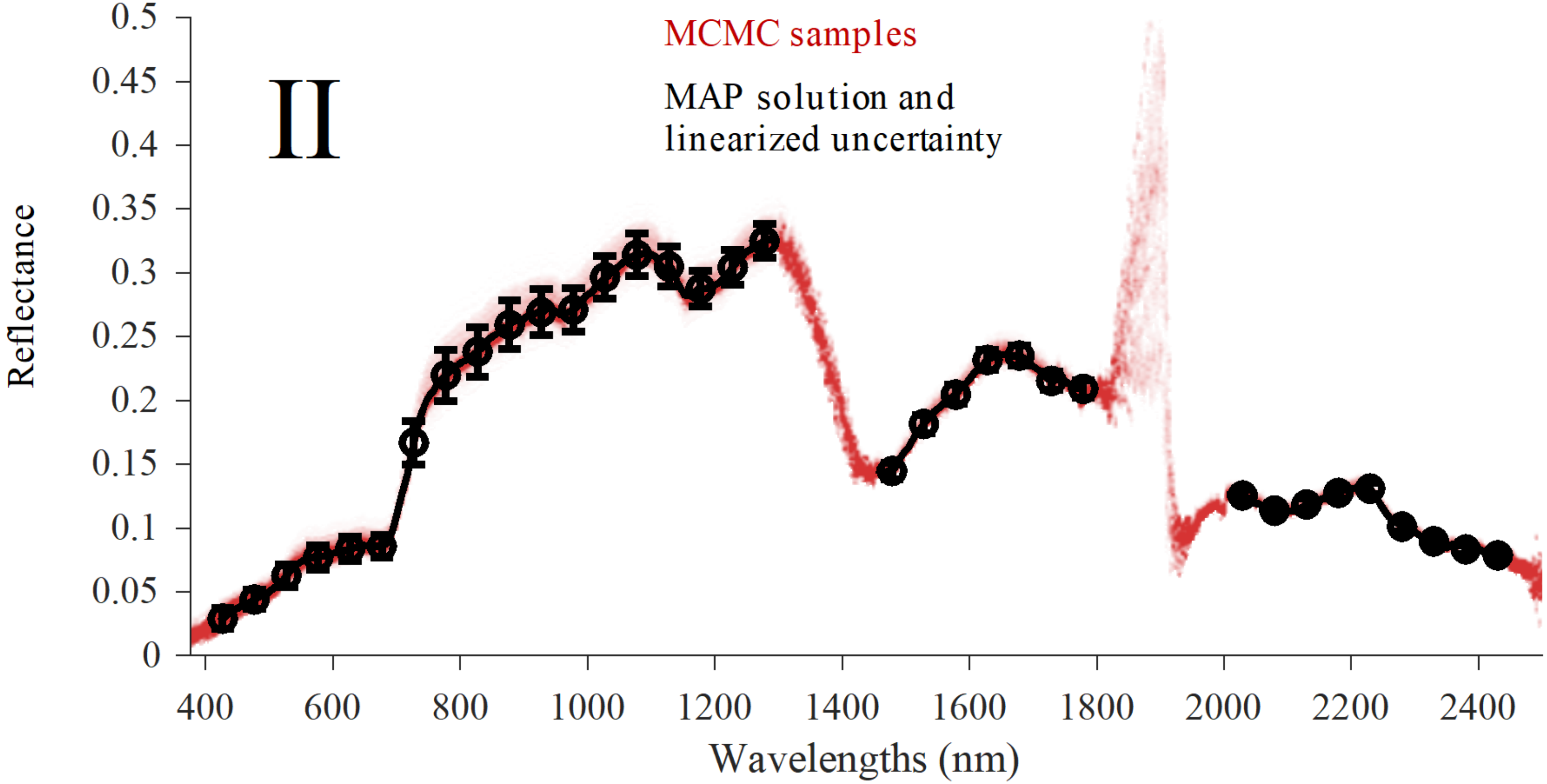
AVIRIS-C f170127t01p00r16 (subset, visible bands)

Combined estimate of H_2O vapor, AOT, surface reflectance and temperature





Maximum A Posteriori vs. MCMC



With due thanks to:

- **Kevin Bowman** (JPL), for much of the source material in these slides
- **Clive D. Rogers,** for theoretical foundations, approach and notation (e.g. *Inverse Methods for Atmospheric Sounding, Theory and Practice*, 2000).
- **NASA Earth Science** for sponsorship of AVIRIS-NG and the AVIRIS-NG India investigation and analysis.
- **The JPL Research and Technology Development and NASA Center Innovation Fund Programs**
- **The JPL Office of Chief Scientist and Technologist**
- **Other coinvestigators, coauthors and colleagues** including Amy Braverman, Jonathan Hobbs, Robert Spurr, Steven Massie, Bruce Kindel, Manoj Mishra, et cetera.

Backup

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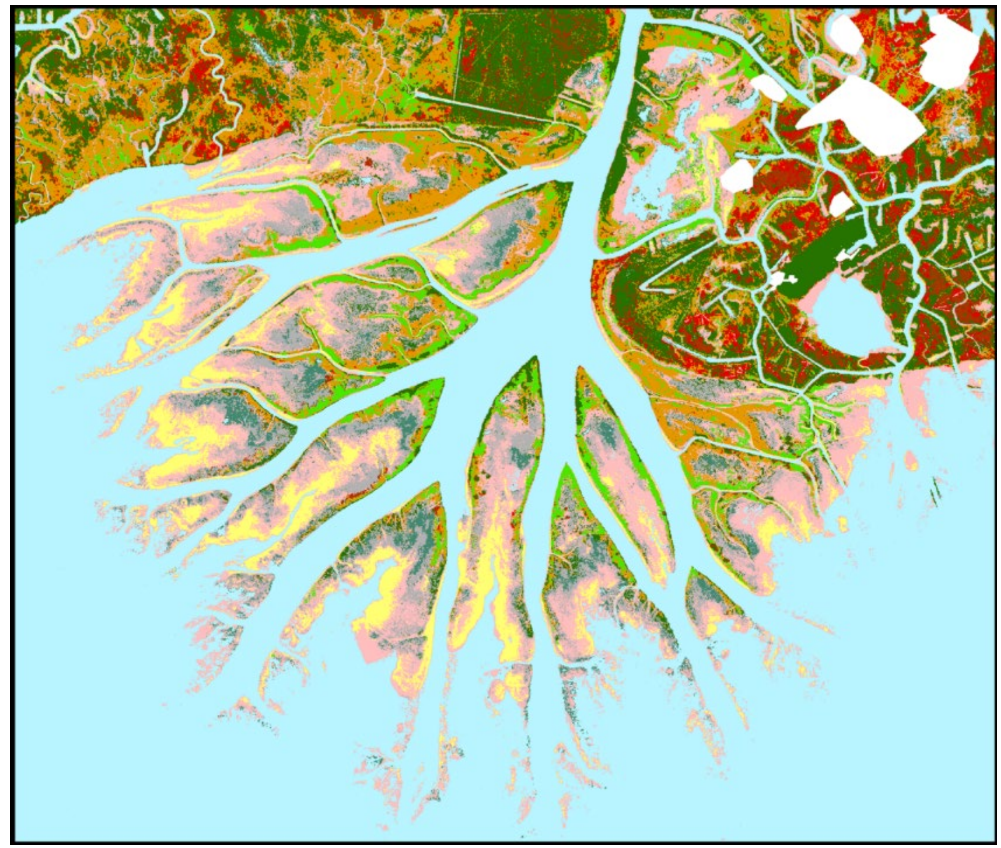
Coastal ecosystems: wetland vegetation

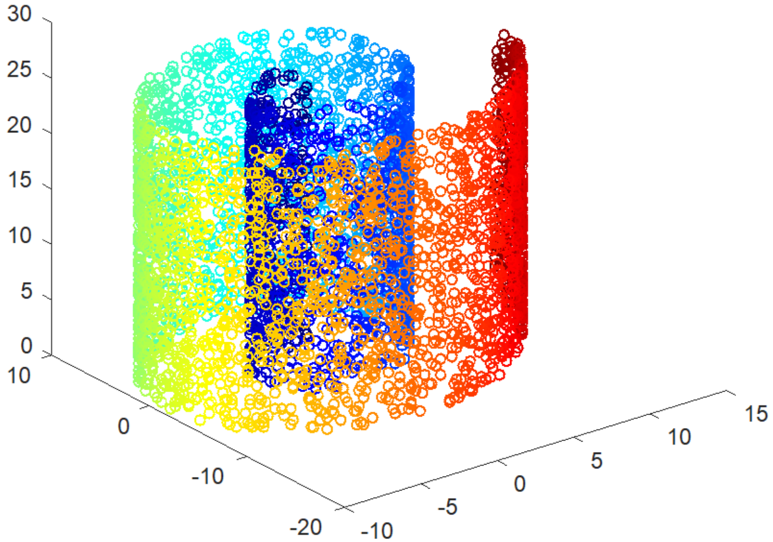
[Daniel Jensen, *TGARS* 2018 and in preparation], Marc Simard / JPL "Flow of Water" 8x SRTD

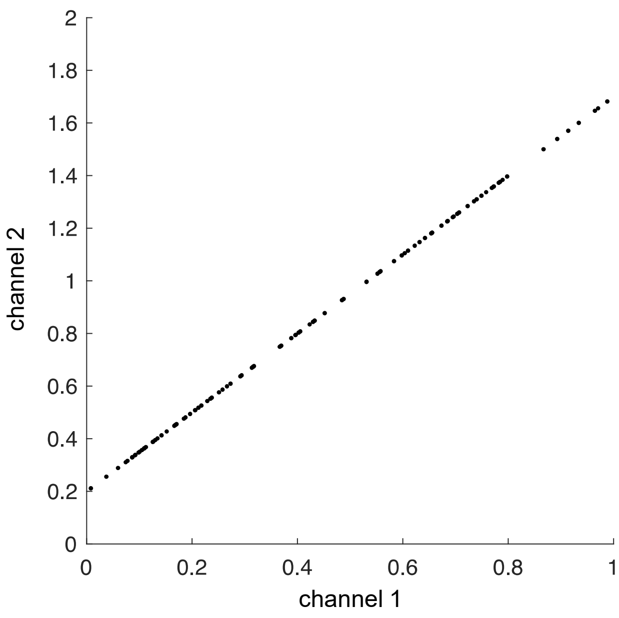
	Nelumbo	Polygonum/ Forbs	Colocasia	Salix/ Forest	Grasses
In Situ Points	50	19	18	30	16
Correct Points	46	10	13	23	8
Percent Correct	92.0	52.6	72.2	76.7	50.0



Intrinsic dimensionality

- The degrees of freedom in a process under study
- Quantifies the measurable diversity in a dataset





Laplacian Eigenmap code via Kye Taylor, Mathworks file exchange

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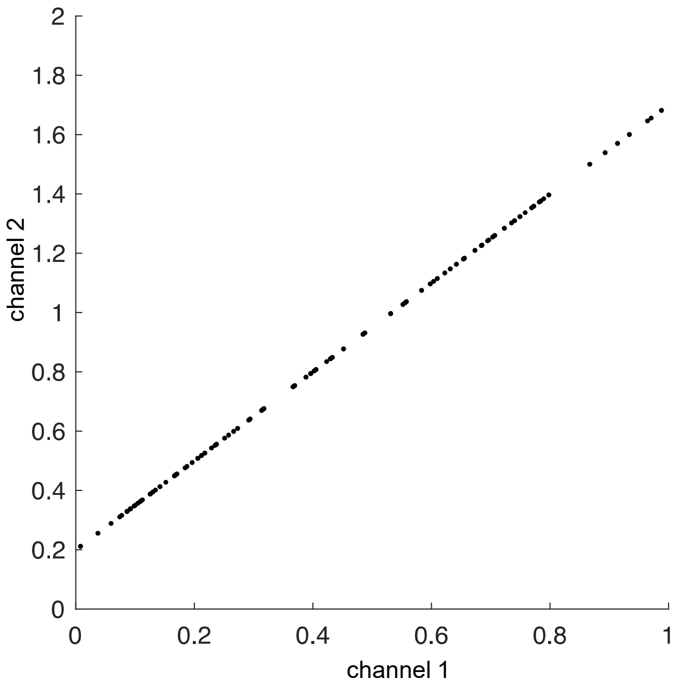
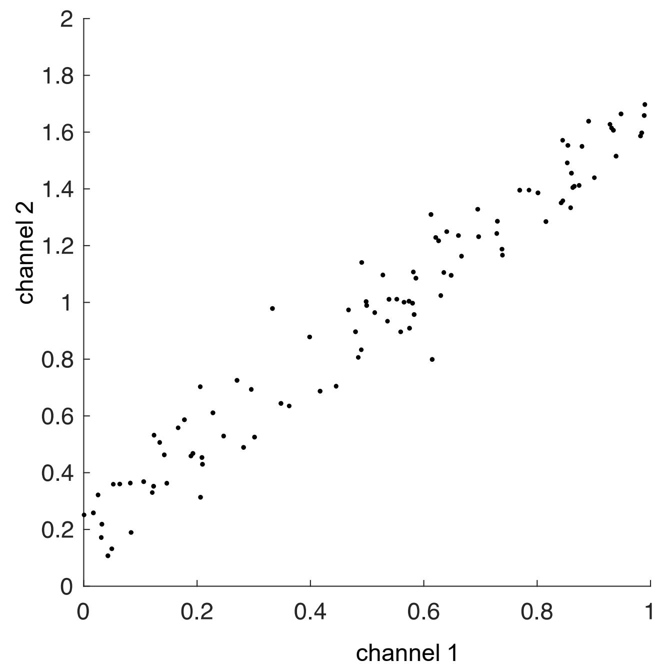
Dimensionality estimates must account for measurement noise





Laplacian Eigenmap code via Kye Taylor, Mathworks file exchange

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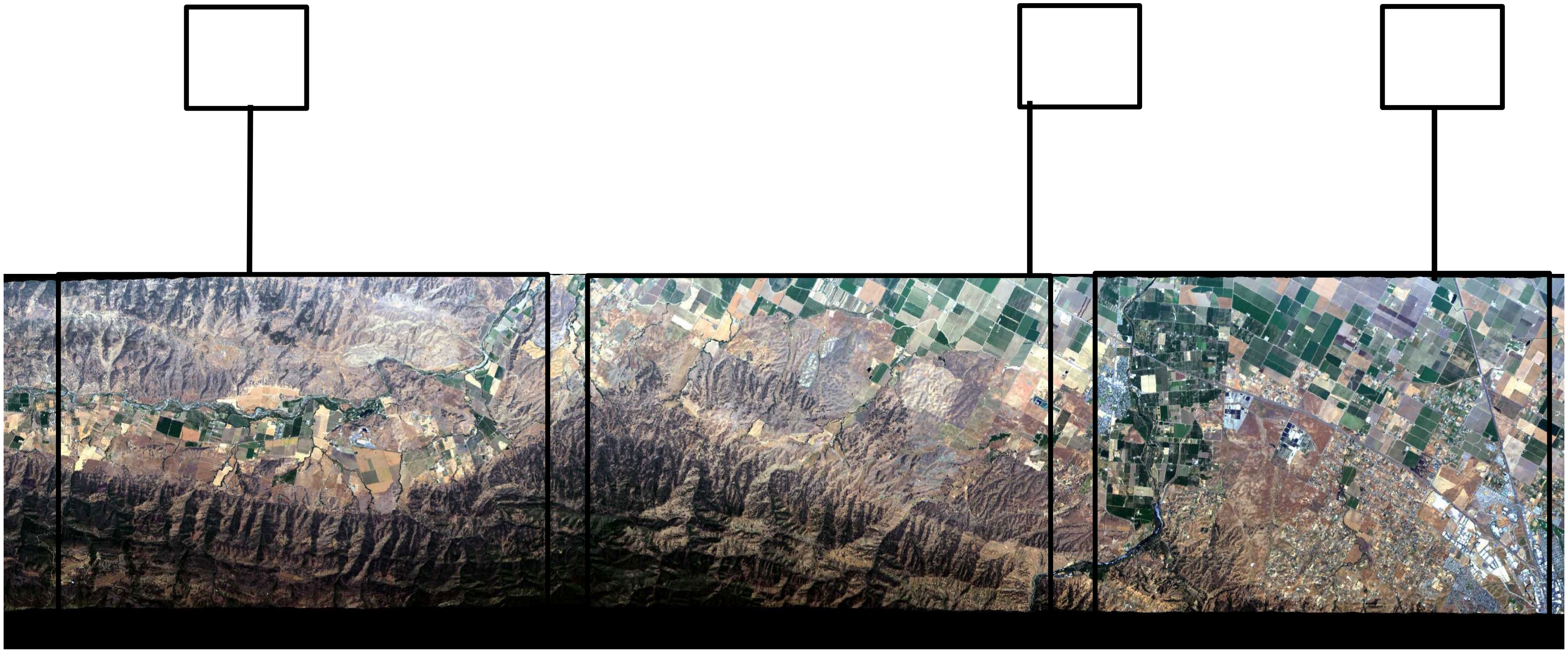
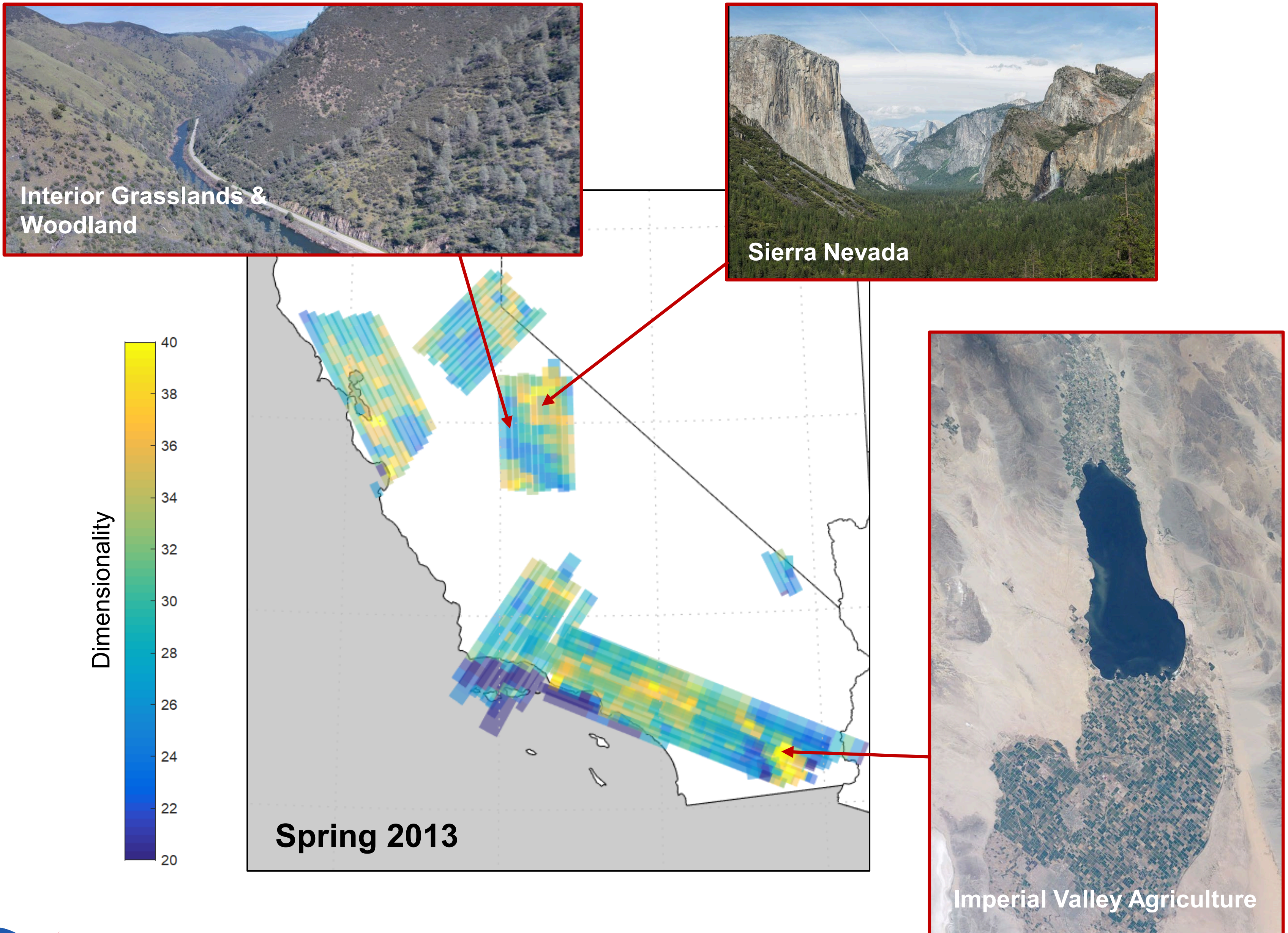
High Intrinsic Dimensionality





Images: Google / NASA / Sierra Nevada Photo by DAVID ILIFF. License: CC-BY-SA 3.0

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Variability due to measurement noise vs. unknown state parameters

Total observation noise

Jacobian WRT unknowns

$$\mathbf{S}_{\boldsymbol{\epsilon}} = \mathbf{S}_y + \mathbf{K}_b \mathbf{S}_b \mathbf{K}_b^T$$

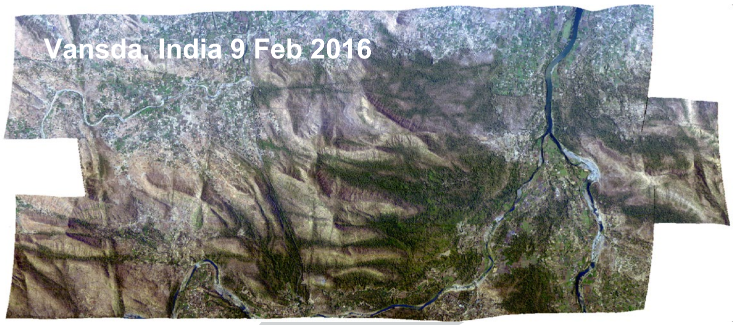
Measurement noise (instrument effects)

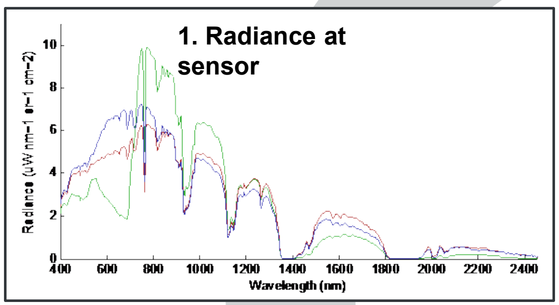
- Photon noise
- Read noise
- Dark current noise

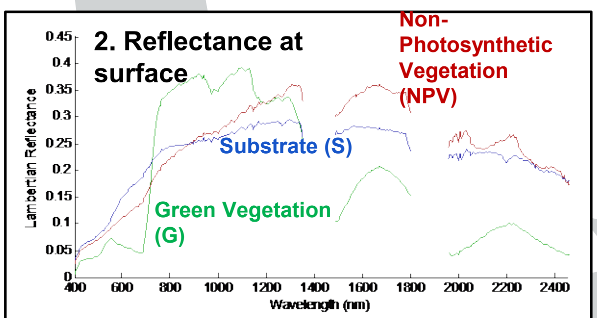
Unknown parameters in the observation system

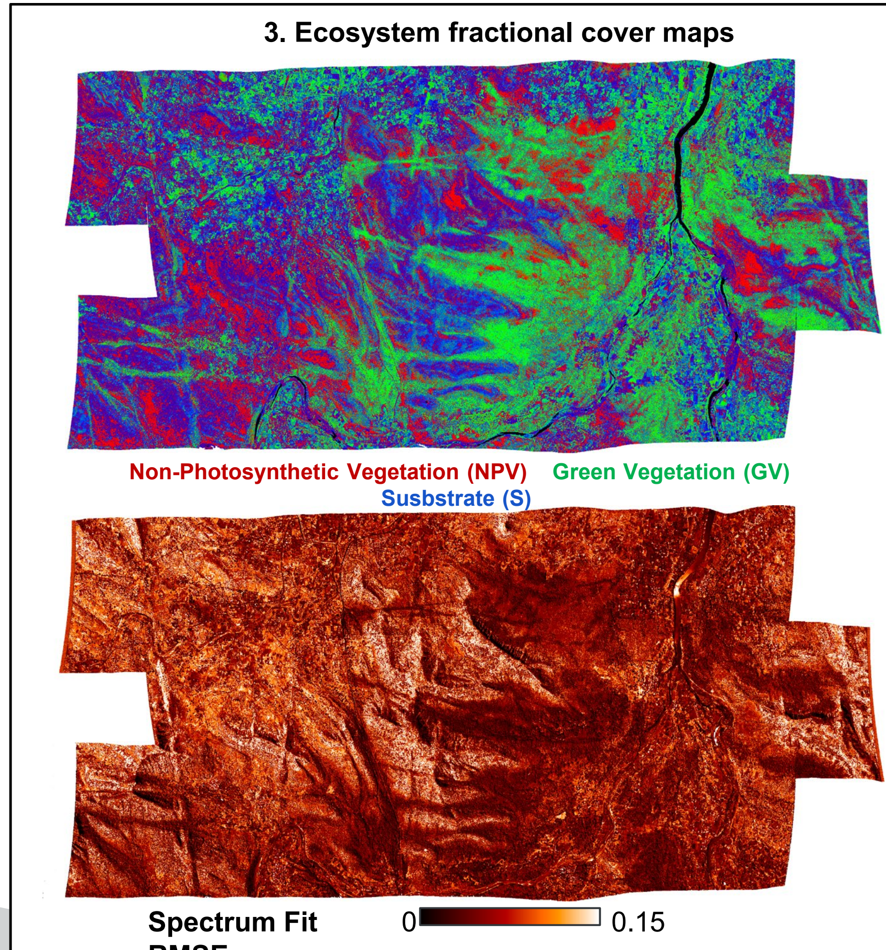
- Sky view factor
- H_2O absorption coefficient intensity
- Systematic radiative transfer error
- Uncorrelated radiative transfer error

Measuring subpixel coverage









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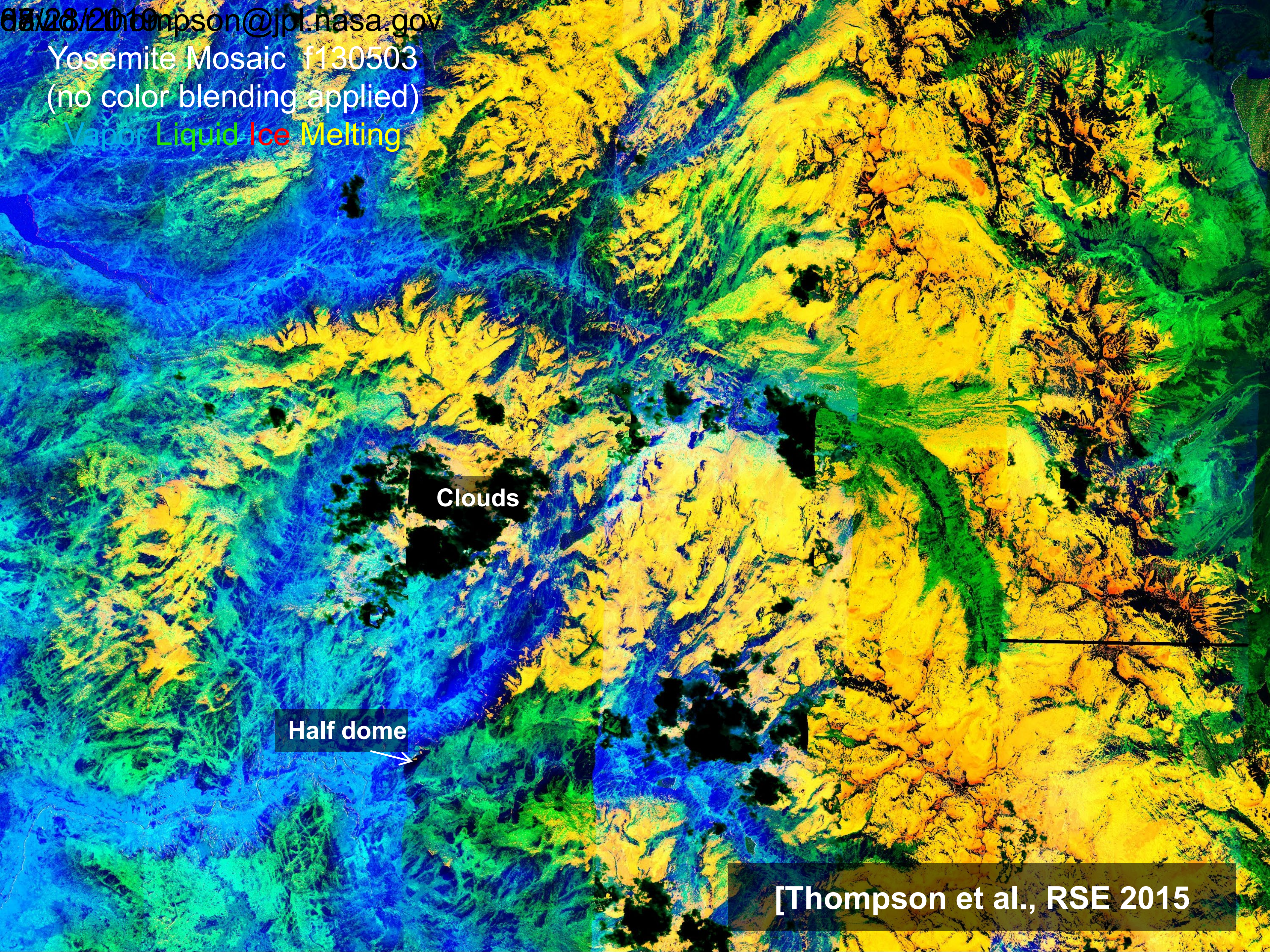
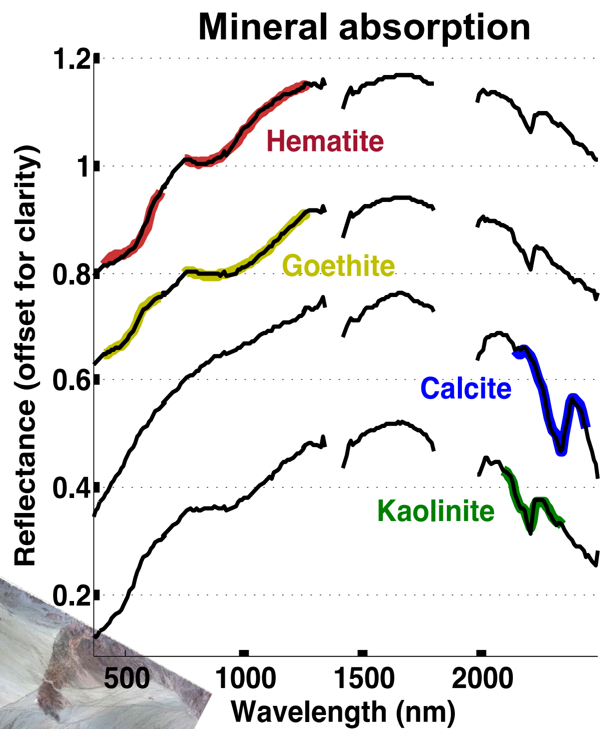
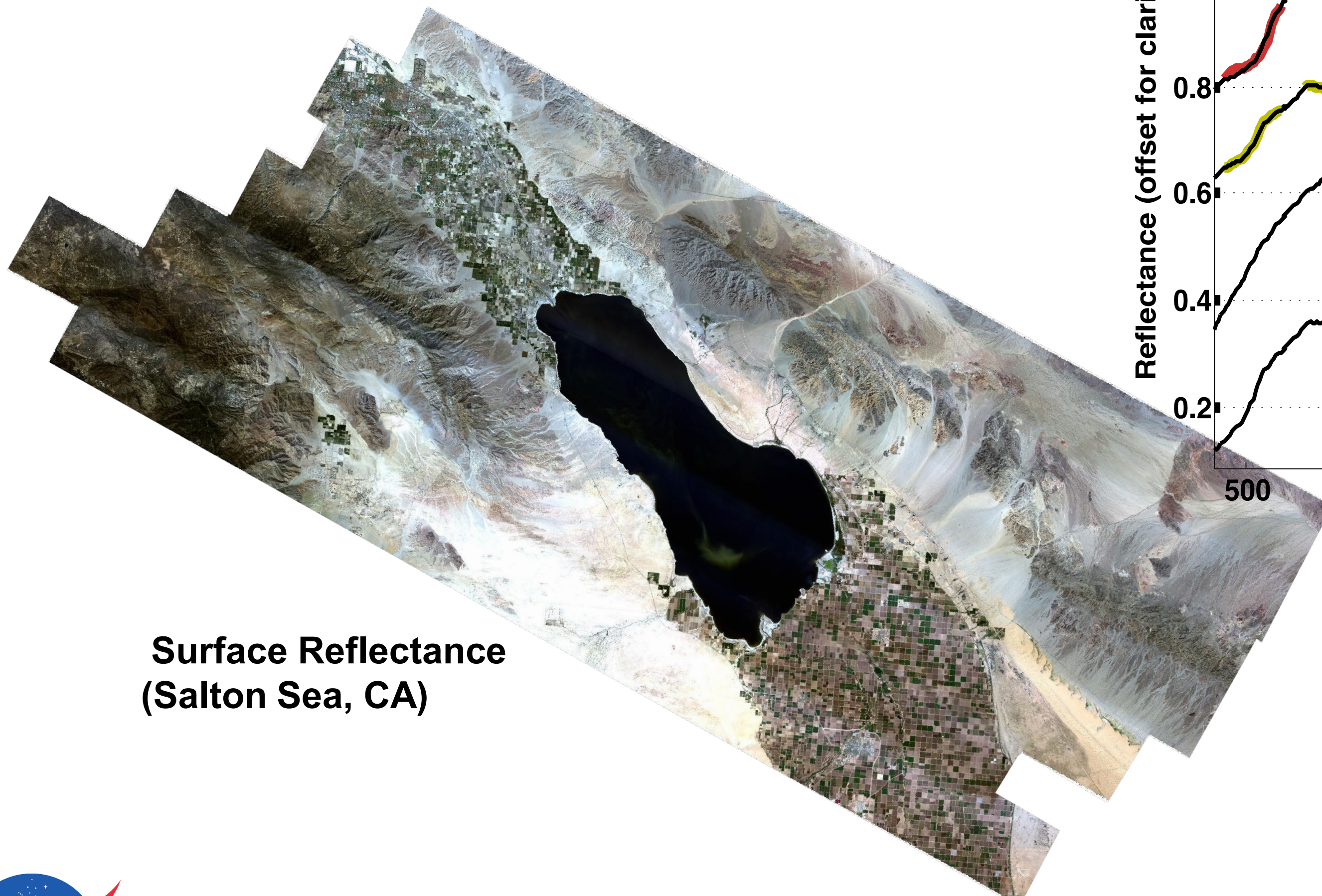

Yosemite Mosaic f130503
(no color blending applied)
Vapor Liquid Ice Melting
Clouds
Half dome
[Thompson et al., RSE 2015

Geologic maps for the EMIT mission





Surface Reflectance (Salton Sea, CA)

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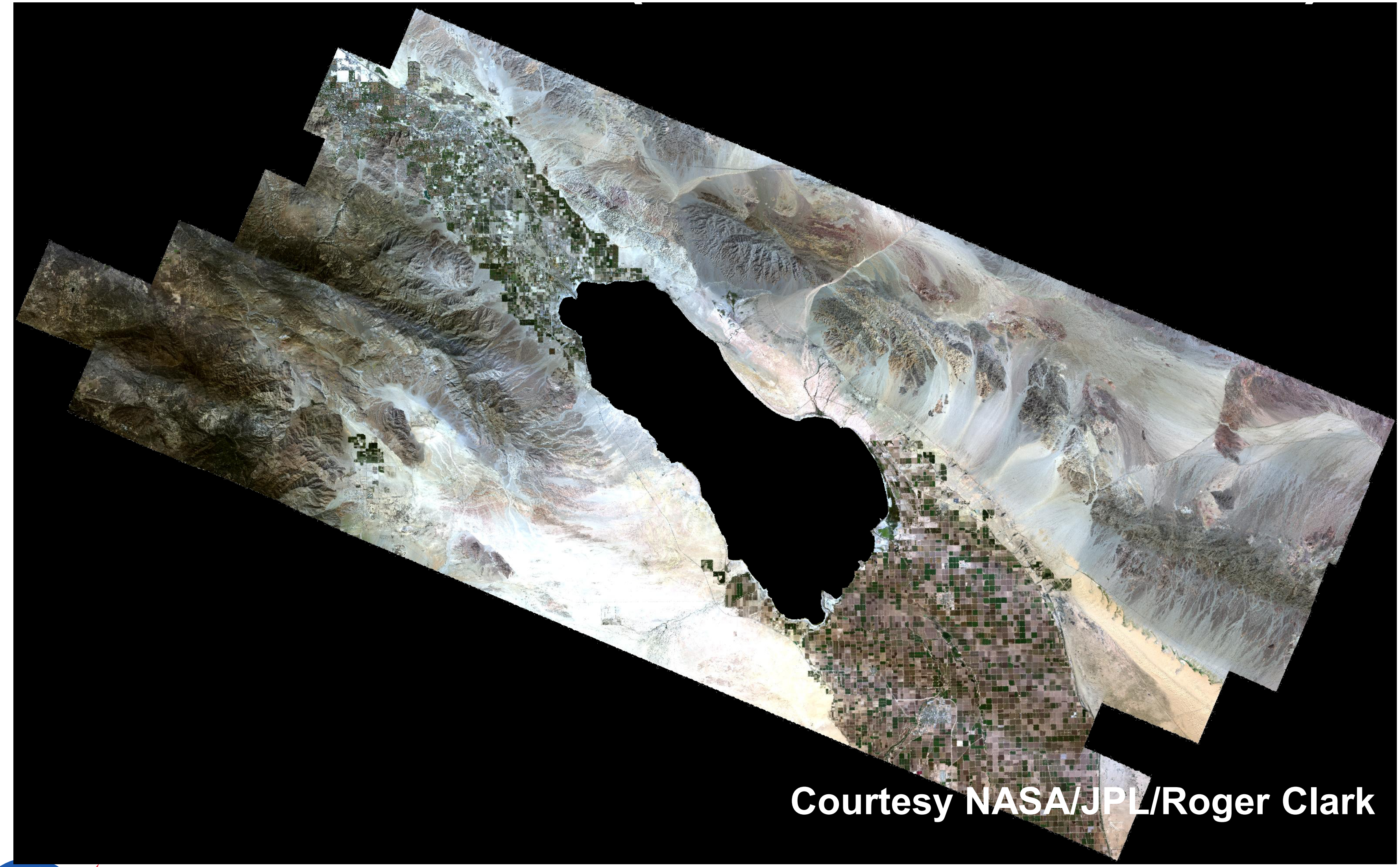

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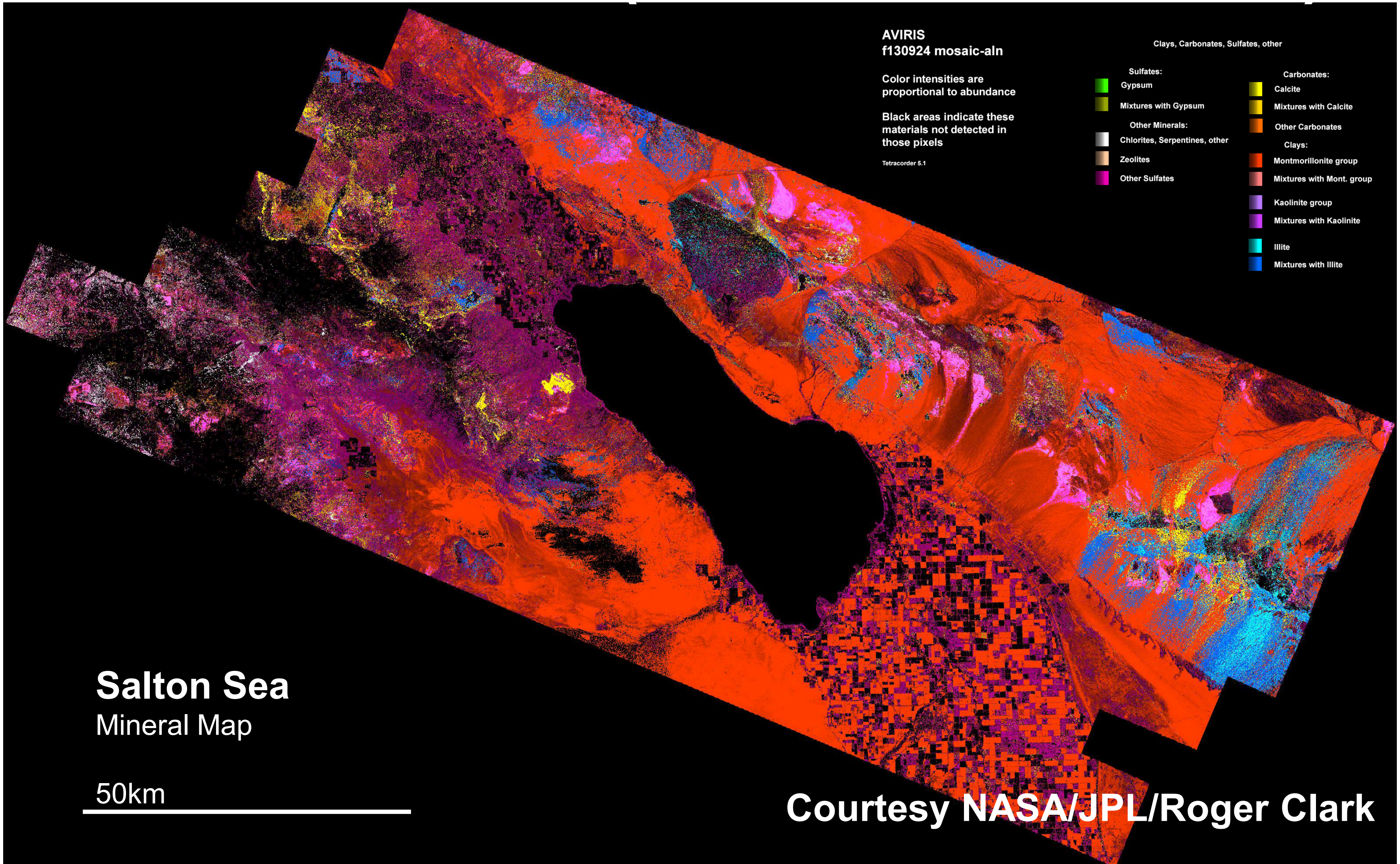
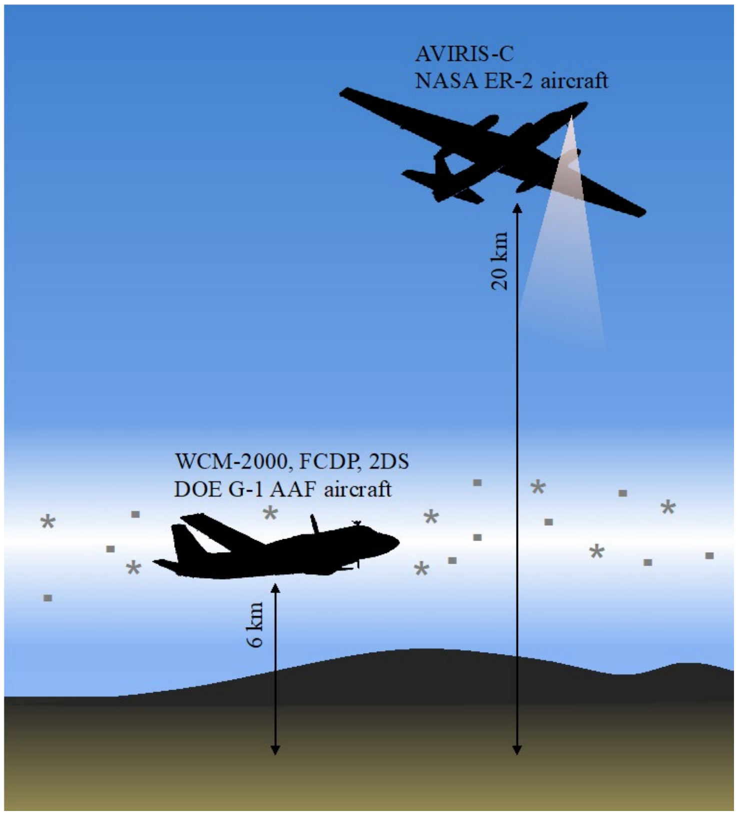
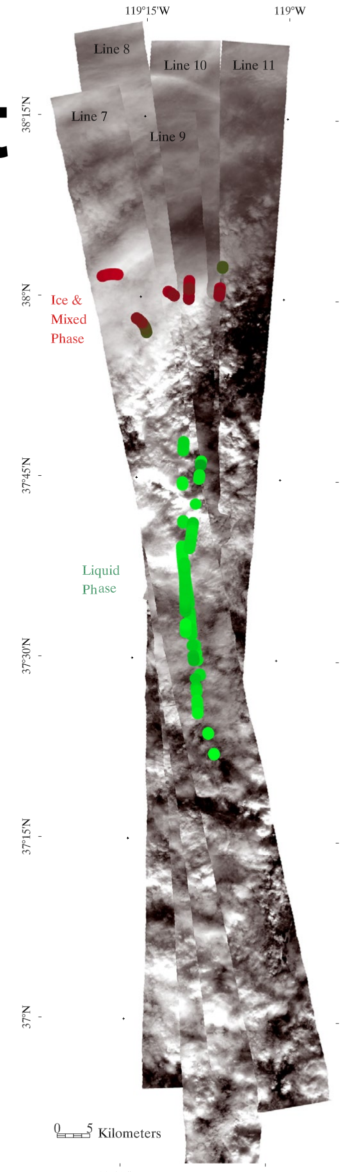


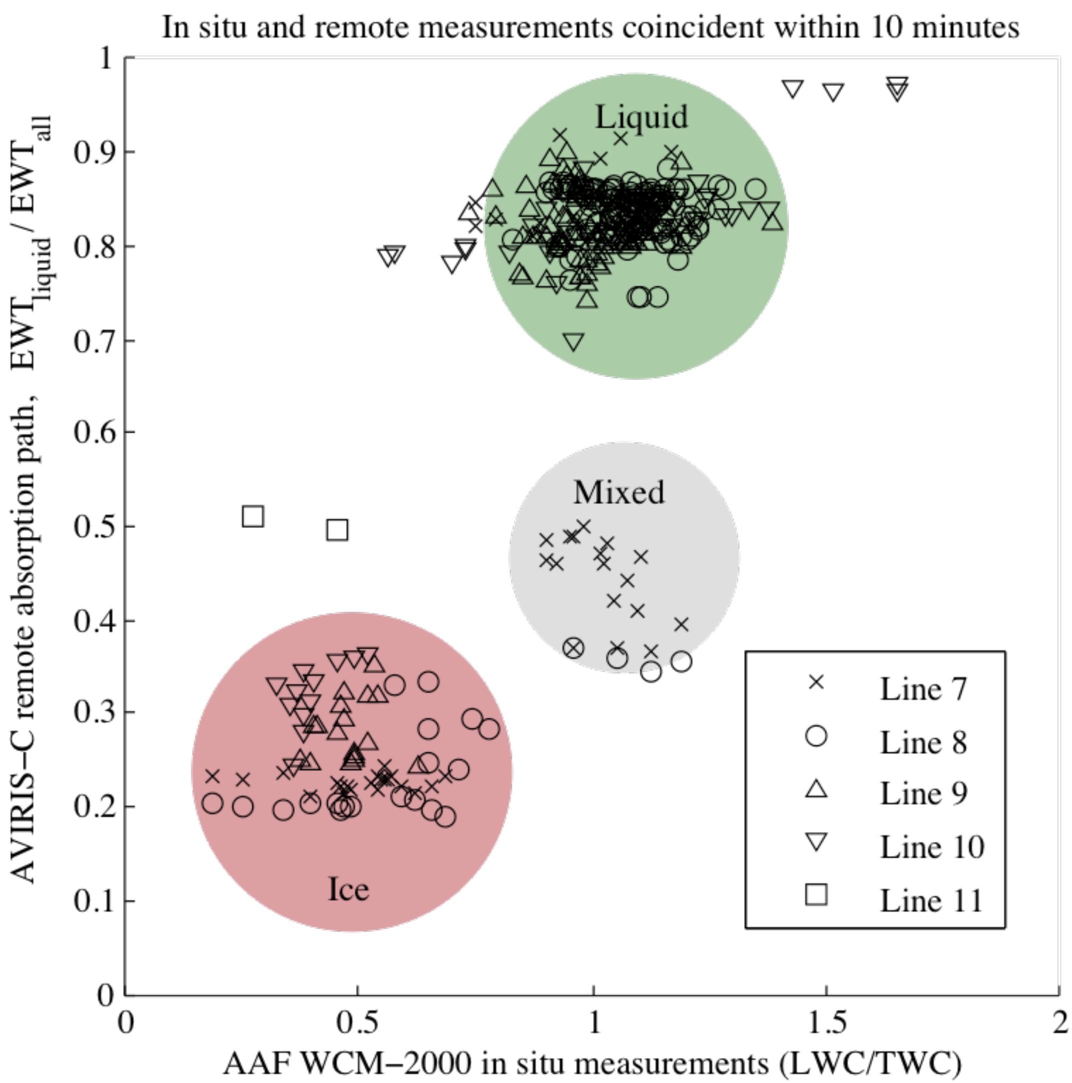
AVIRIS
f130924 mosaic-aln
Color intensities are proportional to abundance
Black areas indicate these materials not detected in those pixels
Tetracorder 5.1
Clays, Carbonates, Sulfates, other
Sulfates:
Gypsum
Mixtures with Gypsum
Other Minerals:
Chlorites, Serpentines, other
Zeolites
Other Sulfates
Carbonates:
Calcite
Mixtures with Calcite
Other Carbonates
Clays:
Montmorillonite group
Mixtures with Mont. group
Kaolinite group
Mixtures with Kaolinite
Illite
Mixtures with Illite
Salton Sea
Mineral Map
50km
Courtesy NASA/JPL/Roger Clark

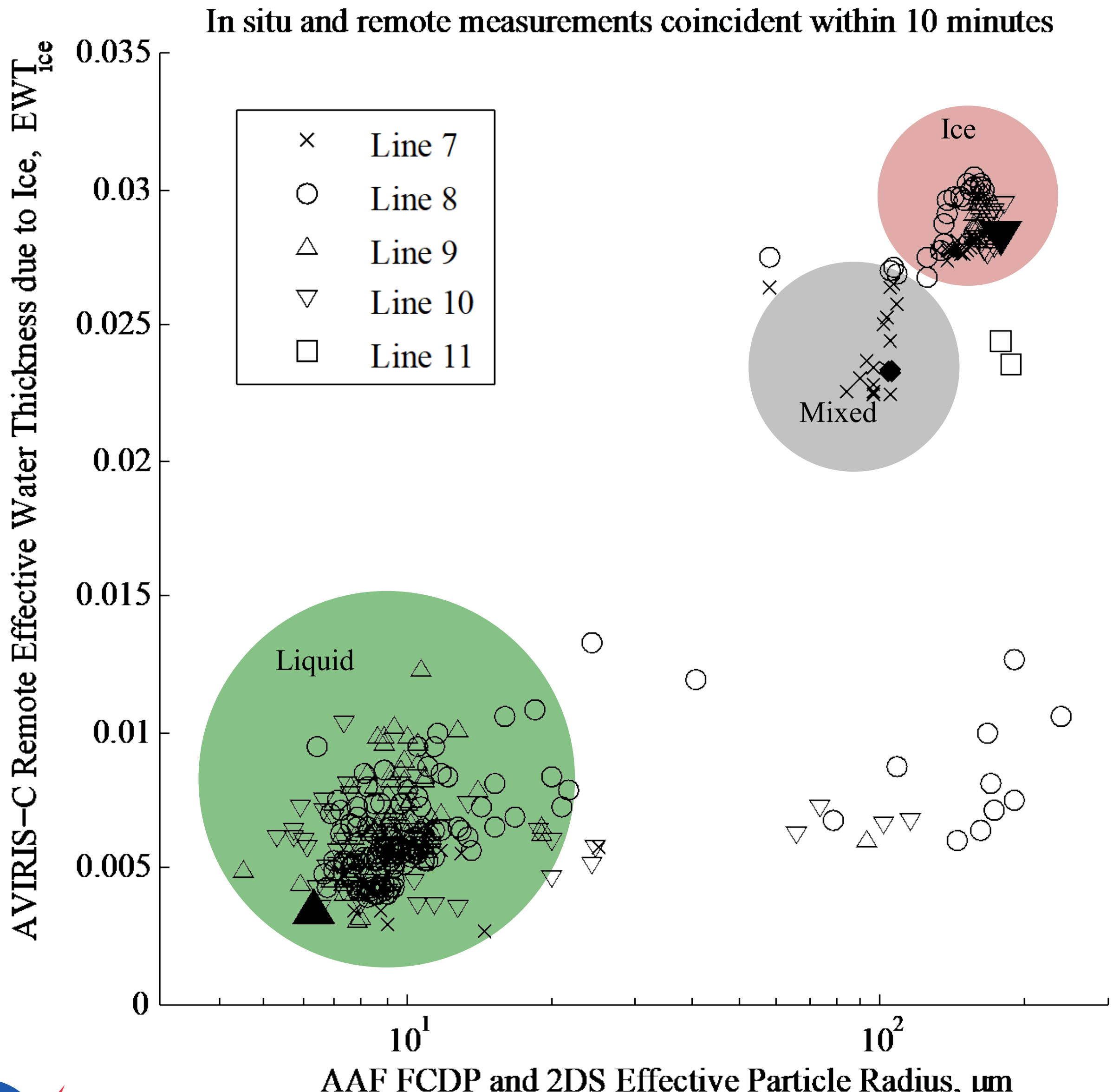
Coincident multi-aircraft measurement

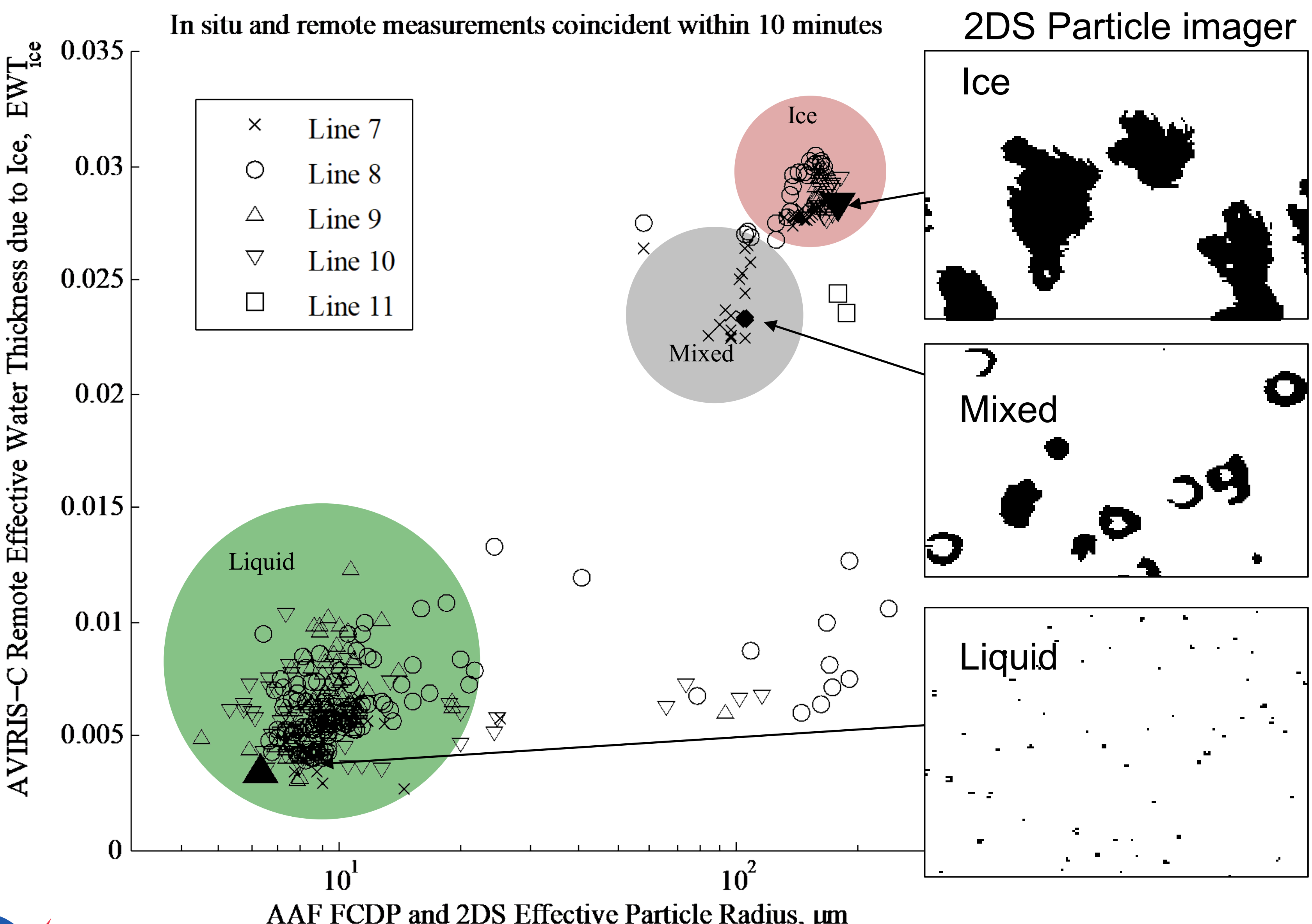




In situ corroborates remote data




In situ and remote measurements coincident within 10 minutes
AVIRIS-C Remote Effective Water Thickness due to Ice, EWT_{ice}
AAF FCDP and 2DS Effective Particle Radius, μm
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
10^1
10^2
Line 7
Line 8
Line 9
Line 10
Line 11
Ice
Mixed
Liquid



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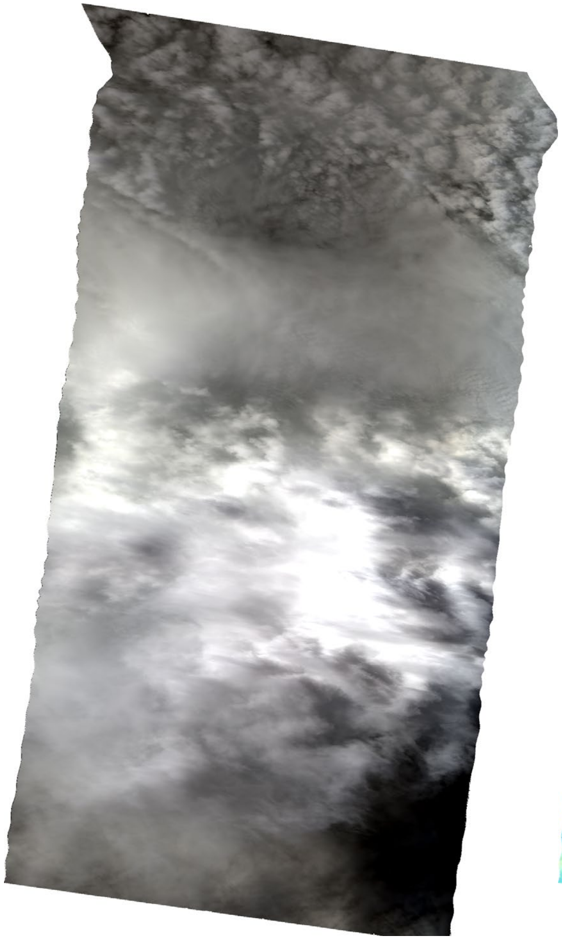
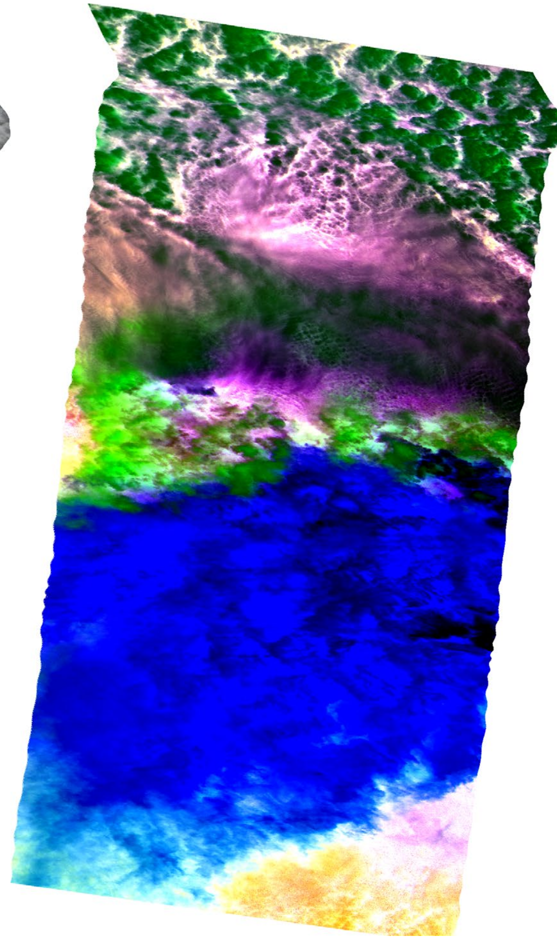
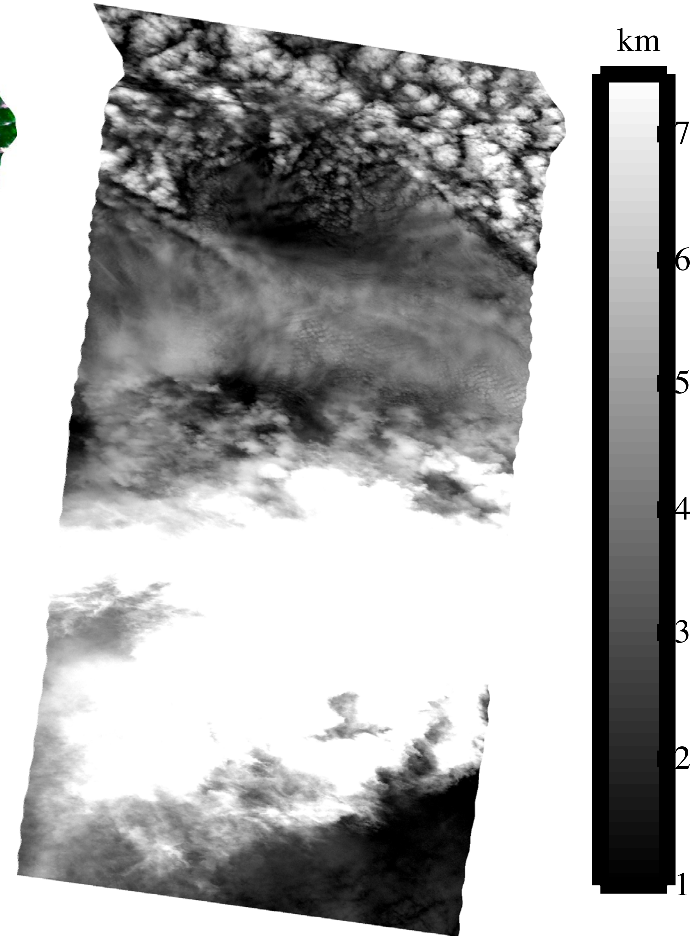
Remote sensing of cloud phase



RGB Image



Ice Liquid Vapor



Pressure Altitude

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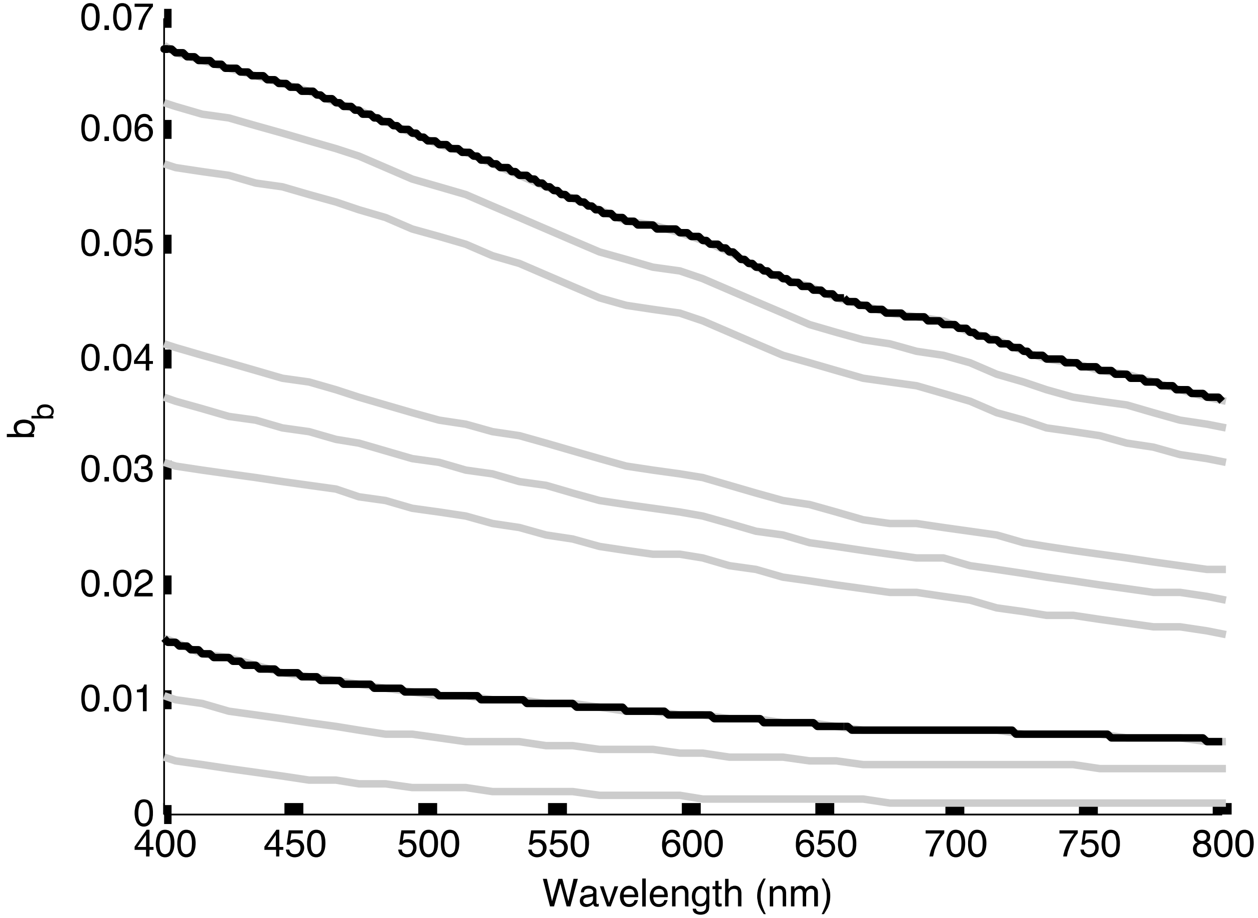
Example of b_b endmember library



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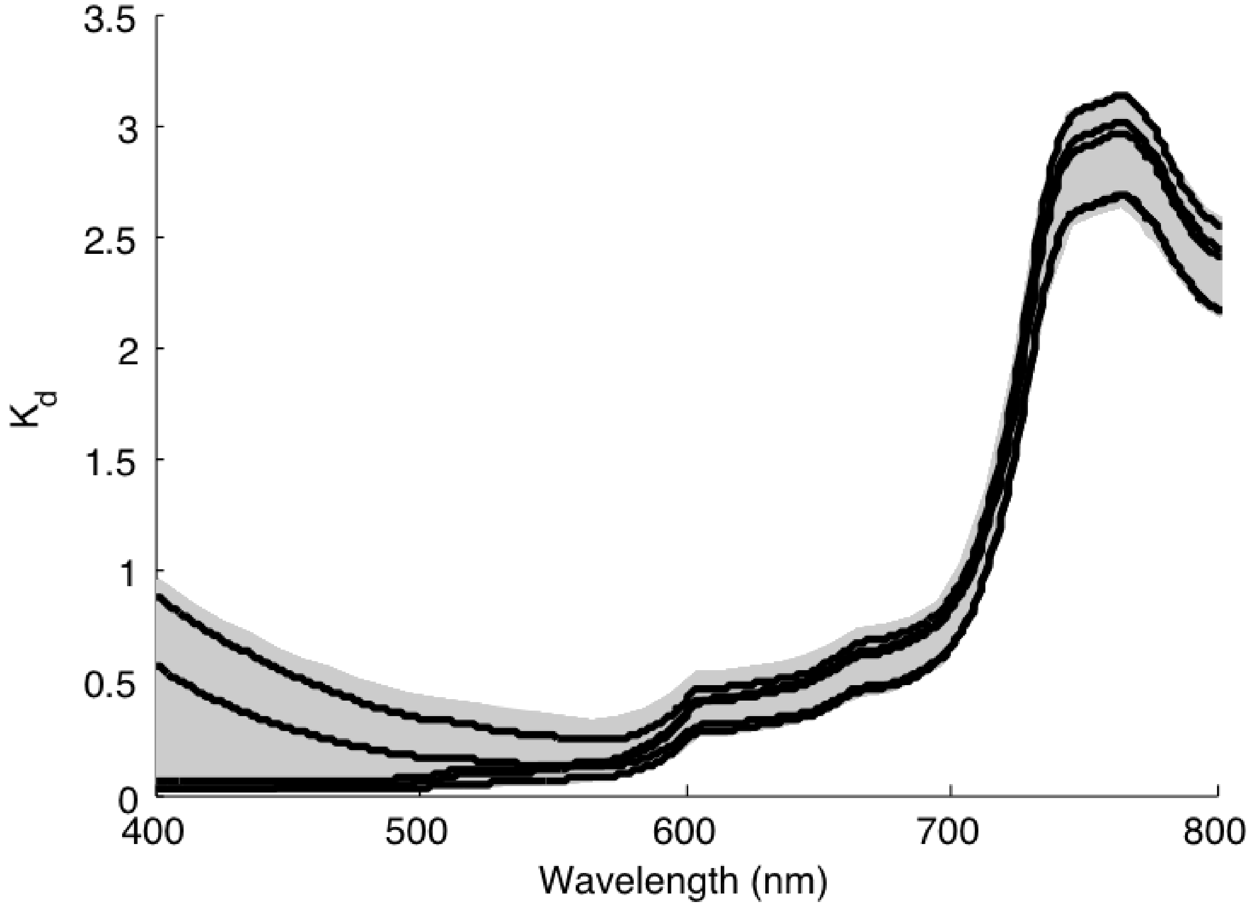
Example of K_d endmember library



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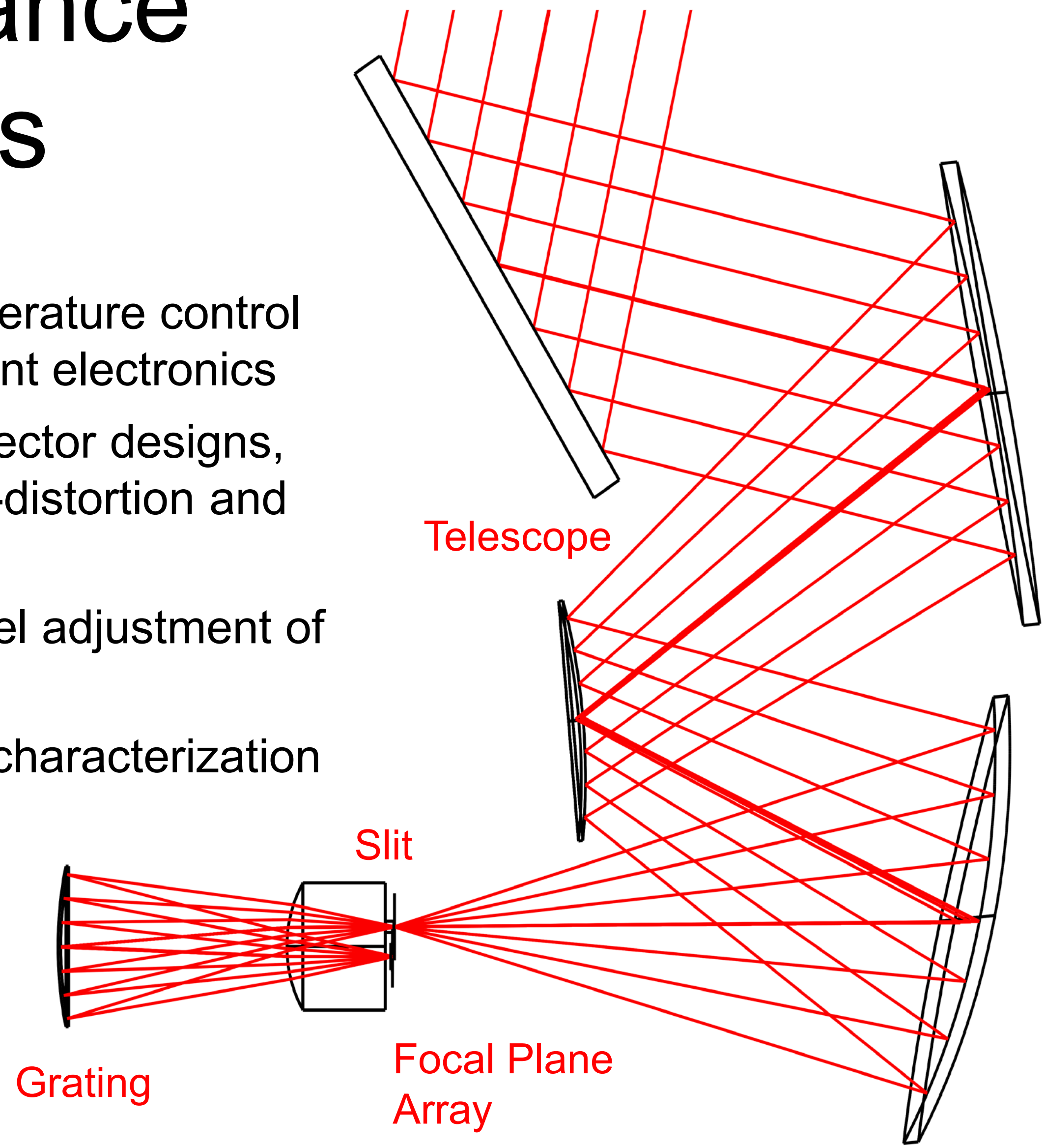
Case studies

- **Instrument characterization** – PSF fitting
- **Gases -** CH_4 monitoring
- **Liquids -** Bathymetry and Benthos
- **Solids-** Optimal Estimation

Performance drivers

- **Stability:** Careful temperature control and low-noise instrument electronics
- **Uniformity:** Single-detector designs, curved gratings for low-distortion and high throughput
- **Alignment:** Micron-level adjustment of optical components
- **Calibration:** Accurate characterization of spectral response



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Procedure

Posit the relation [Maritorena et al., 1994]:

$$Rrs_0 = R_{inf} + (A - R_{inf})\, e^{-2K_d H}$$

Depth

bb / $(2K_d)$ Albedo Attenuation

Optimize via Levenberg Maquardt, minimizing:

$$\begin{aligned} Error(x) = \quad & (Rrs_0 - Rrs_0^*) \\ & + \alpha_{bb590}\,(\mu_{bb50-}\ bb_{590}^*) \\ & + \alpha_{kd450}\,(\mu_{kd450} - K_{d450}^*) \\ & + \alpha_{kd590}\,(\mu_{kd590} - K_{d590}^*) \\ & + \alpha_H\,(\mu_H - H^*) \end{aligned}$$

Model fit vs. measurement

Statistical priors to constrain the other free parameters

Procedure

Posit the relation [Maritorena et al., 1994]:

$$Rrs_0 = R_{inf} + (R_b - R_{inf})\, e^{-2K_d H}$$

bb / (2K_d) Benthic reflectance Attenuation Depth

Procedure

Posit the relation [Maritorena et al., 1994]:

$$Rrs_0 = R_{inf} + (R_b - R_{inf})\, e^{-2K_d H}$$

bb / ($2K_d$)

Benthic reflectance

Attenuation

Depth

Problem: underdetermined

K_d, bb, and R_b yield (3N + 1) parameters for just N measurements

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Procedure

Posit the relation [Maritorena et al., 1994]:

$$Rrs_0 = R_{inf} + (R_b - R_{inf})\, e^{-2K_dH}$$

R_{inf}: bb / (2K_d)

R_b: Benthic reflectance

K_d: Attenuation

H: Depth

Problem: underdetermined

K_d, bb, and R_b yield (3N + 1) parameters for just N measurements

Solution: represent as linear mixtures

Parameterize K_d, bb, and R_b as nonnegative linear combinations of endmember spectra, and retrieve mixing coefficients (~20 DOF)

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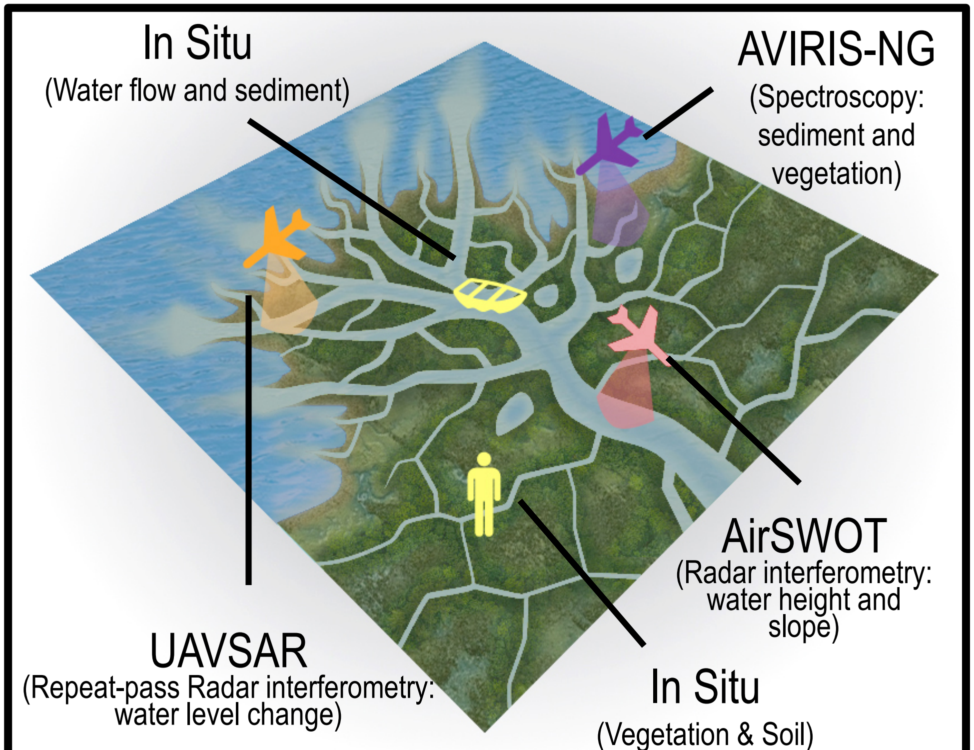
Airborne (2019 – 2024): Delta-X

PI: Marc Simard (JPL)

Urgency: If ignored, Relative Sea Level Rise (RSLR) will very soon have devastating consequences on the livelihood of the half billion people that live in these low-lying coastal regions. Nearly all the world's major river deltas are threatened along with the services they provide: flood protection, carbon sequestration, biodiversity and food supply.



Delta-X Science Question: Will river deltas completely drown, or some parts of these deltas accumulate sufficient sediments and produce enough plants to keep pace with RSLR ?

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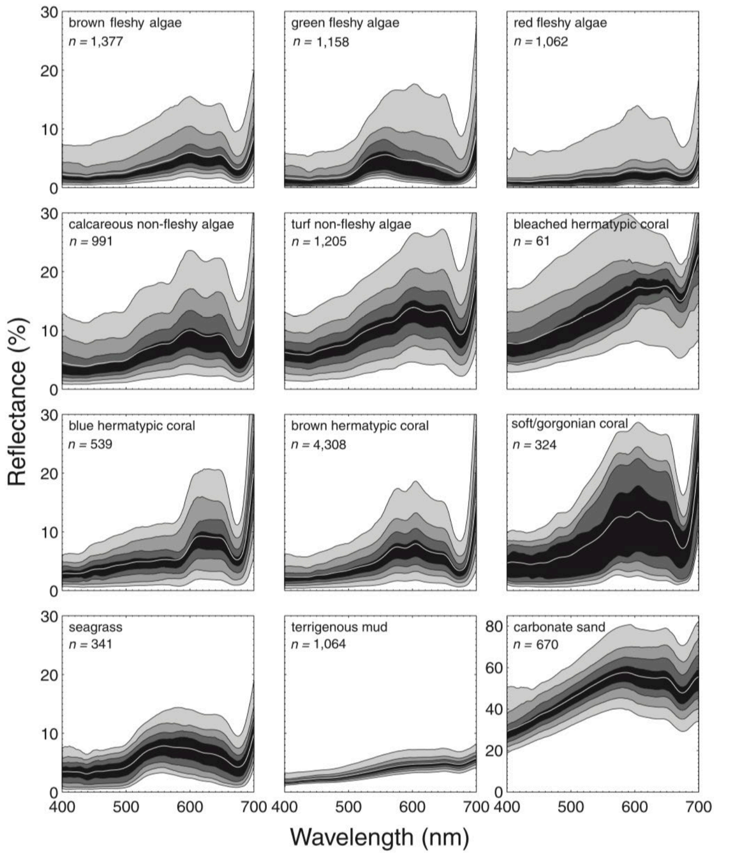
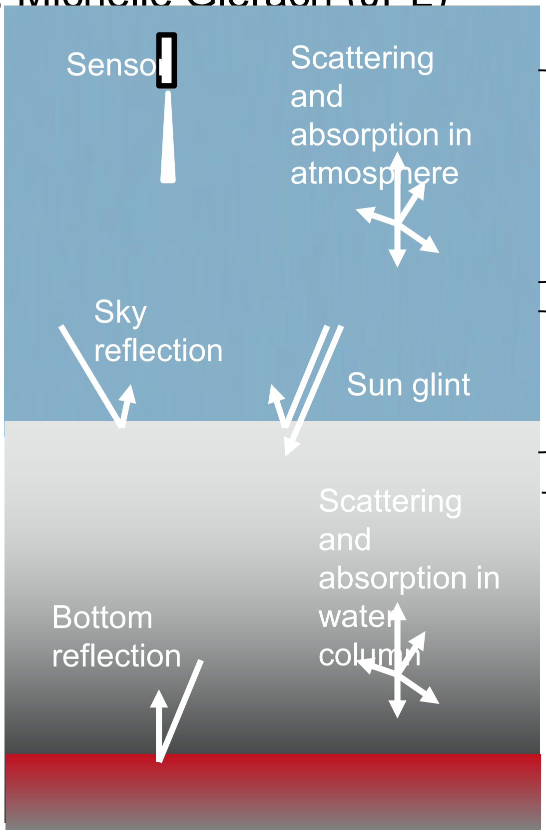
Airborne (2016 – 2019): CORAL

PI: Eric Hochberg (BIOS)
Deputy PI: Michelle Gierach (JPL)



Hochberg et al., *Remote Sensing of Environment* 2003



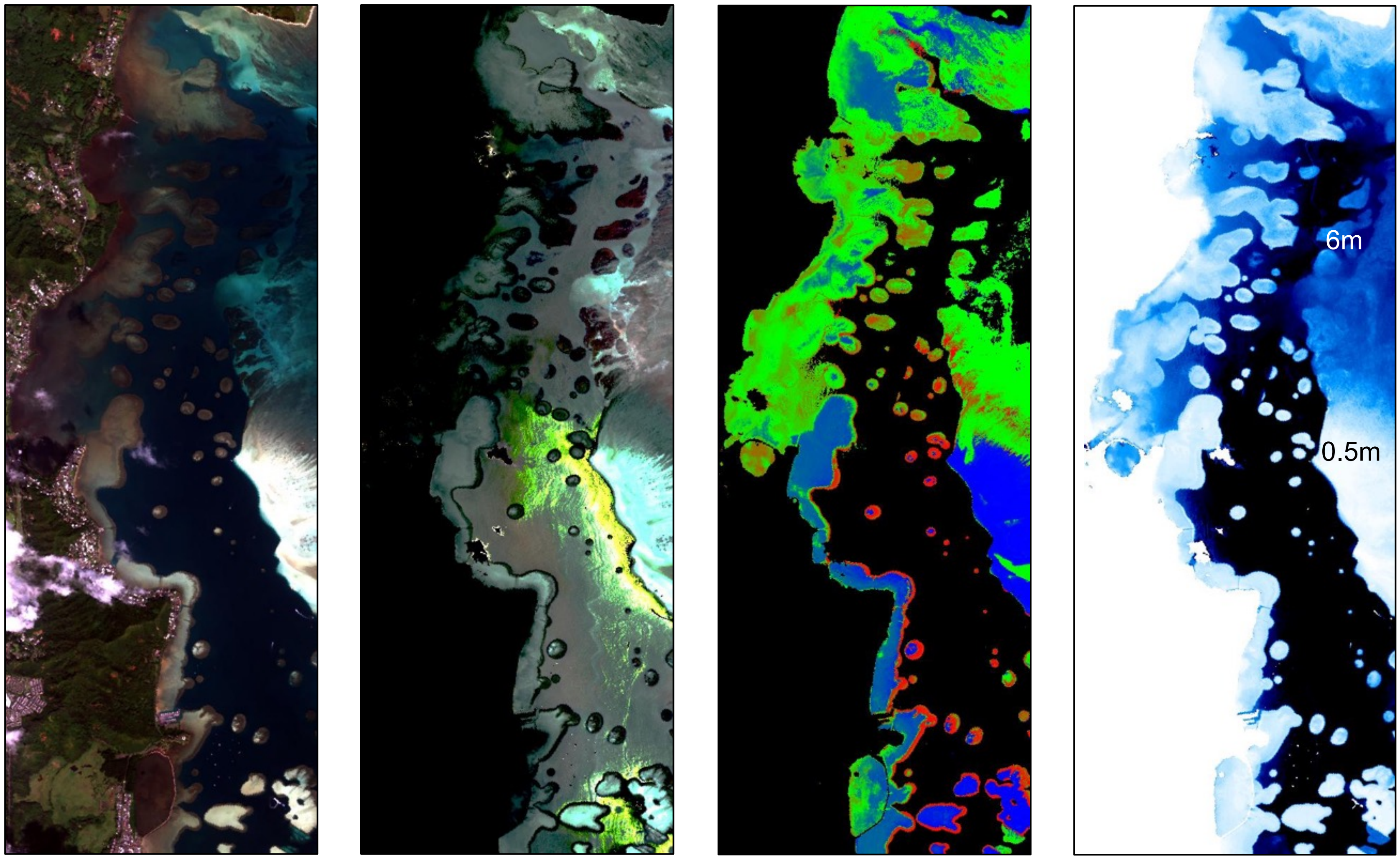
Step 1
Aerosol optical depth τ
Aerosol type ζ
Water leaving reflectance R_{rs}

Step 2
Glint-corrected Rrs_0

Step 3
Backscatter b_b
Attenuation K_d
Depth H
Benthic reflectance R_b

Thompson et al., *Remote Sensing of Environment* 2017

Water-leaving Reflectance | Rb | Benthic Cover | Depth



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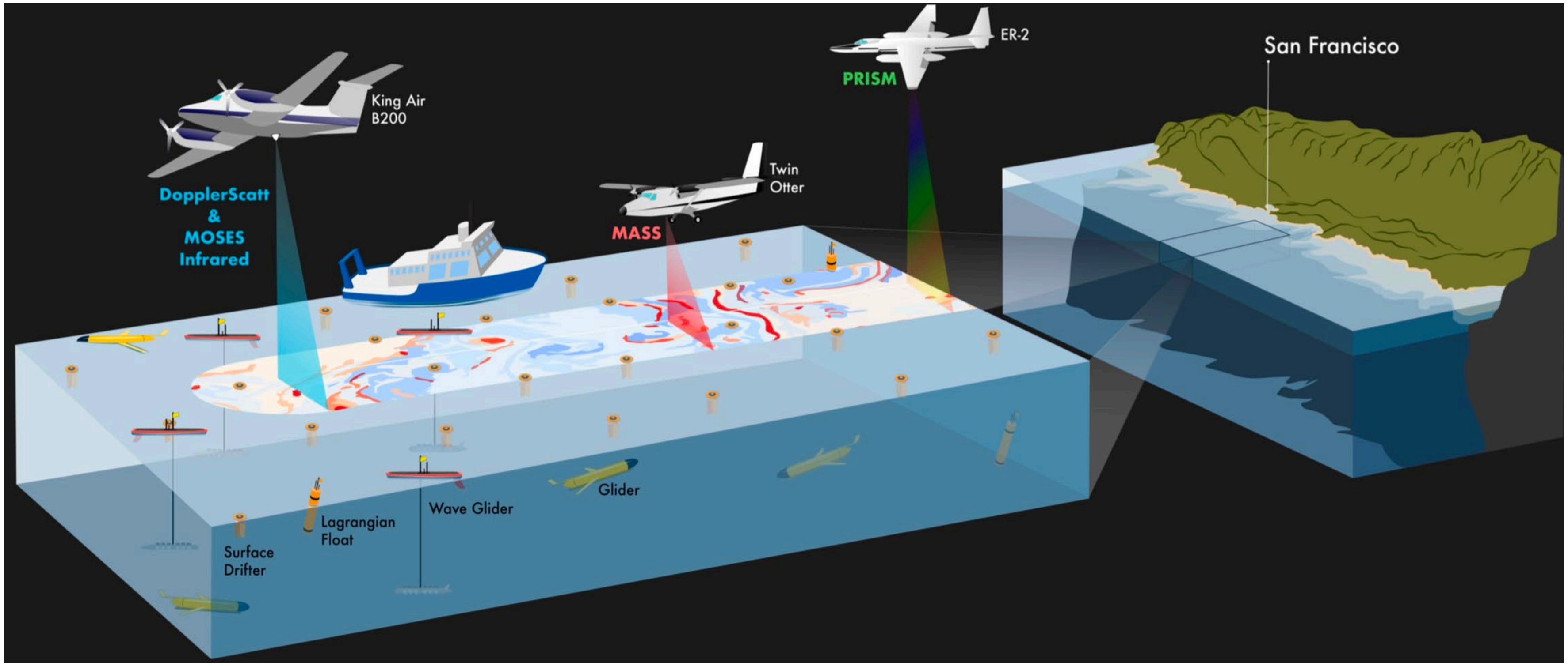

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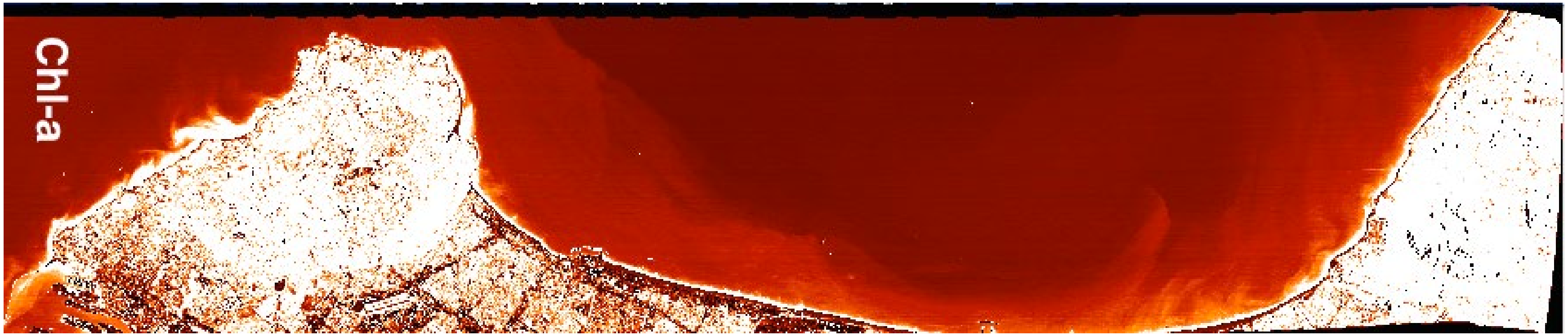
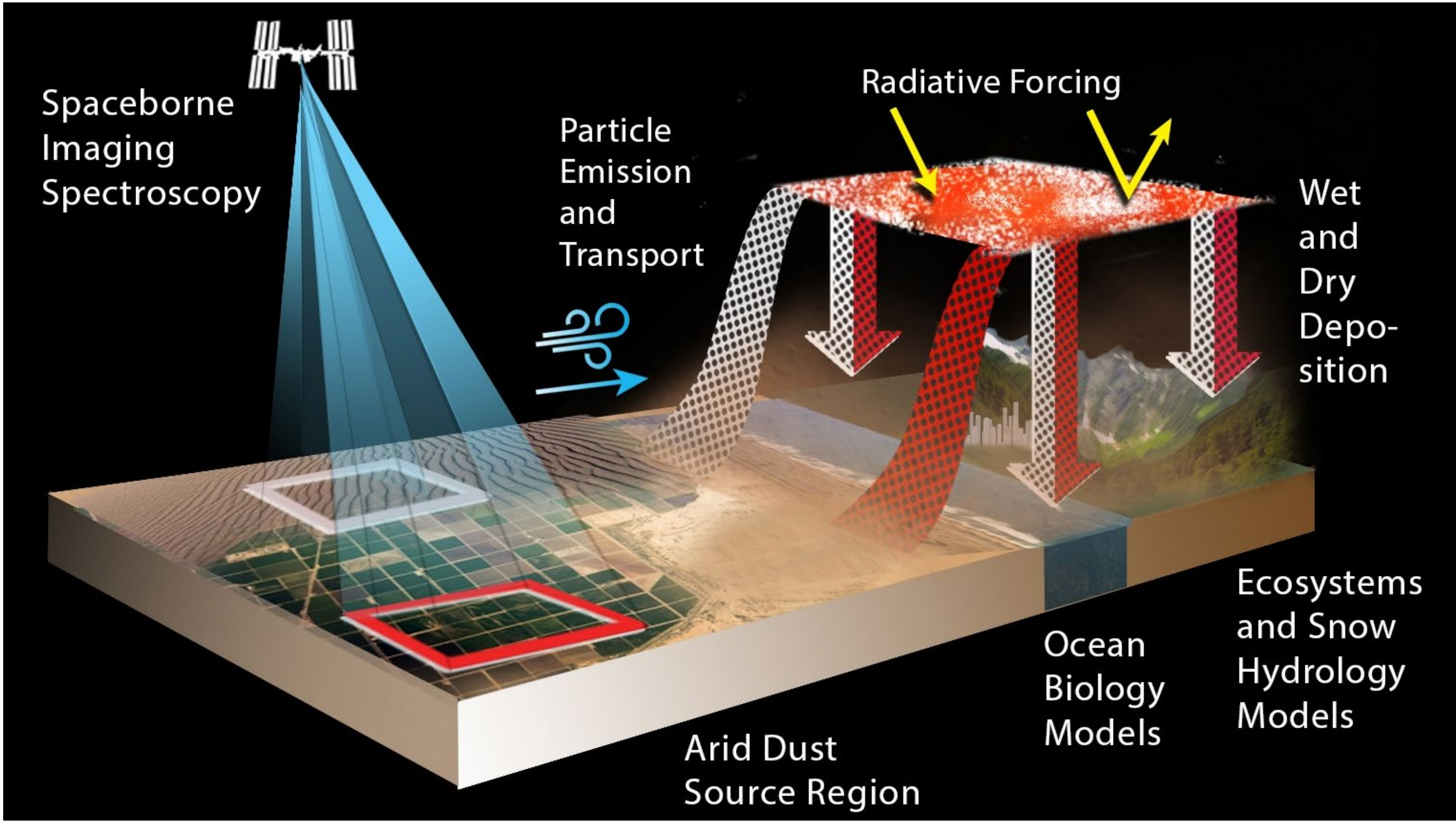
Airborne (2020 - 2024): S-MODE

PI: Tom Farrar, WHOI





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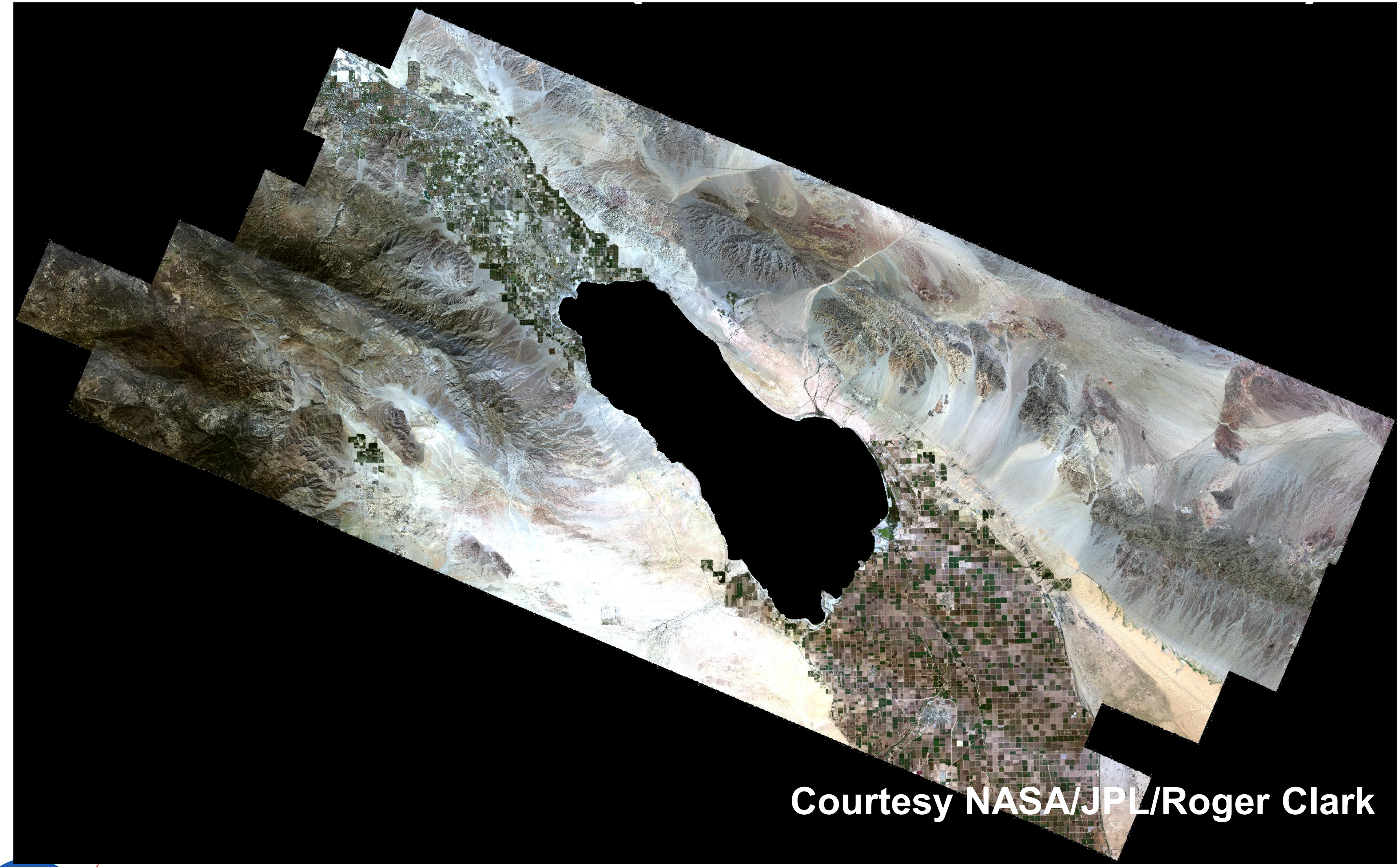
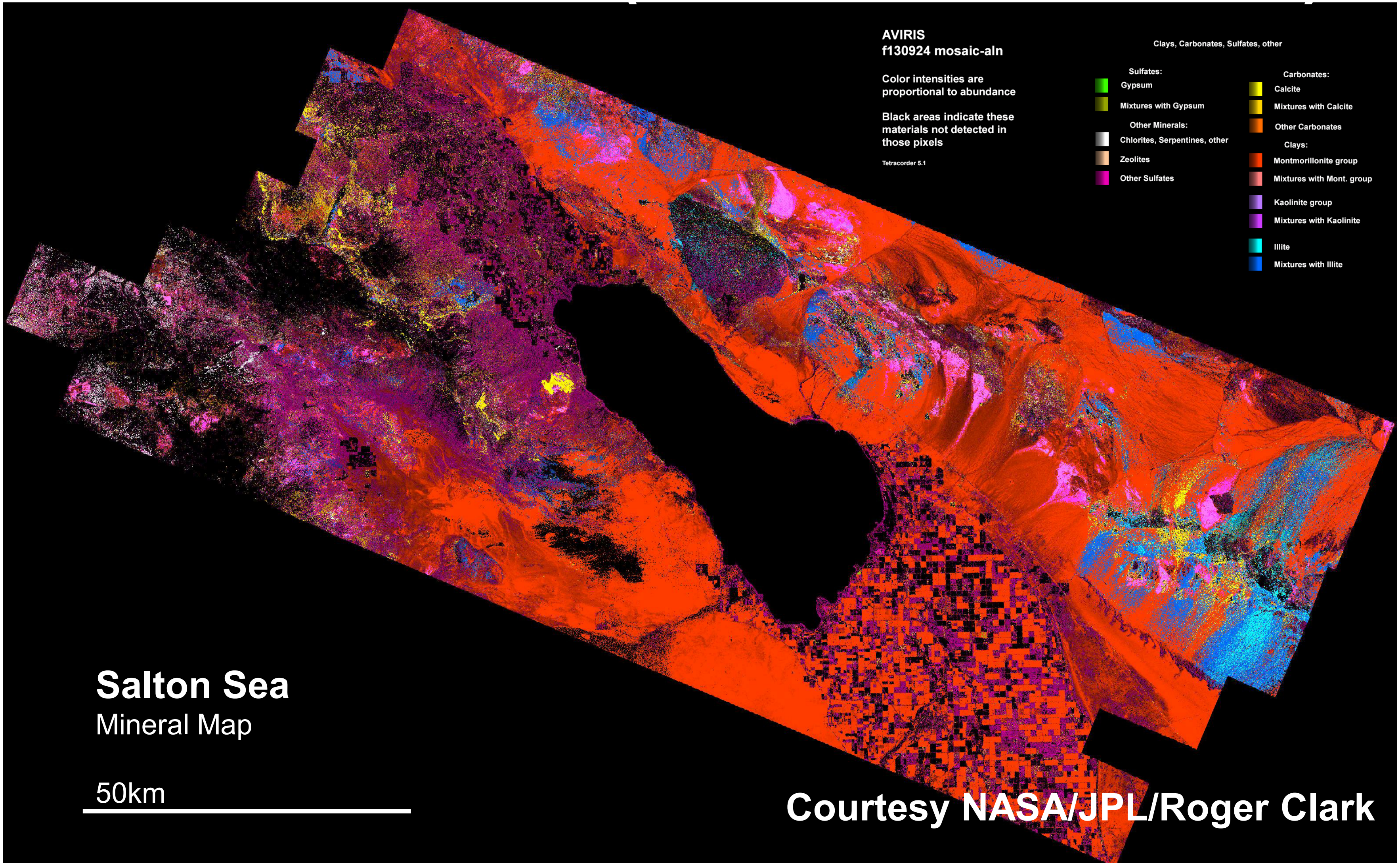

Courtesy NASA/JPL/Roger Clark



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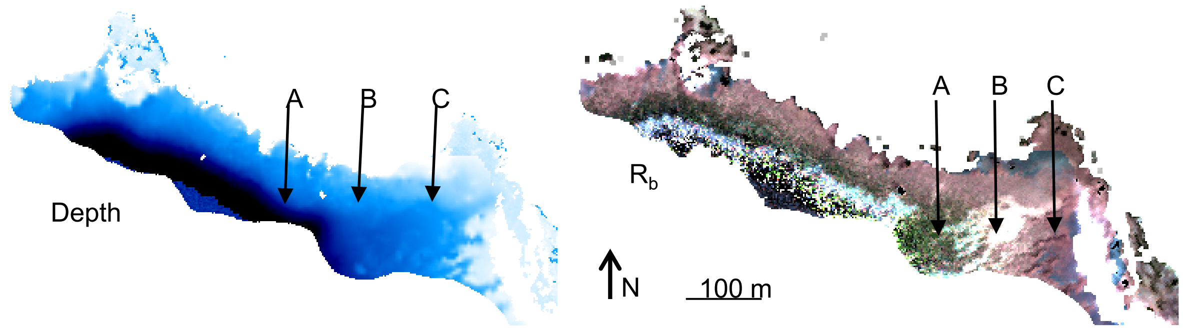
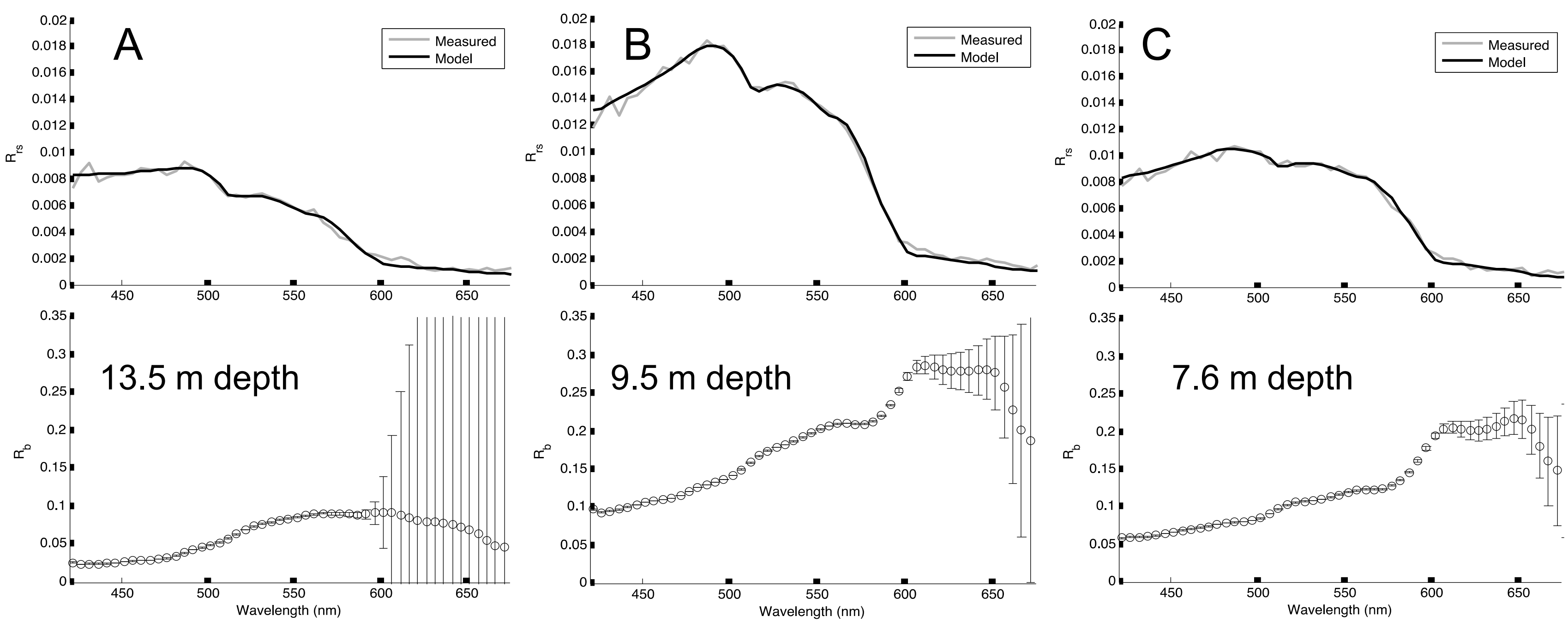
R_{rs} vs. bottom reflectance result





Airborne VSWIR data collected by the Carnegie Airborne Observatory

Depth Estimates