A Brief Introduction to the EMIT Mission

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on behalf of Robert O. Green[1], Natalie Mahowald[2] and the EMIT team
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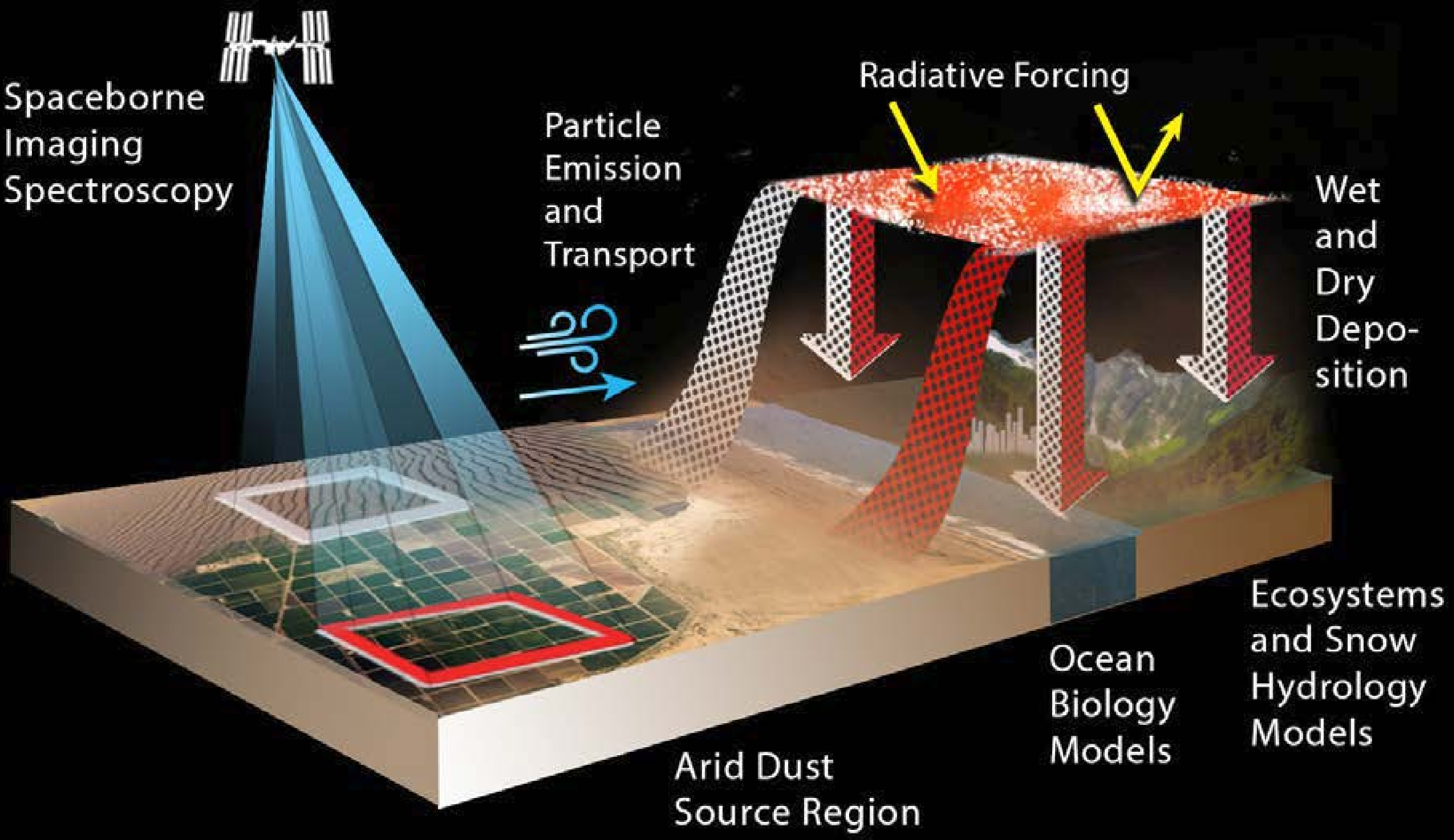
[2] Cornell University

EMIT is supported by the Earth Venture Instrument Program, NASA Science Mission Directorate, Earth Science Division.


MODIS October 26, 2007. Credit:

The Earth surface Mineral dust source InvesTigation (EMIT)



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EMIT Science Objectives

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

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

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

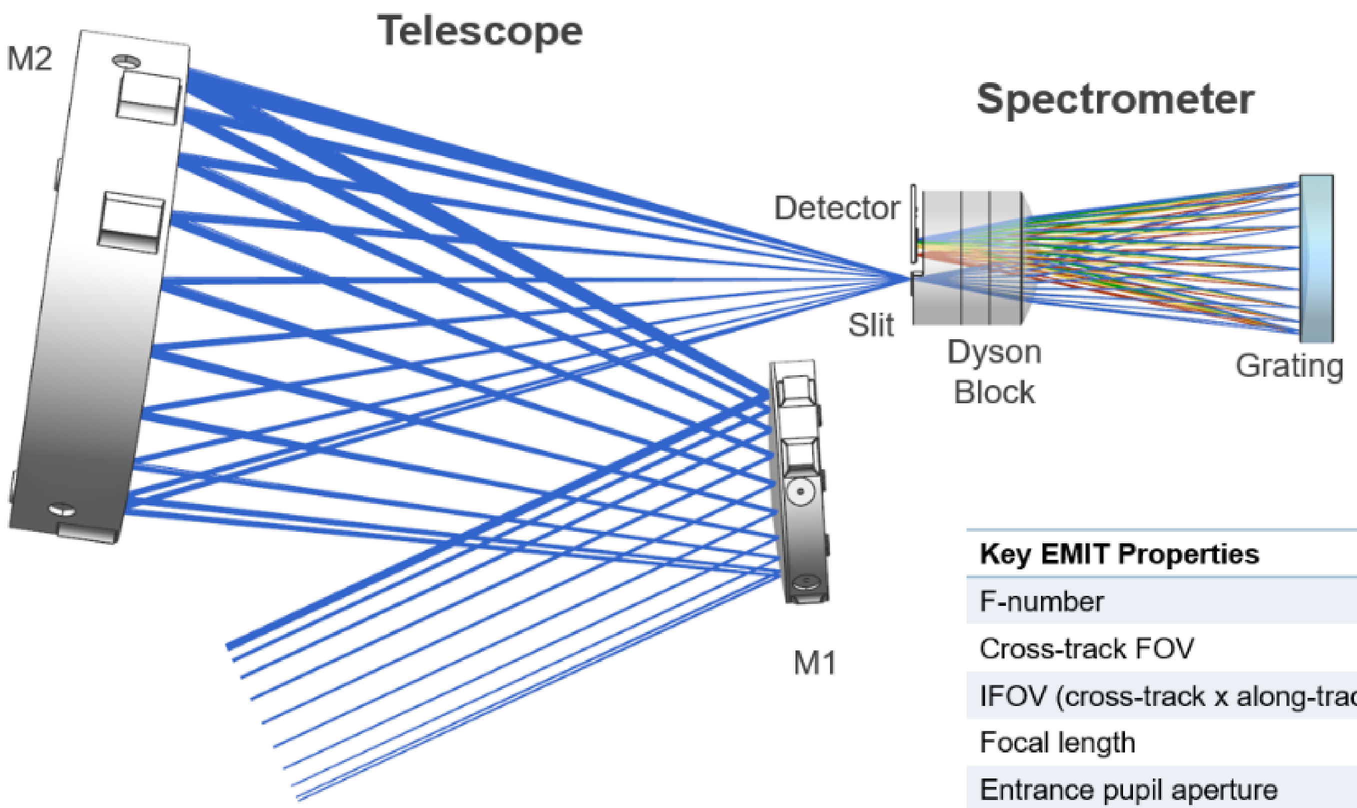
EMIT achieves this objective by initializing Earth System Model forecast models with the mineralogy of soils exposed within at-risk lands bordering arid dust source regions.

EMIT Science Team

Investigator	Institution	Role	Responsibility
Robert O. Green	JPL Caltech	PI	Overall responsibility for EMIT investigation: hardware development, operations, calibration, validation, data processing, retrievals, archiving and achieving science objectives. (L1b, L1bv)
Natalie Mahowald	Cornell University	Deputy PI	Earth system model L4 team lead with responsibility for overall modeling validation as well as lead for the models. (L4, L4v)
David R. Thompson	JPL Caltech	Instrument Scientist, Co-I	L1 product lead and L2a Lead for atmospheric correction. (L1b, L2a, L2av)
Roger Clark	Planetary Science Institute	Co-I	L2b mineral composition lead with validation responsibility. (L2b, L2bv)
Bethany Ehlmann	JPL Caltech	Co-I	Mineral composition and abundance validation; Quantification.
Paul Ginoux (CS)	NOAA, Princeton University	Co-I	Modeling anthropogenic mineral dust and its effects, through mineralogy, on radiation and air quality. Validation with respect to satellite measurements. Modeling of future impacts. (L4, L4v)
Olga Kalashnikova	JPL Caltech	Co-I	Dust optical property modeler. Models of dust optical properties in relation to dust microphysics. Assists with dust atmospheric correction. (L4, L2a)
Ron Miller (CS)	NASA GISS, Columbia University	Co-I	Model lead for GISS GCM and inclusion of EMIT products to achieve the science objectives. (L4, L3, L3v)
Greg Okin	University of California Los Angeles	Co-I	L3 product lead with composited aggregated product validation. (L3, L3v); Vegetation screening in arid lands.
Thomas Painter	University of California Los Angeles	Co-I	Radiative forcing and mineral dust composition validation measurements. (L2av, L2bv, L3)
Carlos Perez	Barcelona Super Computer Center (formerly GISS, Columbia University)	Co-I	Modeling of the mineral dust aerosol cycle with the EMIT-derived high-resolution map of soil mineral content. Evaluation of the models using in situ measurements and satellite retrievals. (L4, L4v, L3, L3v)
Vincent Realmuto	JPL Caltech	Co-I	Measurement to Model lead. Ancillary data layers.
Gregg Swayze (CS)	US Geological Survey	Co-I	Mineral library responsibility and L2b validation measurements and reports. (L2av, L2b, L2bv)
Elizabeth Middleton (CS)	NASA GSFC	Collaborator	Collaborator to assure lessons learned and experience from Hyperion are incorporated.
Luis Guanter	German Centre for Geosciences (GFZ)	Collaborator	Collaborator to maintain connection with EnMAP including potential cross-validation
Eyal Ben Dor	University of Tel Aviv	Collaborator	Collaborator with mineral dust validation data sets.

… and critical affiliates: Longlei Li, Philip Brodrick, Nimrod Carmon, David Connelly, and over 40 members of the instrument project.

The EMIT Instrument

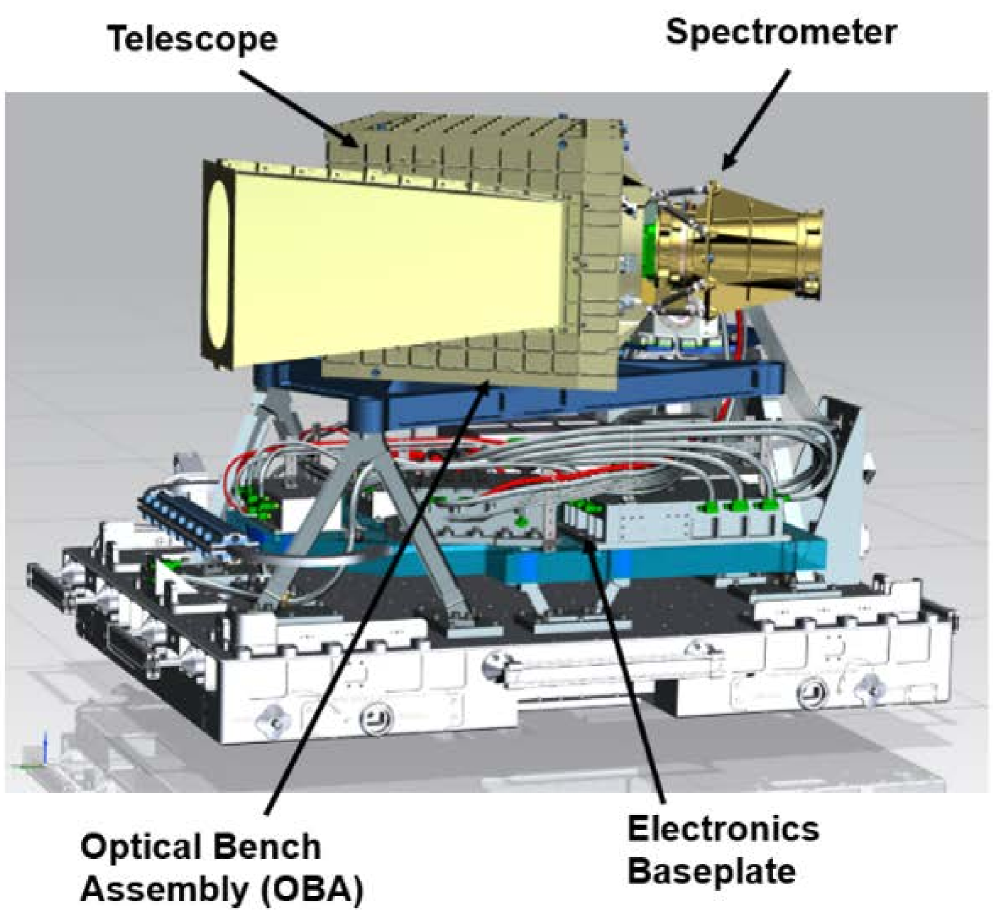


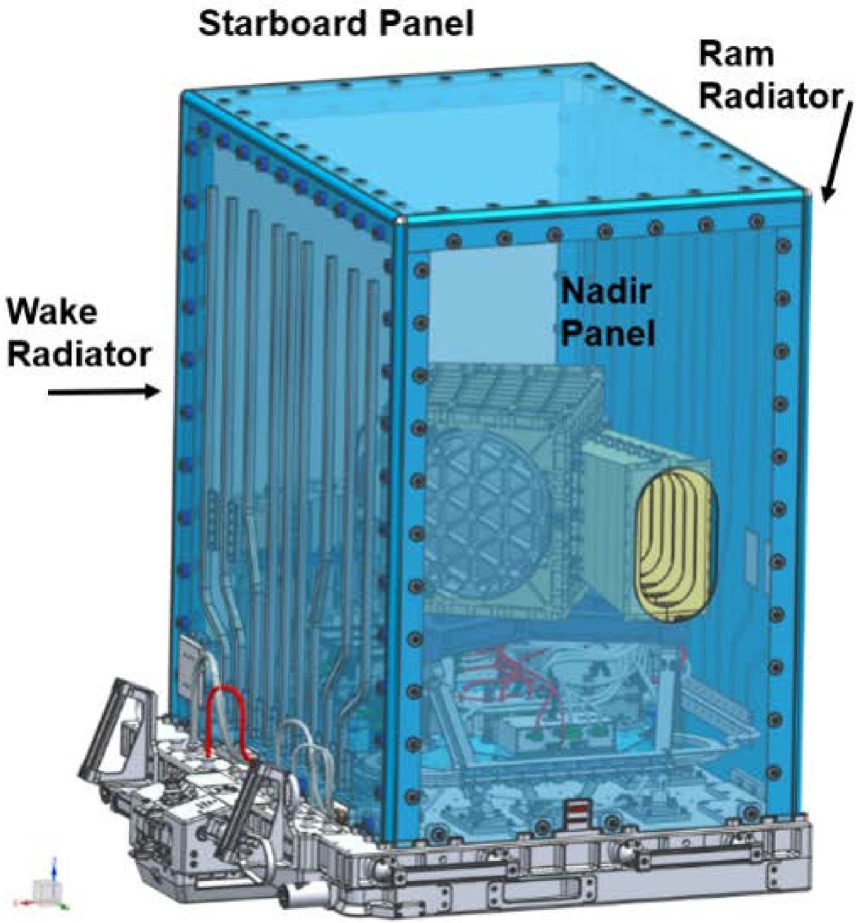
EMIT Imaging Spectrometer Elements

- **Two-mirror Telescope**
  - M1 (y-decentered, asphere)
  - M2 (y-decentered, asphere)
- **Dyson spectrometer**
  - Dyson block: CaF2 lens with step
  - Slit (30 µm width, 37.2 mm length)
  - Diffraction grating (structured blaze)
- **FPA Assembly**
  - Order sorting filter (three zone)
  - Detector (HgMgTe)
    - 1280 x 480 pixel format
    - 30 µm pixel size

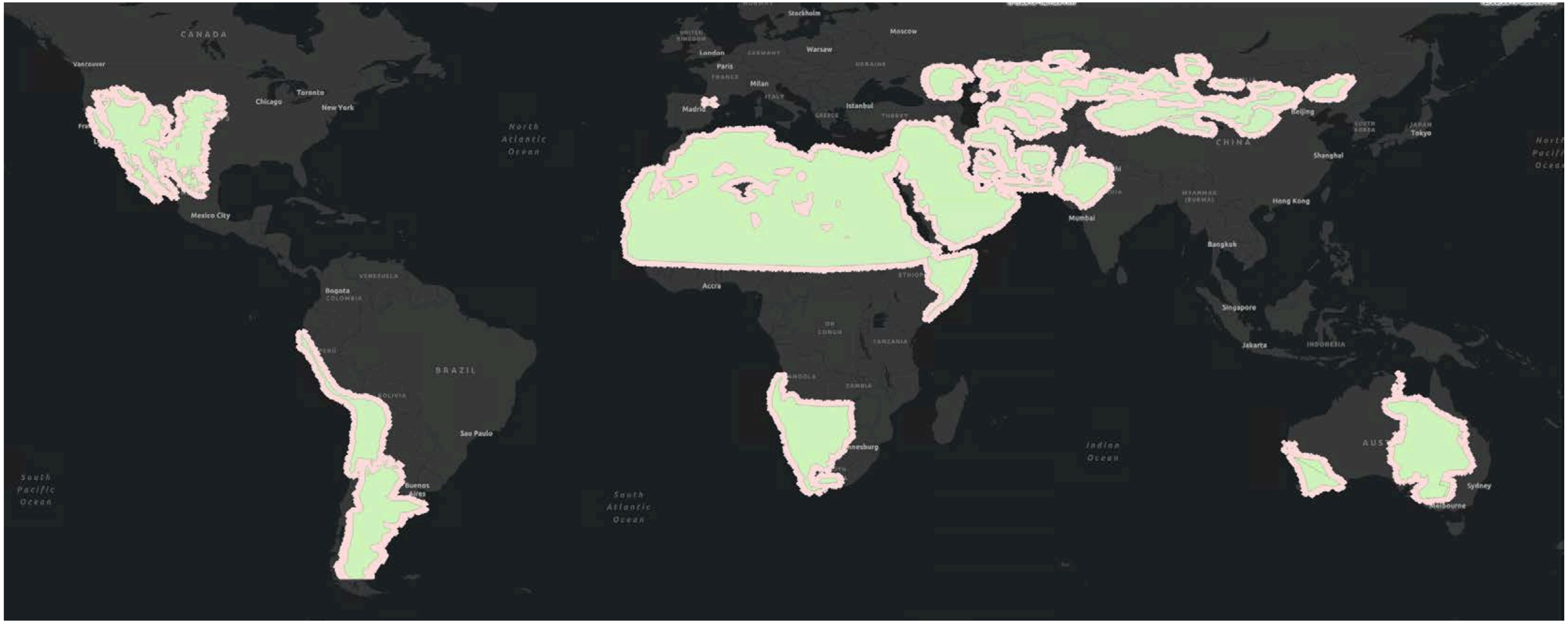
Key EMIT Properties	
F-number	F/1.8
Cross-track FOV	11^0
IFOV (cross-track x along-track)	155 x 171 µrad
Focal length	193.5 mm
Entrance pupil aperture	110 mm
Spectral Range	380 – 2500 nm
Spectral Sampling	7.4 nm

EMIT Instrument Configuration





EMIT Baseline Target Areas



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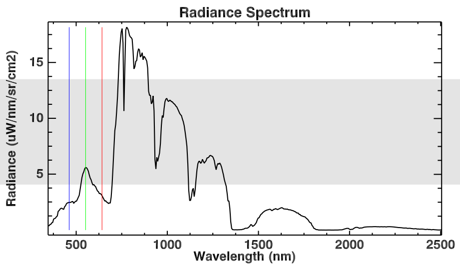
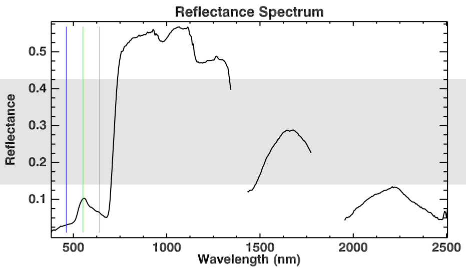
EMIT product needs

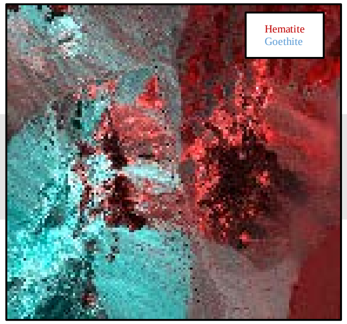
1. Statistically rigorous uncertainty quantification and propagation
2. Accurate, to measure subtle changes in mineral band positions
3. Handle aerosol loadings up to AOD_{550} = 0.4
4. Global application
5. 100 GB / day



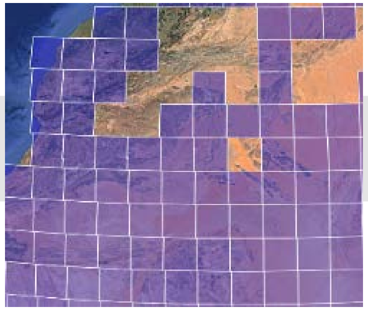
L1: Radiance at sensor



L2a: Surface Reflectance (HRDF)

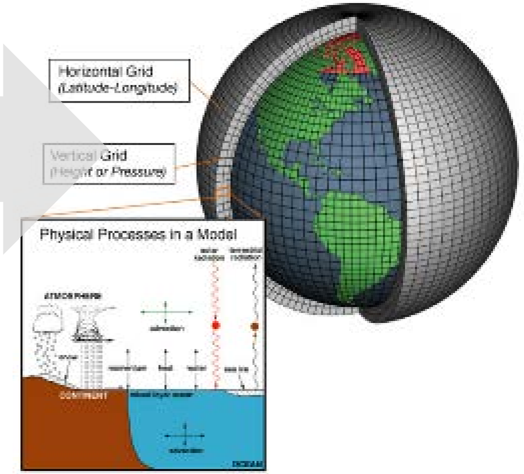


L2b: Mineralogical Maps



L3: Aggregated Mineralogy

L4: CESM, GISS Model Runs



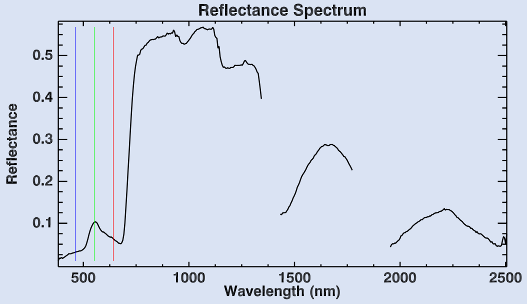
Credit: NCAR

L2a Retrieval Algorithms: The "Forward Model"

State vector

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

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



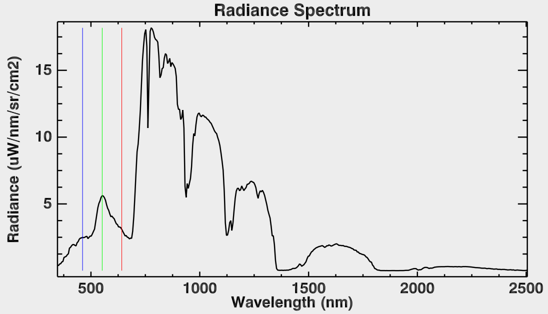
Forward model

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

Measurement

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

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



Forward model components (state vector in **red**)

Instrument: EMIT

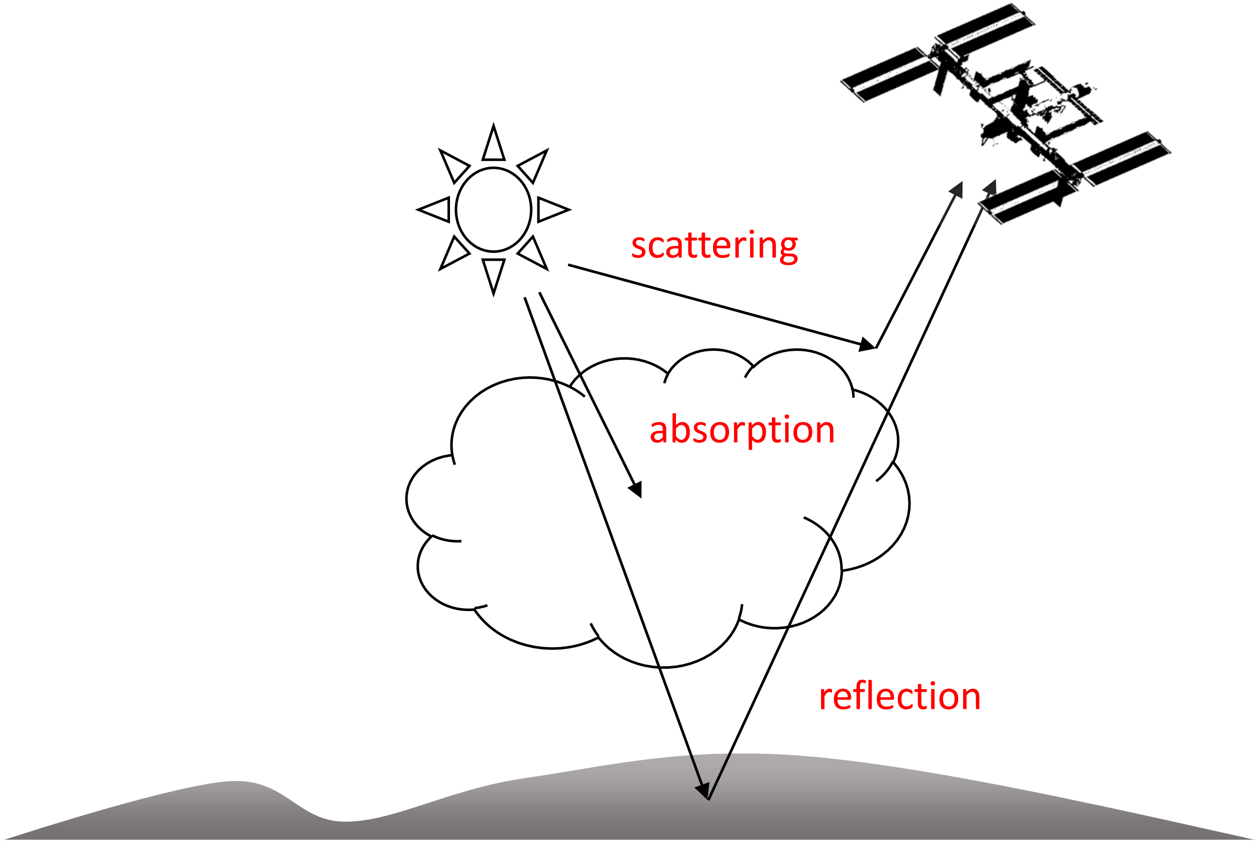
- Instrument model with Wavelength- and signal-dependent SNR
- Photon shot & read noise
- Uncorrelated calibration uncertainty

Atmosphere: MODTRAN 6.0 RTM

- DISORT MS, Correlated-k
- Custom aerosol model with broad priors
- **H_2O column, AOD (1-3 elements)**

Surface: Multi-component Multivariate Gaussians

- **Reflectance estimated independently in each channel (300 elements)**

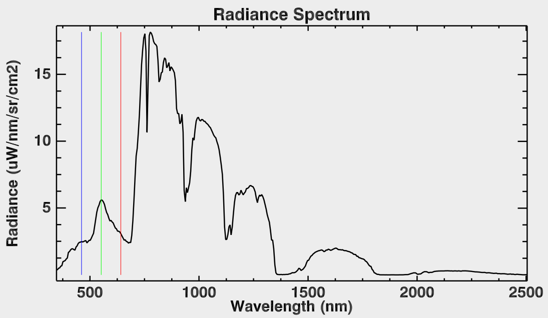


Retrieval Algorithms: The “Inverse Problem”

Measurement

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

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



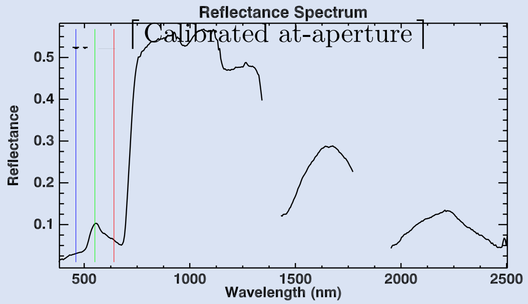
Inversion algorithm

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

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

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

Maximum *A Posteriori* solution

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

Taking the logarithm of p(**x** | **y**), and ignoring terms that are constant with x:

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

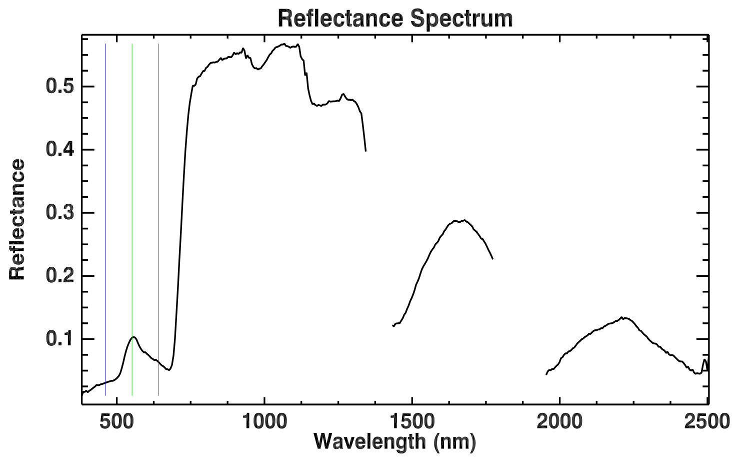
… we can solve it by conjugate gradient descent.

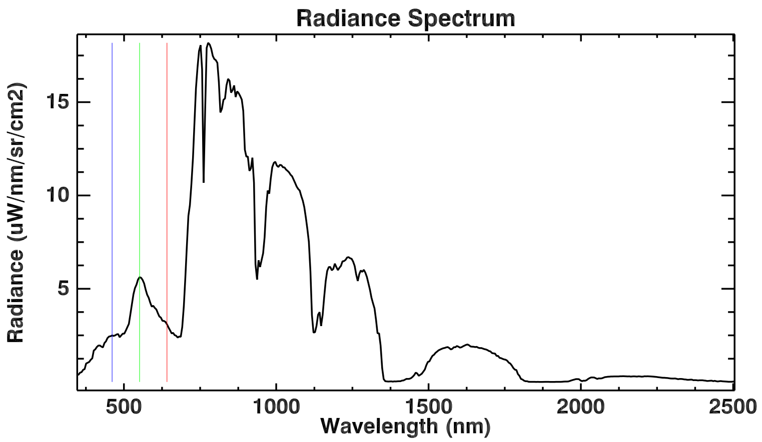
[C. D. Rodgers, 2000]

L2 Inversion: Bayesian Maximum A Posteriori

1. Predict radiance

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



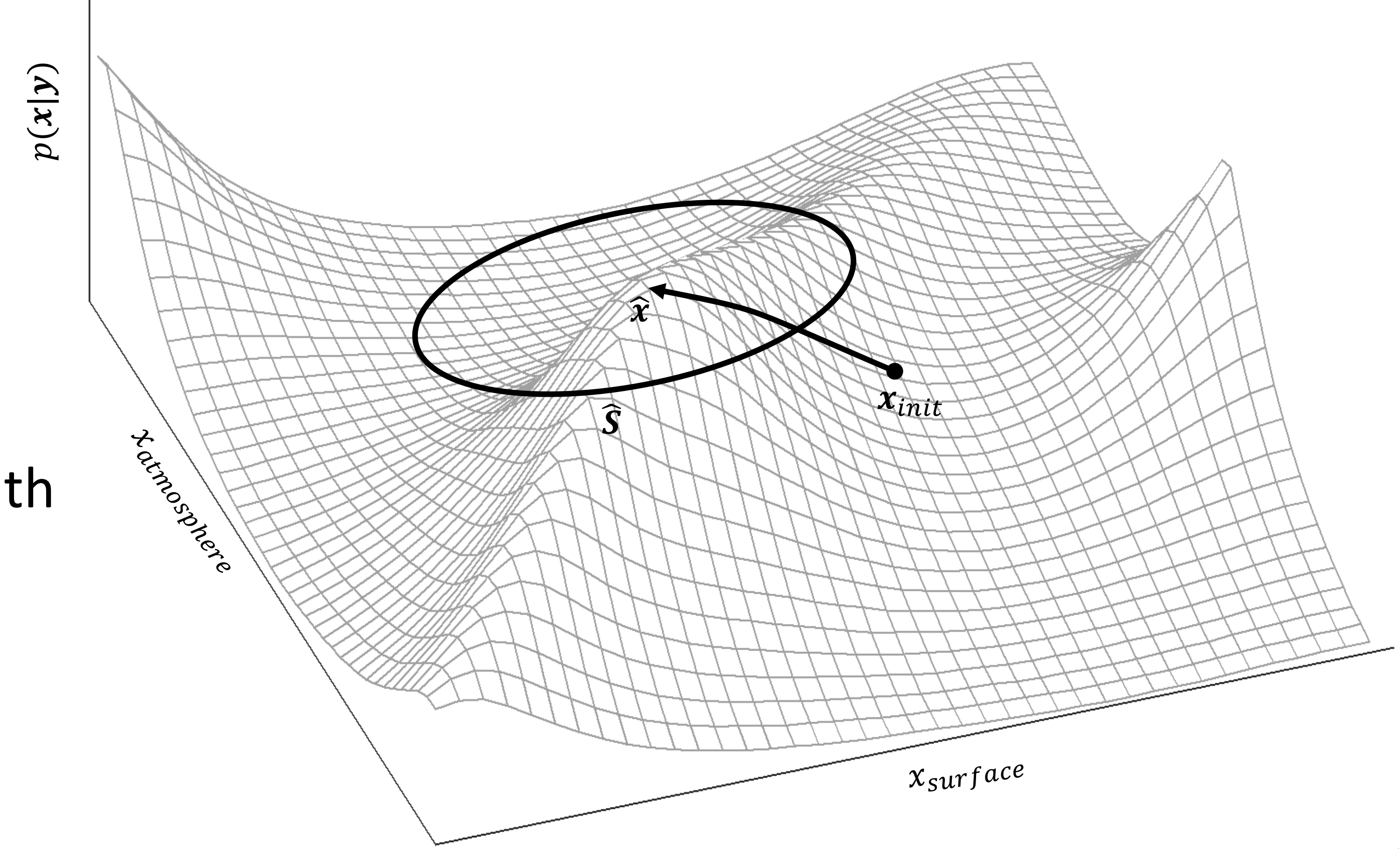


2. Optimize state vector

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

L2 surface reflectance posterior uncertainty

$$\hat{S} = \left(K^T S_e^{-1} K + S_a^{-1}\right)^{-1}$$



x: State vector

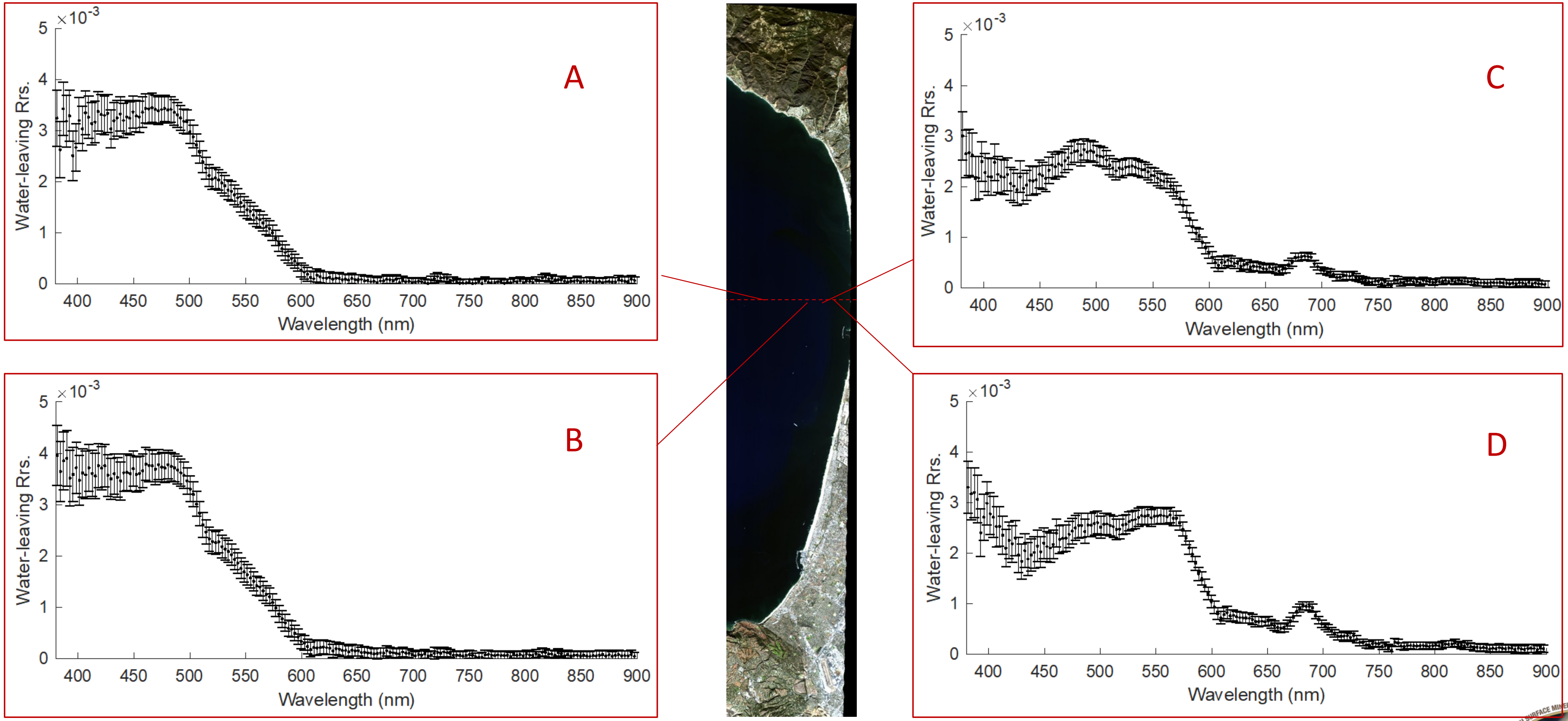
K: Jacobian of radiance with respect to state

S_e: Observation noise

S_a: Prior covariance

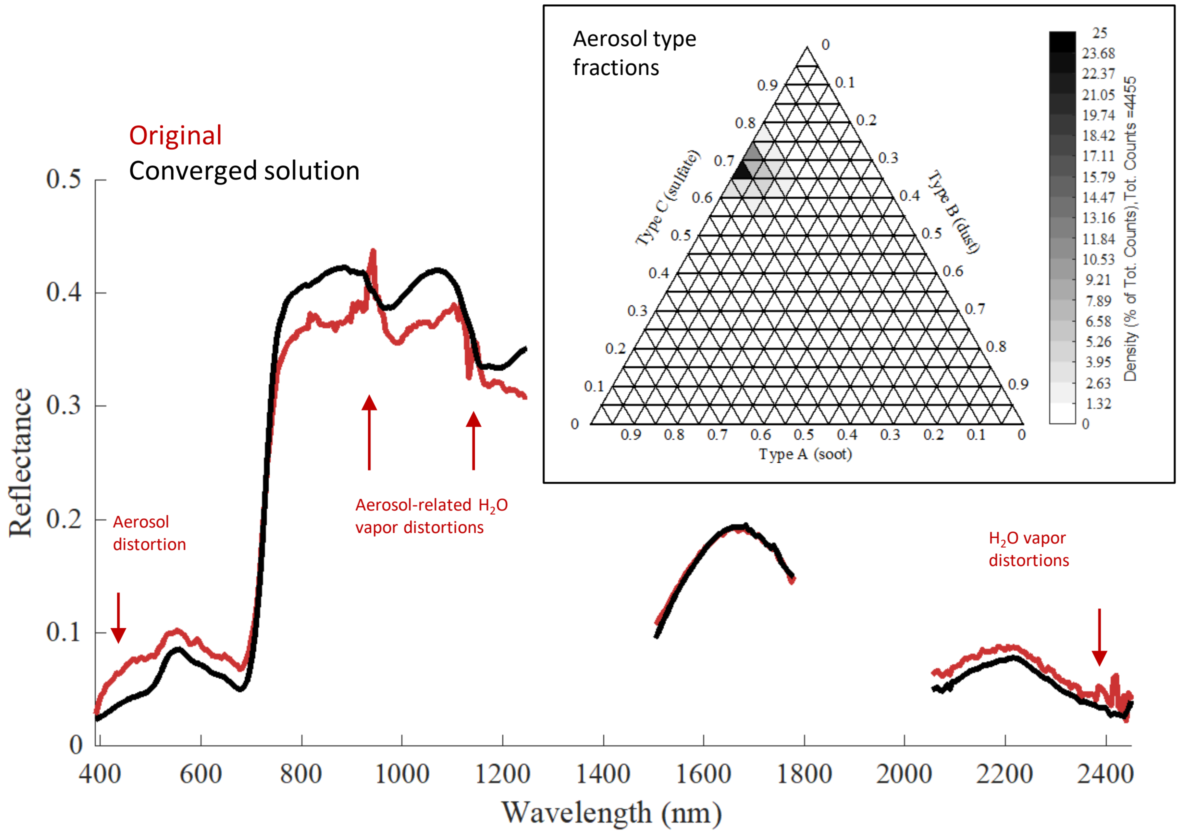
Coastal water applications

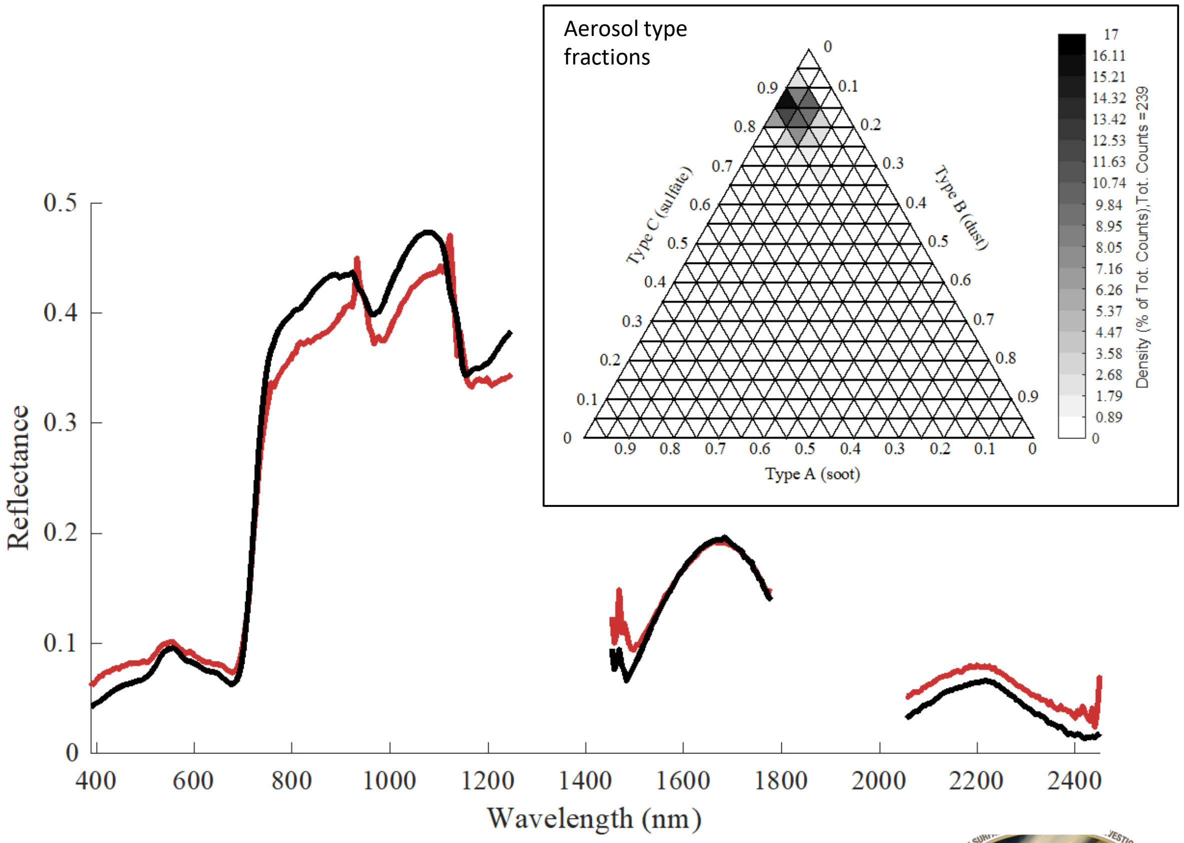
[Frouin et al., *Frontiers in Earth Science* 2019, Thompson et al., *Remote Sensing of Environment, 231, 2019*]



Aerosol retrievals in challenging atmospheres

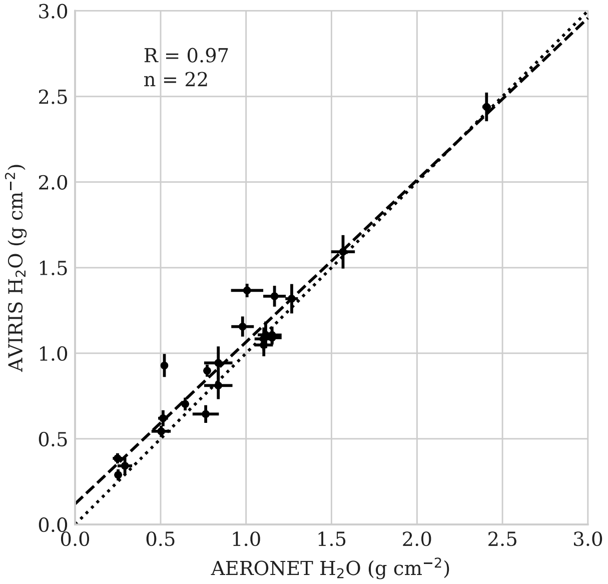
[Thompson et al., Remote Sensing of Environment, *232,* 2019]



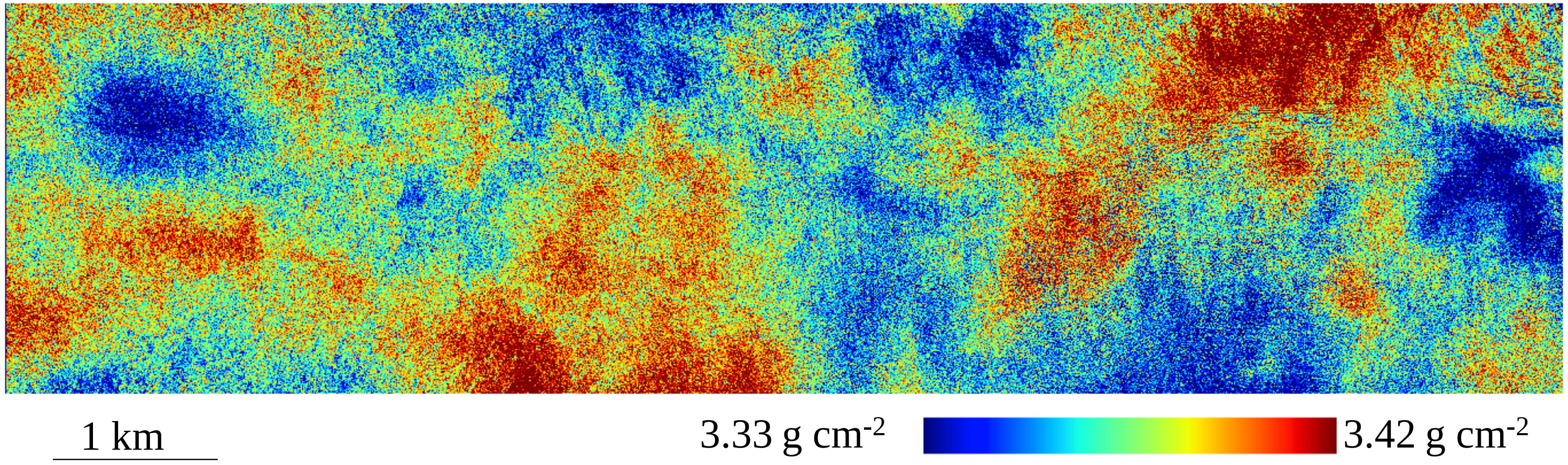


Imaging the atmosphere at high spatial resolution

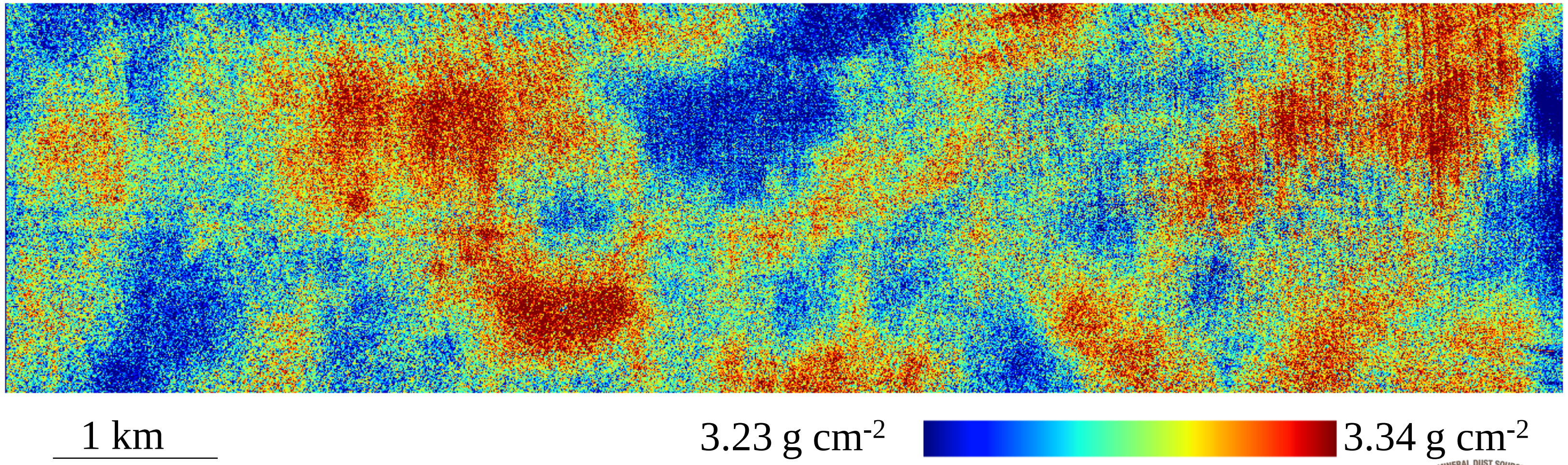
David R Thompson, Matt Lebsock, Mark Richardson, Philip G Brodrick, Brian Kahn, and others



Column average H_2O vapor, flightline C (ang20180514t055115)

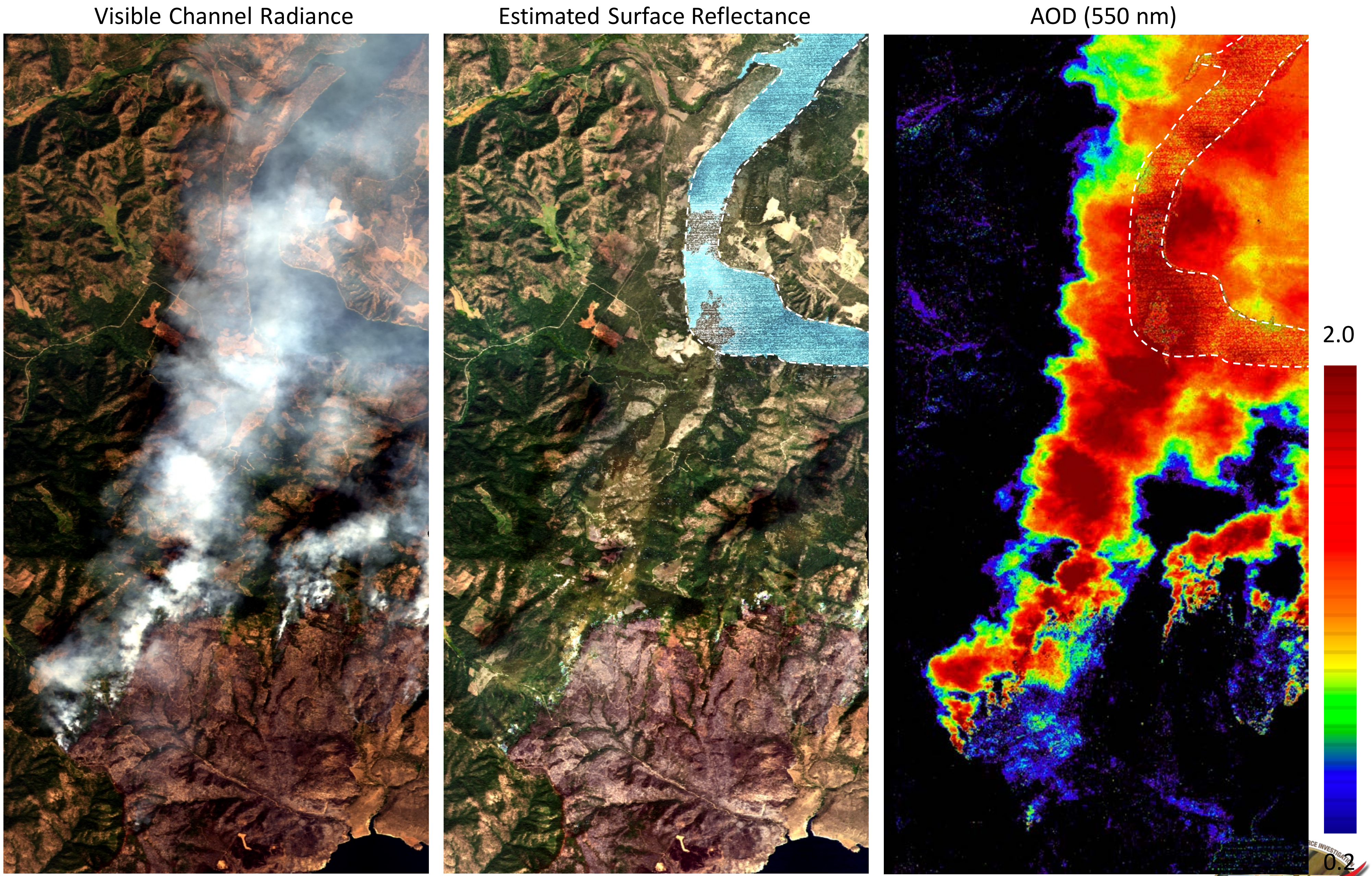


Column average H_2O vapor, flightline D (ang20180514t060206)

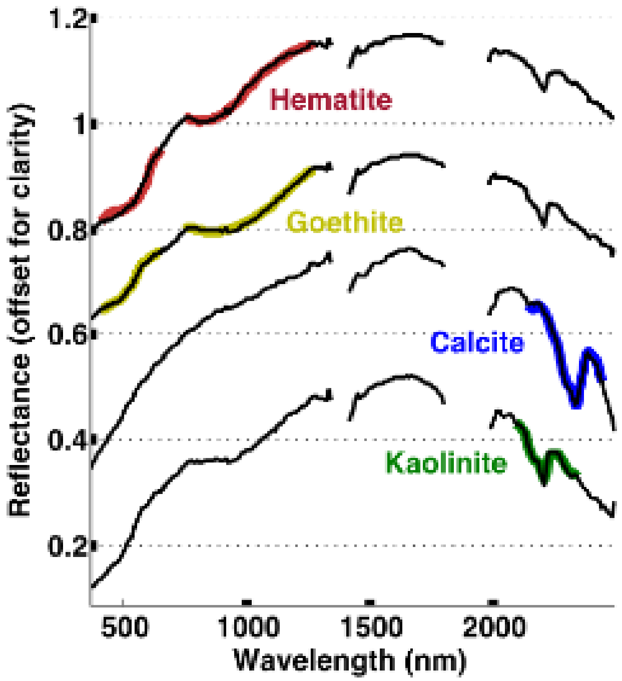


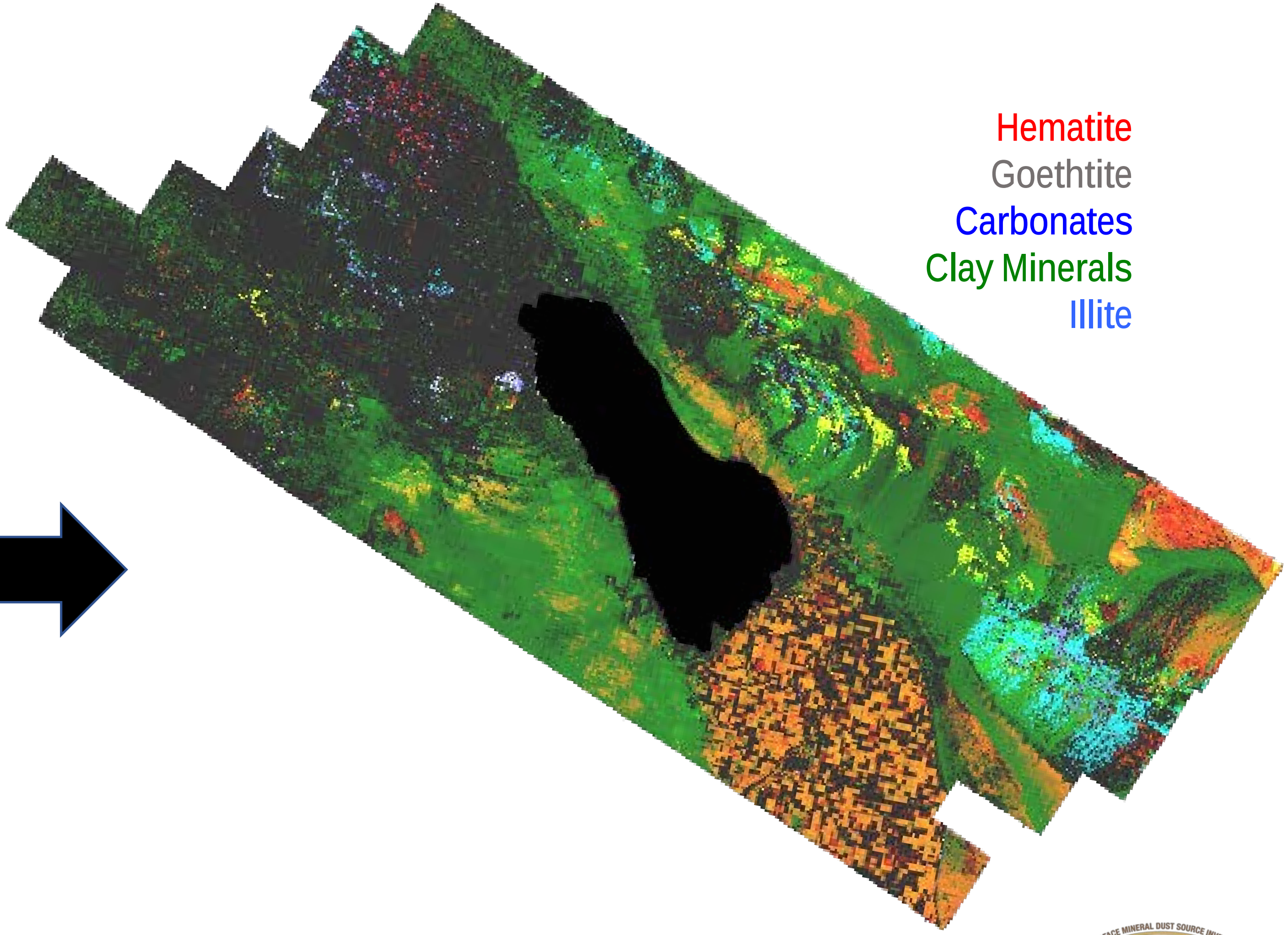
FIRE-X AQ Campaign

Michael Garay
Olga Kalashnikova
Philip G Brodrick
David R Thompson



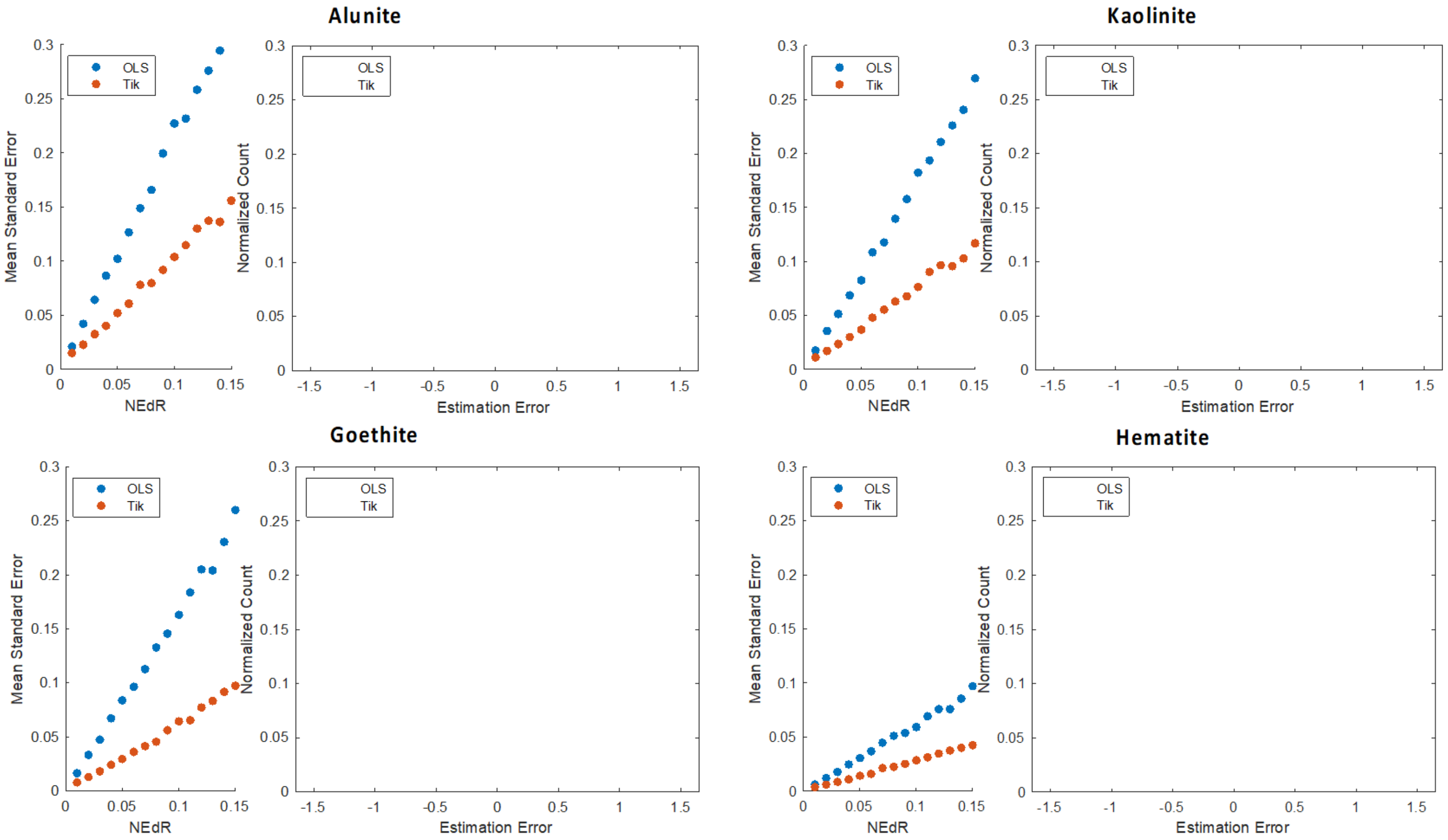
L2a EMIT mineral signatures





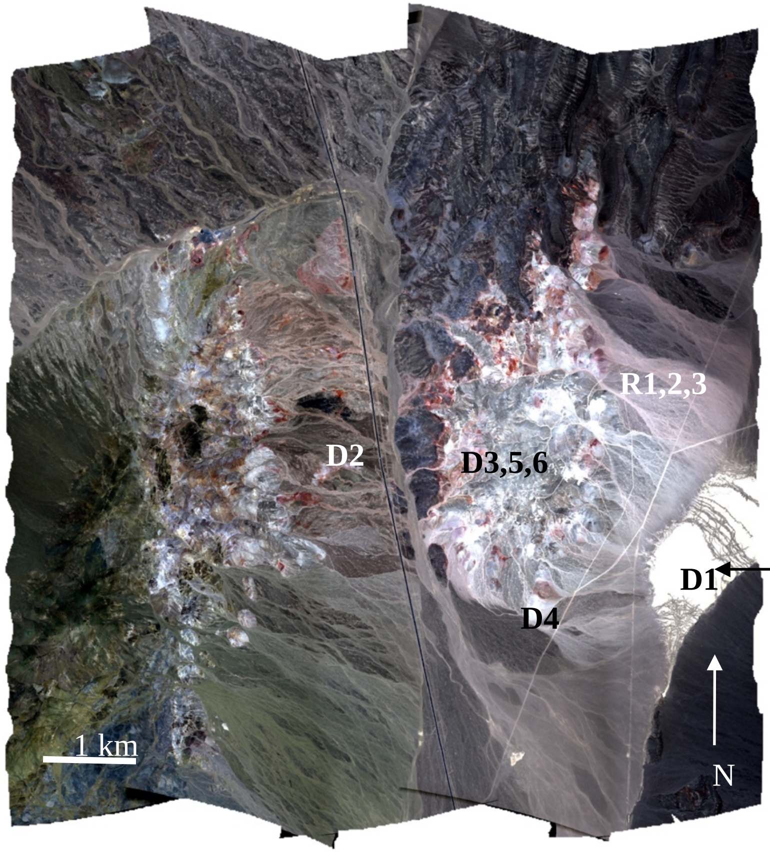
Using predictive uncertainties to improve downstream (L3) algorithms

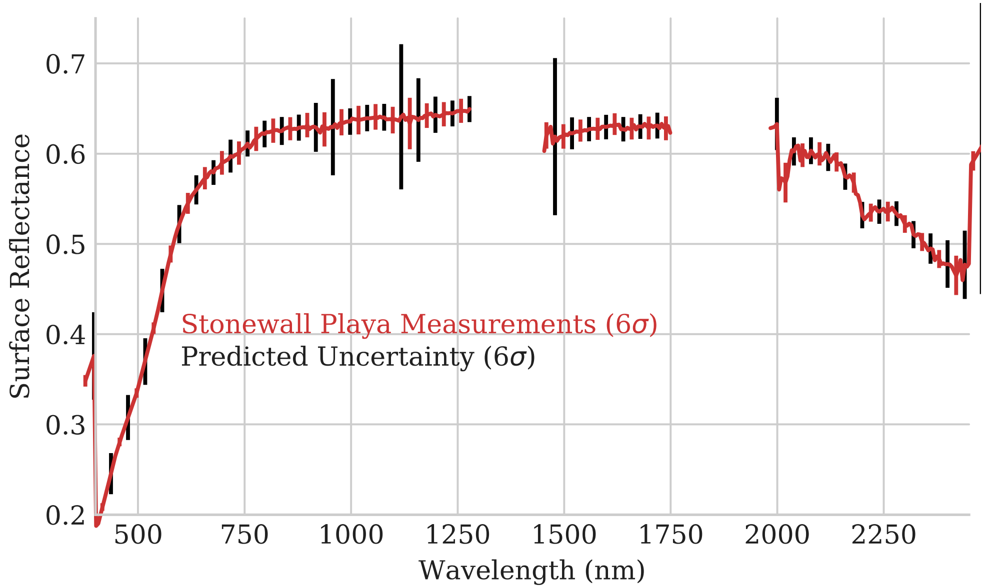
[Carmon et al., *Rem. Sens. Environ., in press*]

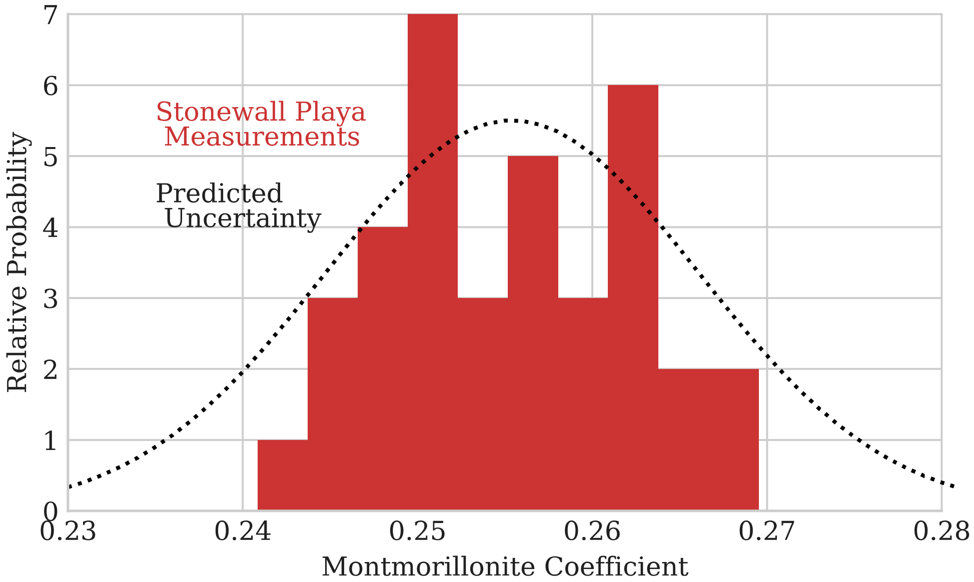


Validation of uncertainty predictions

[Thompson et al., Remote Sensing of Environment 2020]

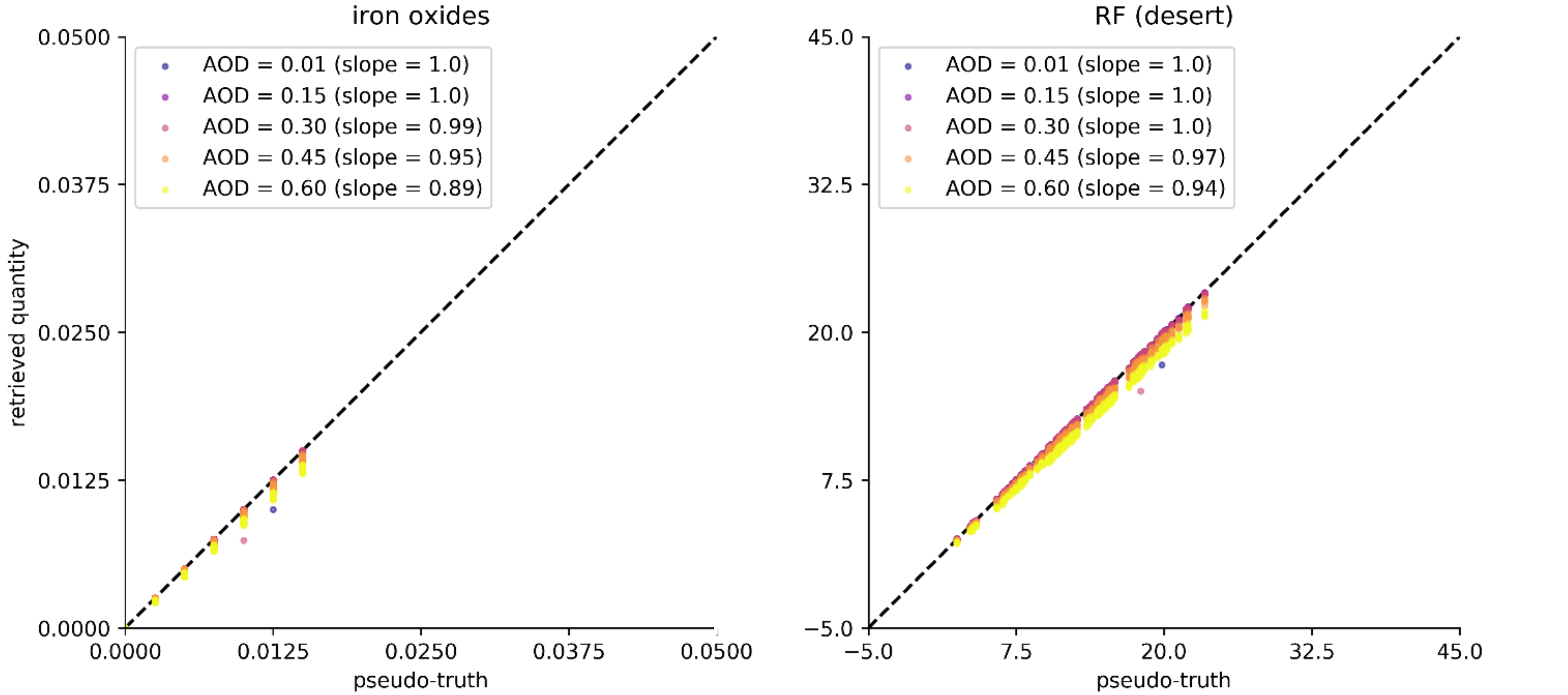






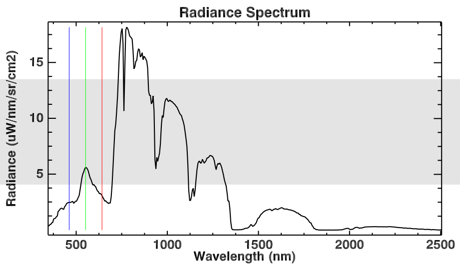
EMIT measurments significantly improve uncertainty in ESM radiative forcing predictions

[Connelly et al.,. in review]

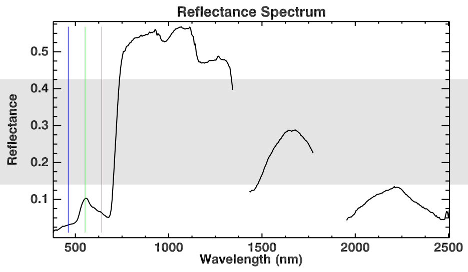


Summary

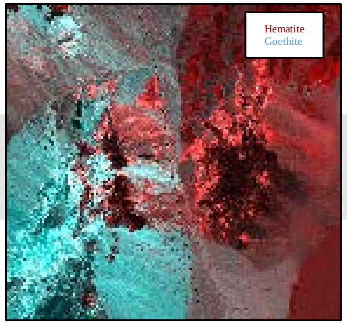
- EMIT will measure VSWIR solar-reflected spectroscopy at 60m resolution across a significant fraction of Earth's terrestrial area
- EMIT will distribute uncertainty estimates with every product level
- EMIT intends to significantly improve our understanding of mineral dust interactions with Earth's climate.



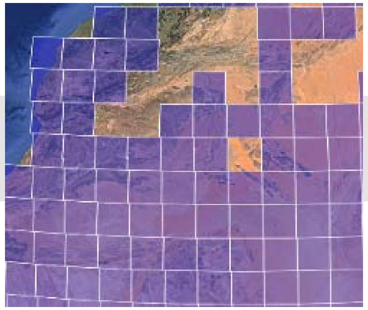
L1: Radiance at sensor



L2a: Surface Reflectance (HRDF)

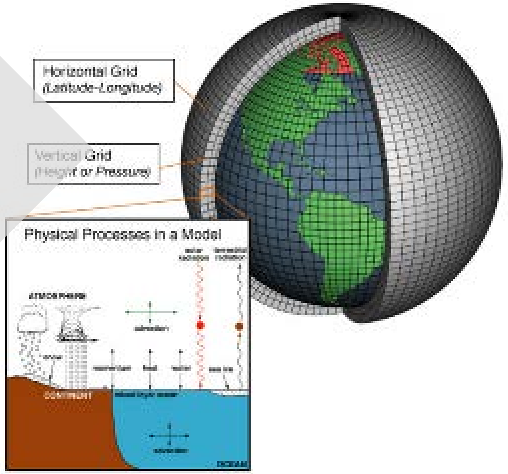


L2b: Mineralogical Maps



L3: Aggregated Mineralogy

L4: CESM, GISS Model Runs



Credit: NCAR

Resources

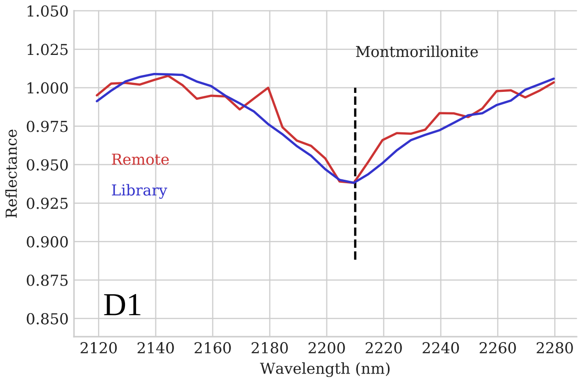
Source code: https://github.com/isofit/isofit

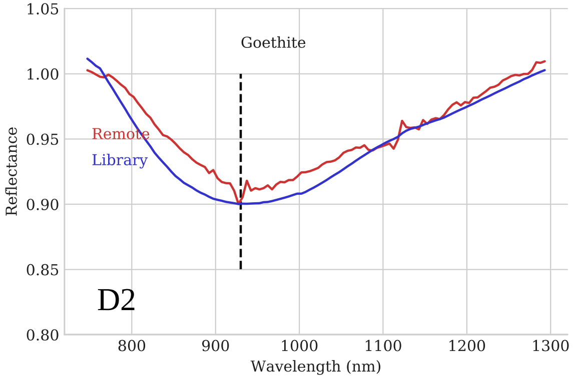
Tutorials: https://github.com/davidraythompson/istutor (modules 11-14)

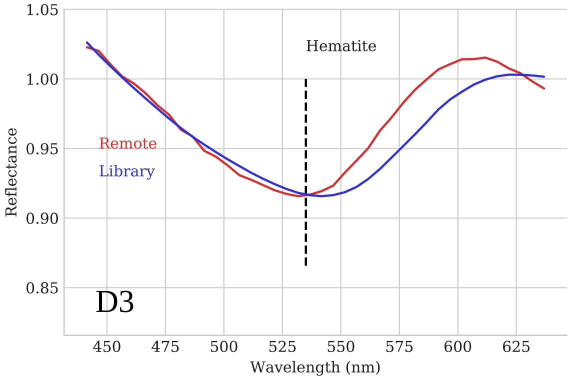
Bibliography:

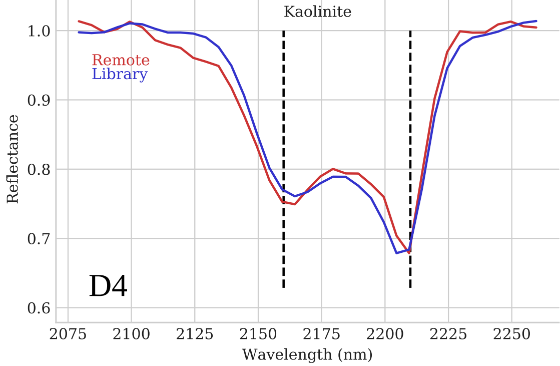
1. N. Carmon, D. R. Thompson, J. Susiluoto, N. Bohn, D. S. Connelly, M. J. Turmon, K. Cawse-Nicholson, R. O Green, M. R Gunson. **Uncertainty Quantification for Global Remote Spectroscopy of Surface Composition**. *Remote Sensing of Environment*, in review, 2020.
2. D. R. Thompson, Alberto Candela, Nimrod Carmon, Roger N. Clark, David Connelly, Bethany Ehlmann, Robert O. Green, Raymond Kokaly, Nathalie Mahowald, Gregory Okin, Gregg A. Swayze, Michael Turmon, and David S. Wettergreen, "**Quantifying Uncertainty for Remote Spectroscopy of Surface Composition**," *Remote Sensing of Environment*. In press, 2020.
3. D. R. Thompson, K. N. Babu, A. Braverman, M. Eastwood, R. O. Green, J. Hobbs, J. B. Jewell, M. Mishra, A. Mathur, V. Natraj, F. C. Seidel, P. Townsend, M. Turmon. "**Optimal Estimation of Spectral Surface Reflectance in Challenging Atmospheres**," *Remote Sensing of Environment*, 232, 111258, 2019.
4. R. Frouin, B. Franz, A. Ibrahim, K. Knobelspiesse, Z. Ahmad, B. Cairns, J. Chowdhary, H. M. Dierssen, O. Dubovik, J. Tan, A. B. Davis, D. J. Diner, O. Kalashnikova, D. R. Thompson, L. R. Remer, E. Boss, O. Coddington, B-C Gao, L. Gross, O. Hasekamp, A. Omar, B. Pelletier, D. Ramon, P-W. Zhai., **Atmospheric correction of satellite ocean-color imagery during the PACE era**. *Frontiers in Marine Science* 7: 145, 2019.
5. D. R. Thompson, K. Cawse-Nicholson, Z. Erickson, C. Fichot, C. Frankenberg, B-C. Gao, M. M. Gierach, R. O. Green, D. Jensen, V. Natraj, A. Thompson. "**A unified approach to estimate land and water reflectances with uncertainties for coastal imaging spectroscopy**," *Remote Sensing of Environment* 231, 111198, 2019.
6. B. D. Bue, D. R. Thompson, S. Deshpande, M. Eastwood, C. Fichot, R. O. Green, T. Mullen, V. Natraj, and M. Parente, "**Neural Network Radiative Transfer for Imaging Spectroscopy**." *Atmospheric Measurement Techniques* 12, 2567–2578, 2019 https://doi.org/10.5194/amt-12-2567-2019
7. D. R. Thompson, V. Natraj, R. O. Green, M. Helmlinger, B.-C. Gao, and M. L. Eastwood, "**Optimal Estimation for Imaging Spectrometer Atmospheric Correction**." *Remote Sensing of Environment* 216, p. 355-373, 2018.

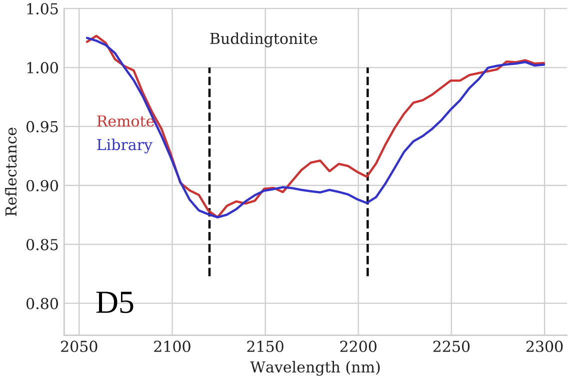
Extras

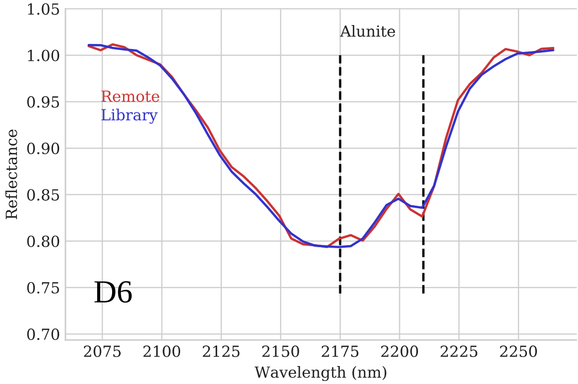

Montmorillonite
Remote
Library
D1
Reflectance
1.050
1.025
1.000
0.975
0.950
0.925
0.900
0.875
0.850
2120 2140 2160 2180 2200 2220 2240 2260 2280
Wavelength (nm)


Goethite
Remote
Library
D2
Reflectance
1.05
1.00
0.95
0.90
0.85
0.80
800 900 1000 1100 1200 1300
Wavelength (nm)


Hematite
Remote
Library
D3
Reflectance
1.05
1.00
0.95
0.90
0.85
450 475 500 525 550 575 600 625
Wavelength (nm)

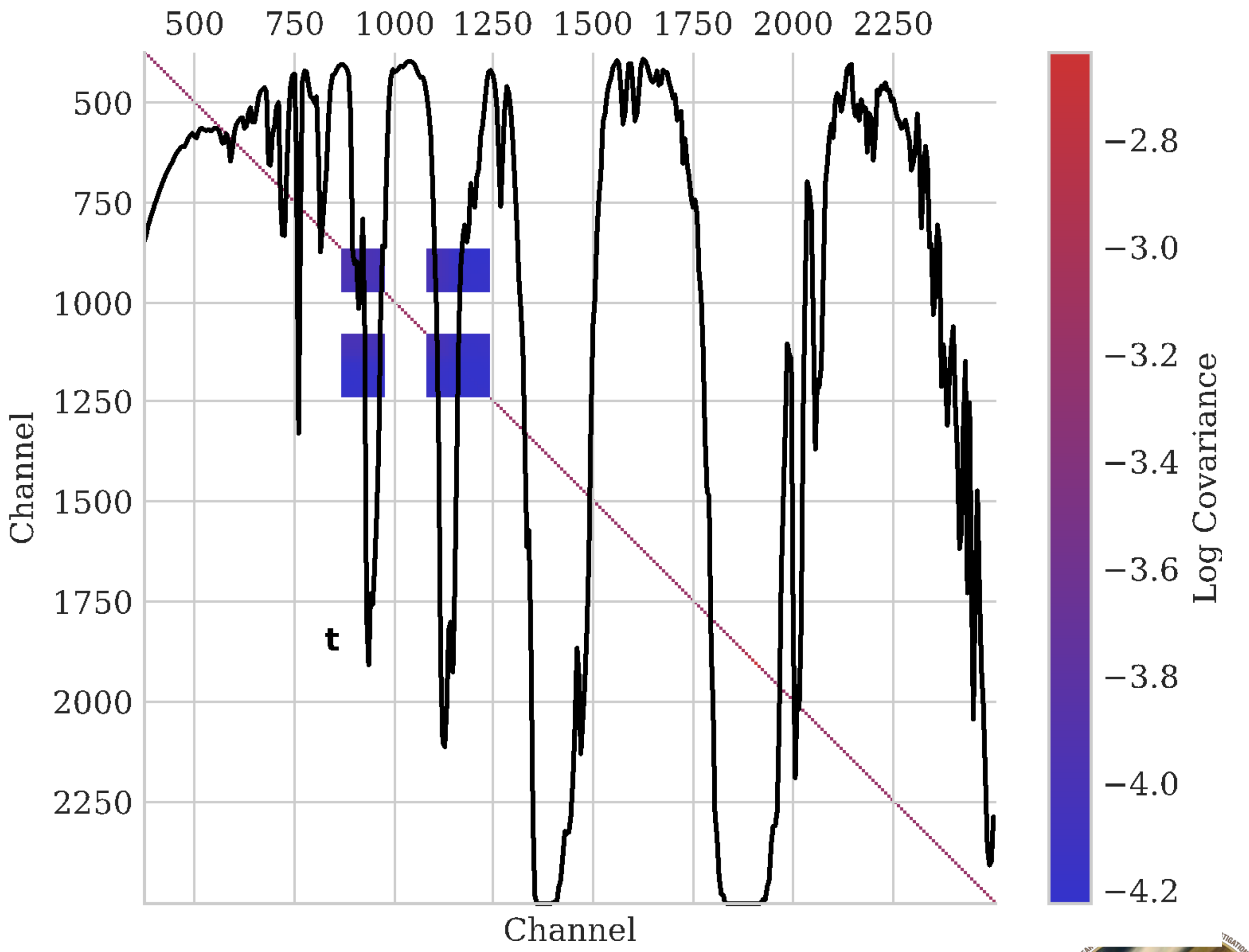

Kaolinite
Remote
Library
D4
Reflectance
1.0
0.9
0.8
0.7
0.6
2075 2100 2125 2150 2175 2200 2225 2250
Wavelength (nm)


Buddingtonite
Remote
Library
D5
Reflectance
1.05
1.00
0.95
0.90
0.85
0.80
2050 2100 2150 2200 2250 2300
Wavelength (nm)


Alunite
Remote
Library
D6
Reflectance
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
2075 2100 2125 2150 2175 2200 2225 2250
Wavelength (nm)

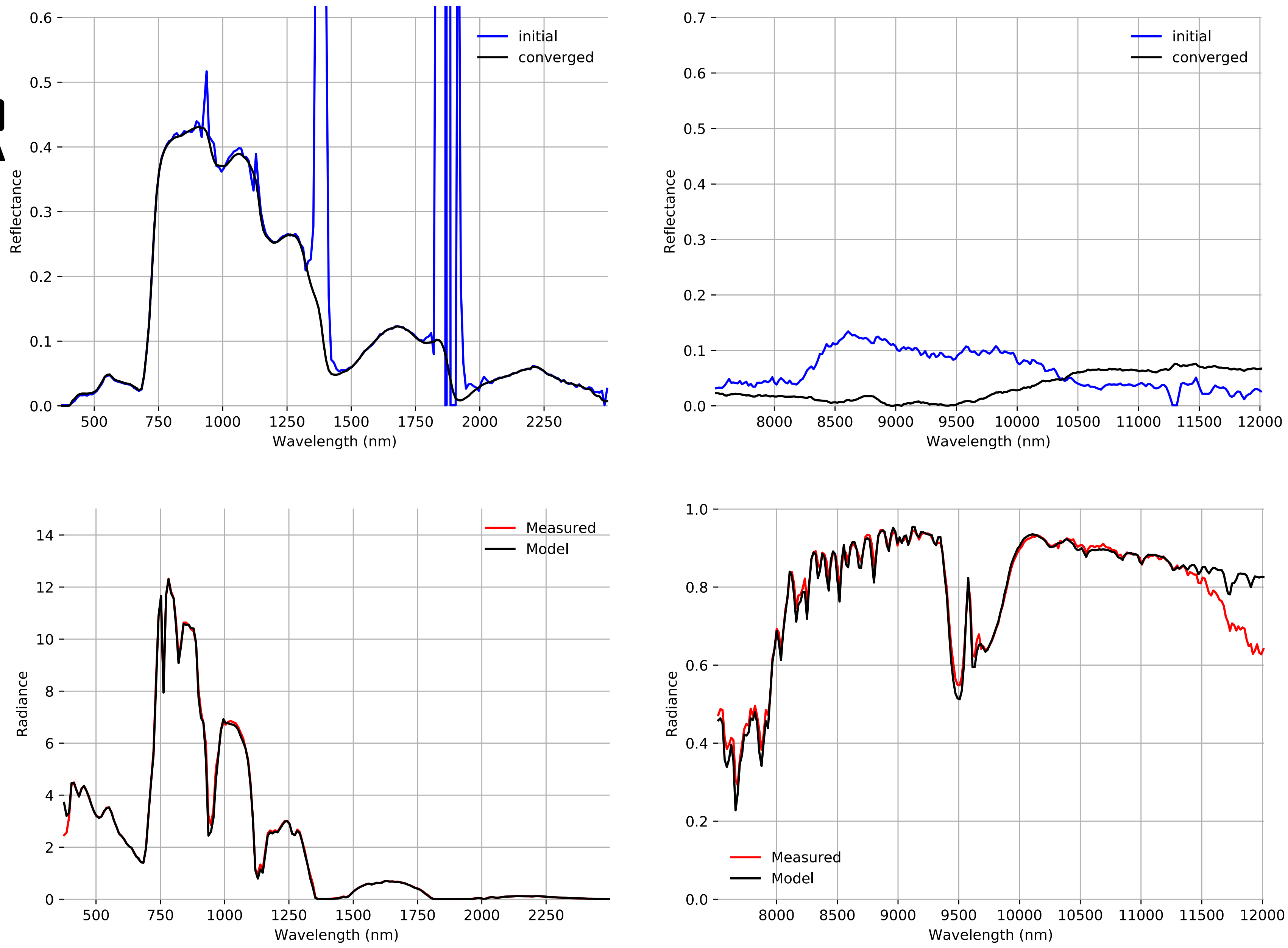
Surface prior covariance

- A collection of multivariate Gaussians
- Fit via a "universal" library and further regularized to reduce bias
- We remove all correlations outside water vapor absorption windows
- This preserves fidelity of sharp high-contrast mineral features not included in the original library



Simultaneous VSWIR + Thermal IR inversions

Jay Fahlen,
Philip G. Brodrick,
David R. Thompson,
and others



Solution: Generalized observation noise

Total observation noise

Jacobian WRT unknowns

$$\mathbf{S}_{\epsilon} = \mathbf{S}_{y} + \mathbf{K}_{b}\mathbf{S}_{b}\mathbf{K}_{b}^{T}$$

Measurement noise (instrument effects)

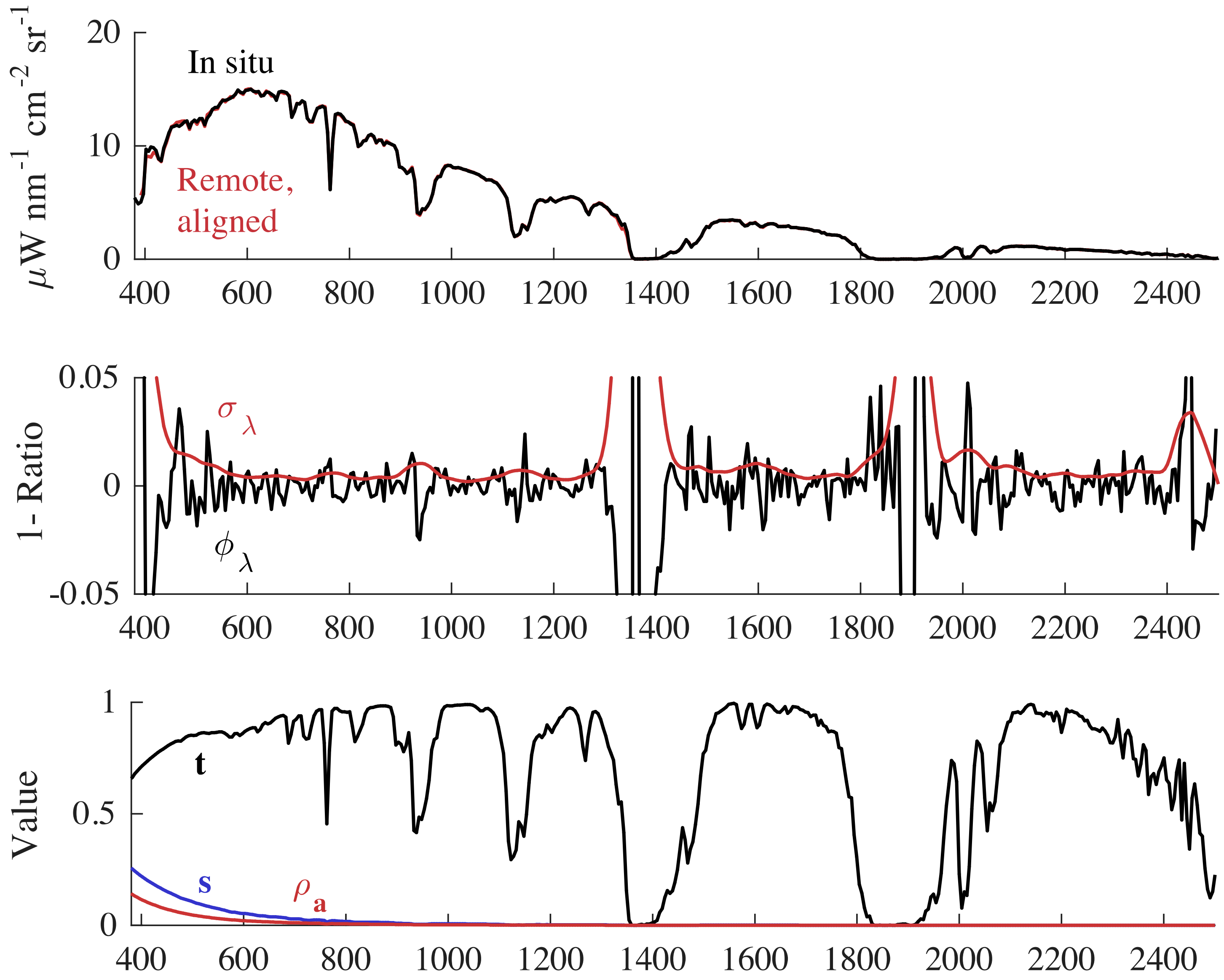
- Photon noise
- Read noise
- Dark current noise

Unknown parameters in the observation system

- Model mismatch error
- Calibration error
- Systematic radiative transfer error
- Uncorrelated radiative transfer error

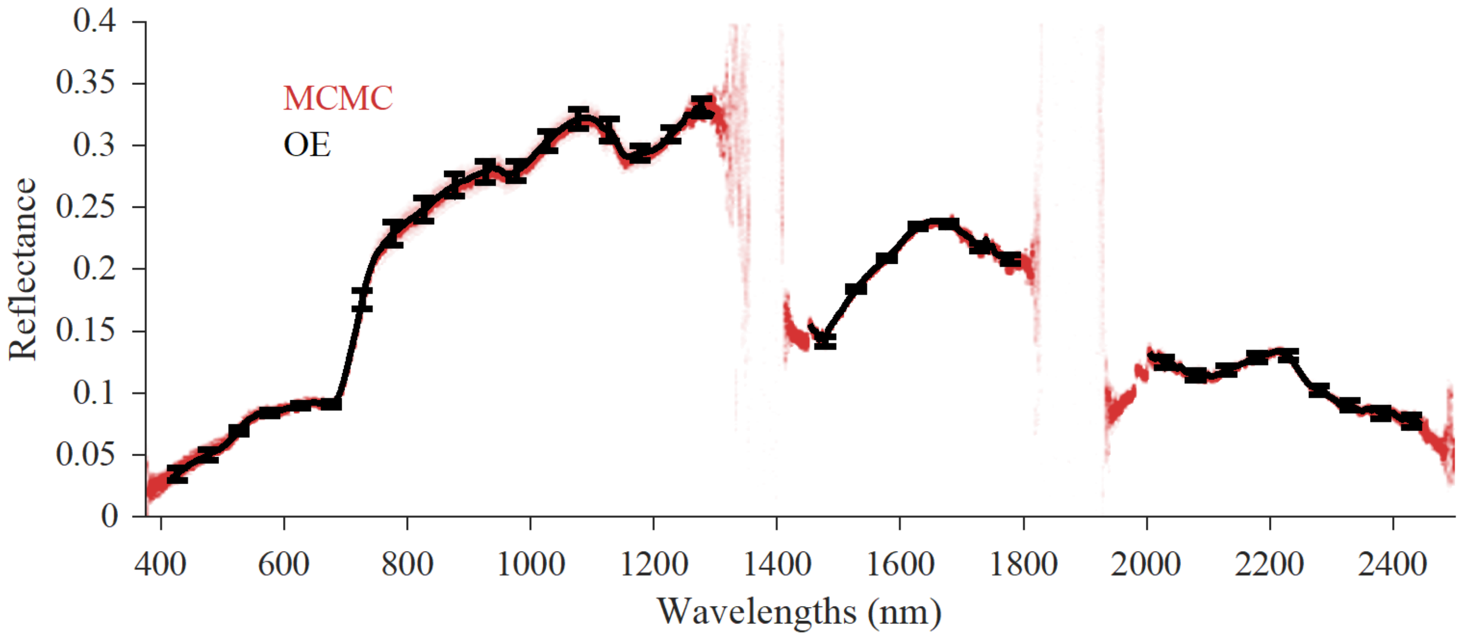
Estimating model uncertainties with observed residuals

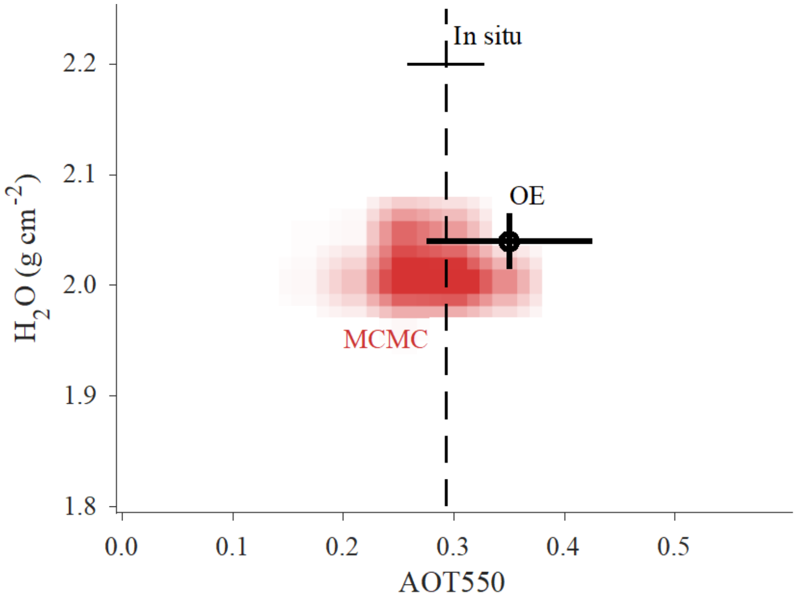
[Thompson et al., *Remote Sens. Environ 2018]*



Sample-based posterior estimation

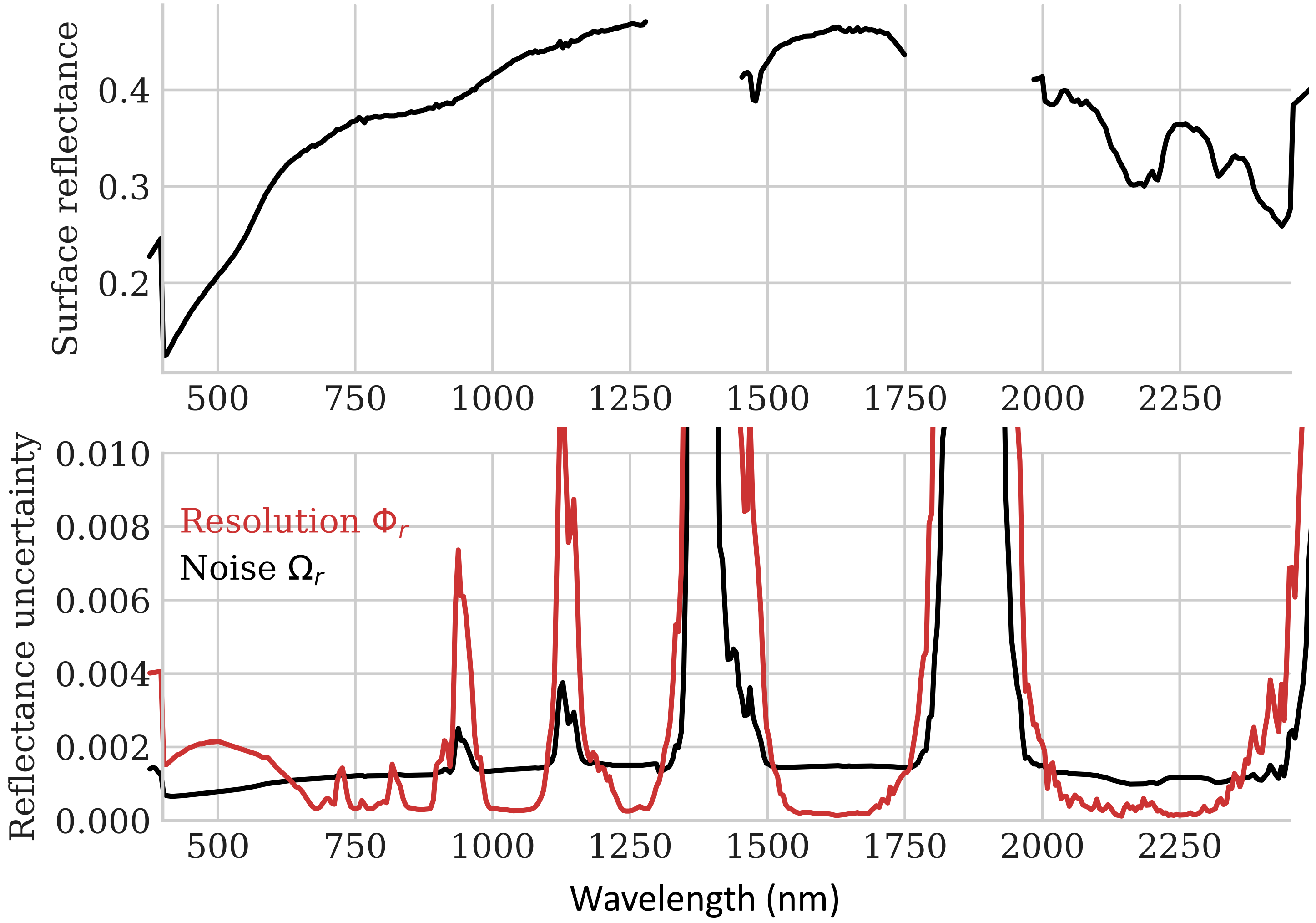
Computationally more challenging but captures the full posterior Linearized estimates work well for reflectance terms





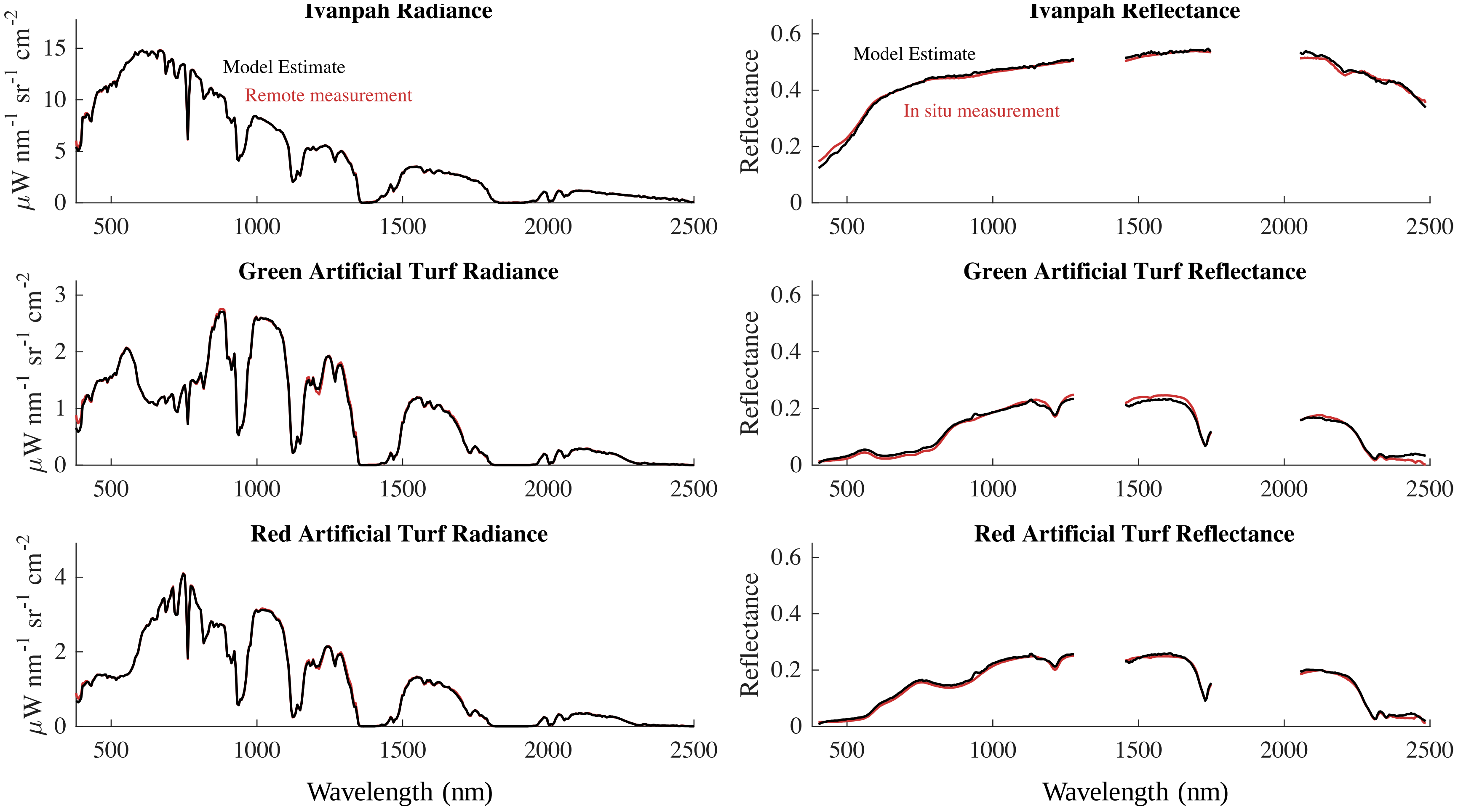
[Thompson et al., *Remote Sensing of Environment* 231, 2019]

Posterior uncertainty decomposition



Reflectance estimate vs. in situ

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



The observation noise

The observation noise term is very flexible. It typically incorporates both instrument noise as well as unknowns in the observation system that are not retrieved.

Total observation noise

Jacobian WRT unknowns

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

Measurement noise (instrument effects)

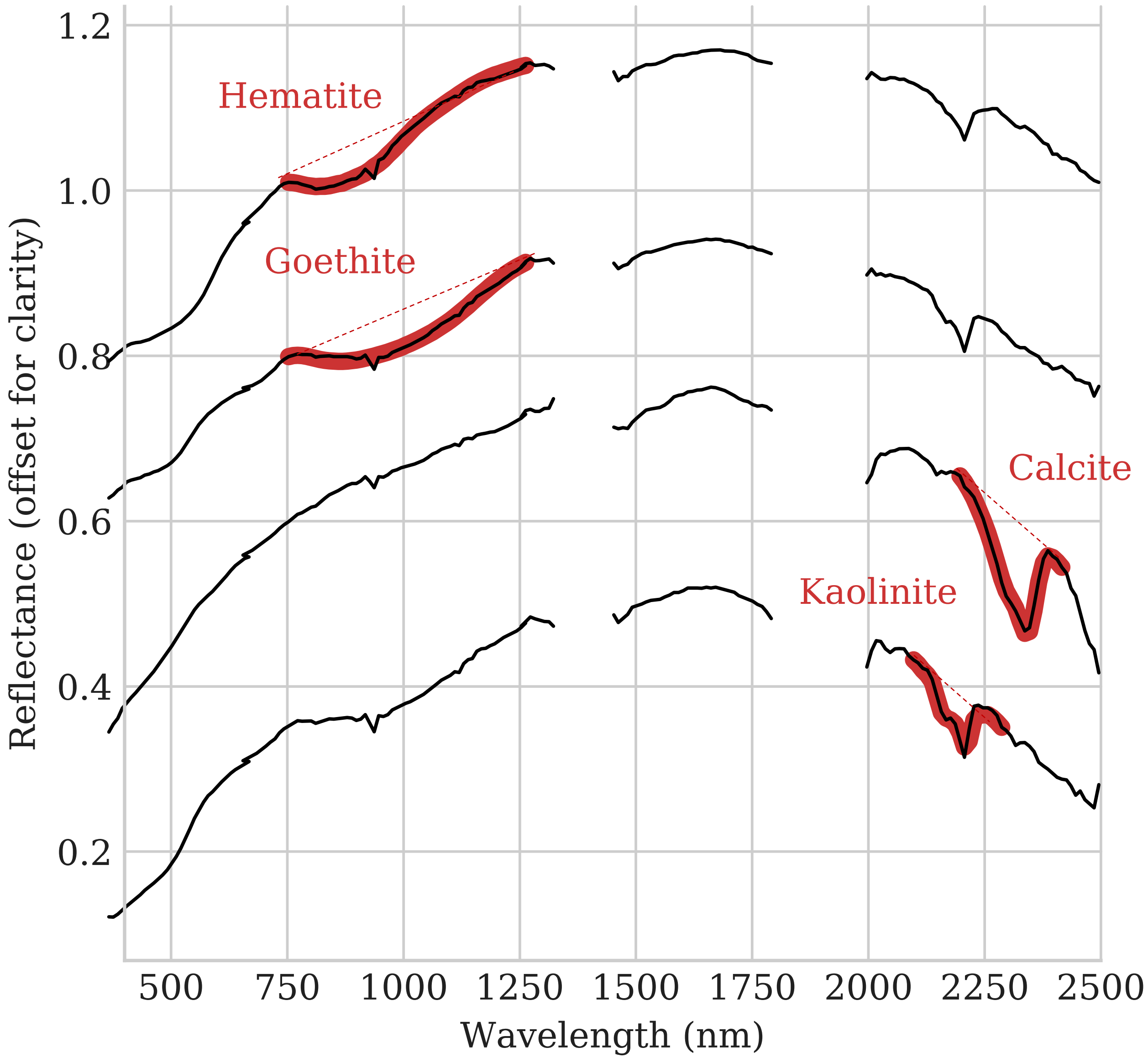
- Photon noise
- Read noise
- Dark current noise

Unknown parameters in the observation system

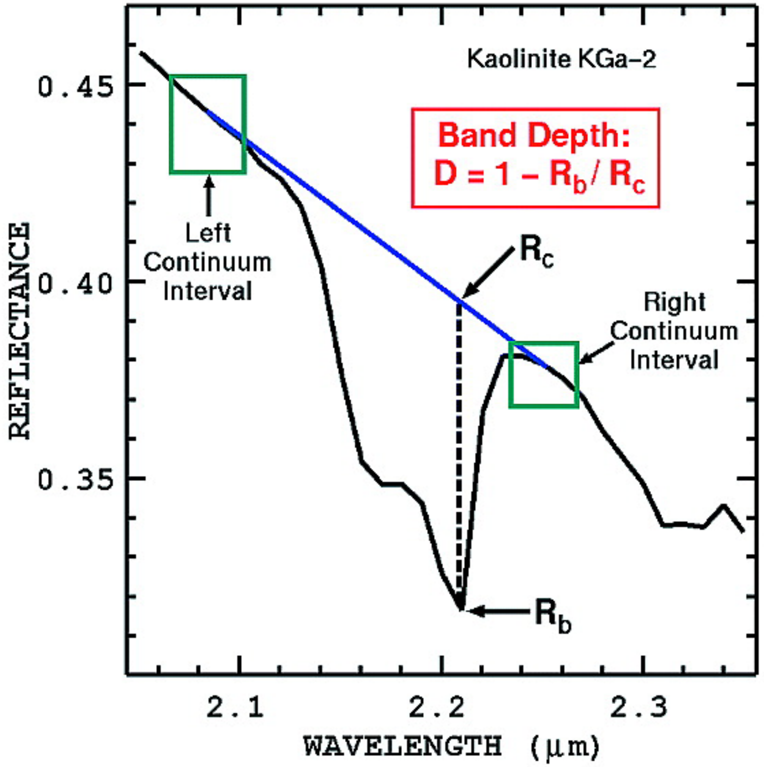
- Sky view factor
- H_2O absorption coefficient intensity
- Systematic radiative transfer error
- Uncorrelated radiative transfer error

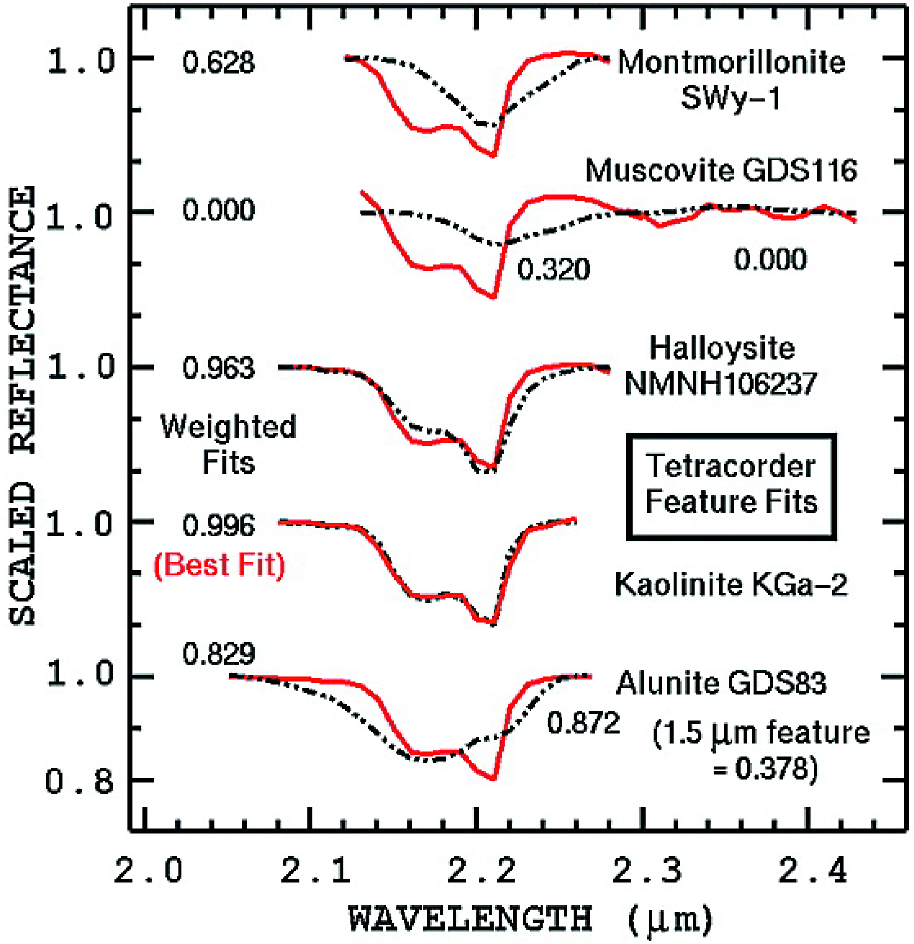
Mineral feature fitting

- Retrofit the Clark et al. (2003) technique
- Use a library of absorption signatures from the USGS
- Fit the continuum-removed feature depth
- The best-fitting signature "wins"
- Handle mixtures with dedicated library spectra



Mineral feature fitting





Images from Clark et al., Imaging spectroscopy: Earth and planetary remote sensing with the USGS Tetracorder and expert systems, Journal of Geophysical Research: Planets, Volume: 108, Issue: E12, First published: 06 December 2003, DOI: (10.1029/2002JE001847)

Formulation as Tikhonov Regression

$$\underbrace{\boldsymbol{\rho}_c}_{\text{Continuum-removed reflectance measurement}} = \underbrace{\boldsymbol{K}_m \boldsymbol{x}_m}_{\text{Linear operator transforms library absorption feature}} + \epsilon \quad \text{for} \quad \underbrace{\epsilon \sim \mathcal{N}(0, \boldsymbol{\Psi}_c)}_{\text{Via reflectance uncertainty propagated form L2}}$$

Formulation as Tikhonov Regression

$$\underbrace{\boldsymbol{\rho}_c}_{\text{Continuum-removed reflectance measurement}} = \underbrace{\boldsymbol{K}_m \boldsymbol{x}_m}_{\text{Linear operator transforms library spectrum}} + \epsilon \quad \text{for} \quad \underbrace{\epsilon \sim \mathcal{N}(0, \boldsymbol{\Psi}_c)}_{\text{Via reflectance uncertainty propagated form L2}}$$

$$\hat{\boldsymbol{x}}_m = \underbrace{\boldsymbol{\mu}_m}_{\text{Uninformed mineral depth priors}} + (\boldsymbol{K}_m^T \boldsymbol{\Psi}_c^{-1} \boldsymbol{K}_m + \underbrace{\boldsymbol{\Sigma}_m^{-1}}_{\text{Uninformed mineral depth priors}})^{-1} \boldsymbol{K}_m^T \boldsymbol{\Psi}_c^{-1} (\boldsymbol{\rho}_c - \boldsymbol{K}_m \boldsymbol{\mu}_m)$$

Maximum A Posteriori One-of-N spectrum selection

$$\underbrace{p(m|\boldsymbol{\rho}_c)}_{\text{Posterior probability of mineral m given measured continuum-removed reflectance}} = Zp(\boldsymbol{\rho}_c|\hat{\boldsymbol{x}}_m)p(m)$$

Maximum A Posteriori One-of-N spectrum selection

$$\underbrace{p(m|\boldsymbol{\rho}_c)}_{\text{Posterior probability of mineral m given measured continuum-removed reflectance}} = \underbrace{Z}_{\text{Normalization factor}} \overbrace{p(\boldsymbol{\rho}_c|\hat{\boldsymbol{x}}_m)}^{\text{Log conditional probability density for a given mineral m}} \underbrace{p(m)}_{\text{Regional or uninformed prior}}$$

Maximum A Posteriori One-of-N spectrum selection

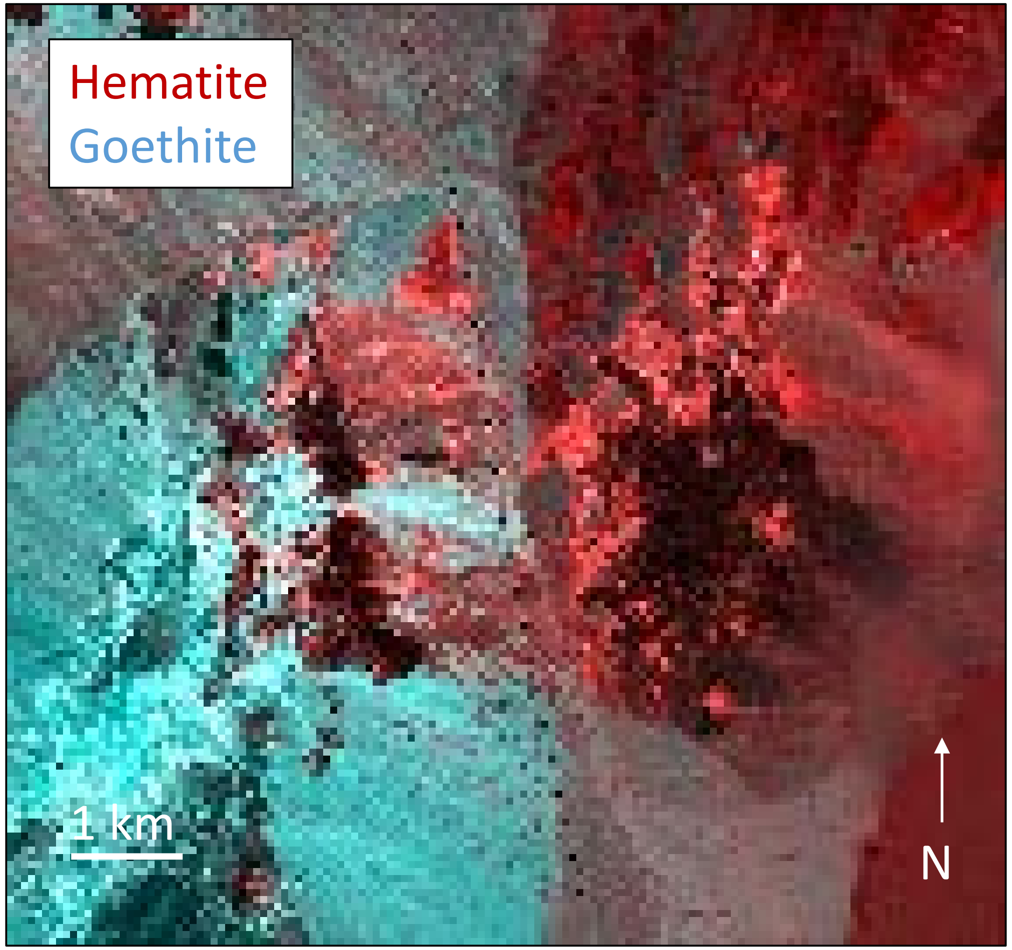
$$\underbrace{p(m|\boldsymbol{\rho}_c)}_{\text{Posterior probability of mineral m given measured continuum-removed reflectance}} = \underbrace{Z}_{\text{Normalization factor}} \overbrace{p(\boldsymbol{\rho}_c|\hat{\boldsymbol{x}}_m)}^{\text{Log conditional probability density for a given mineral m}} \underbrace{p(m)}_{\text{Regional or uninformed prior}}$$

$$\log p(\boldsymbol{\rho}_c|\hat{\boldsymbol{x}}_m) \propto -(\boldsymbol{K}_m\hat{\boldsymbol{x}}_m - \boldsymbol{\rho}_c)^T \boldsymbol{\Psi}_c^{-1}(\boldsymbol{K}_m\hat{\boldsymbol{x}}_m - \boldsymbol{\rho}_c)$$

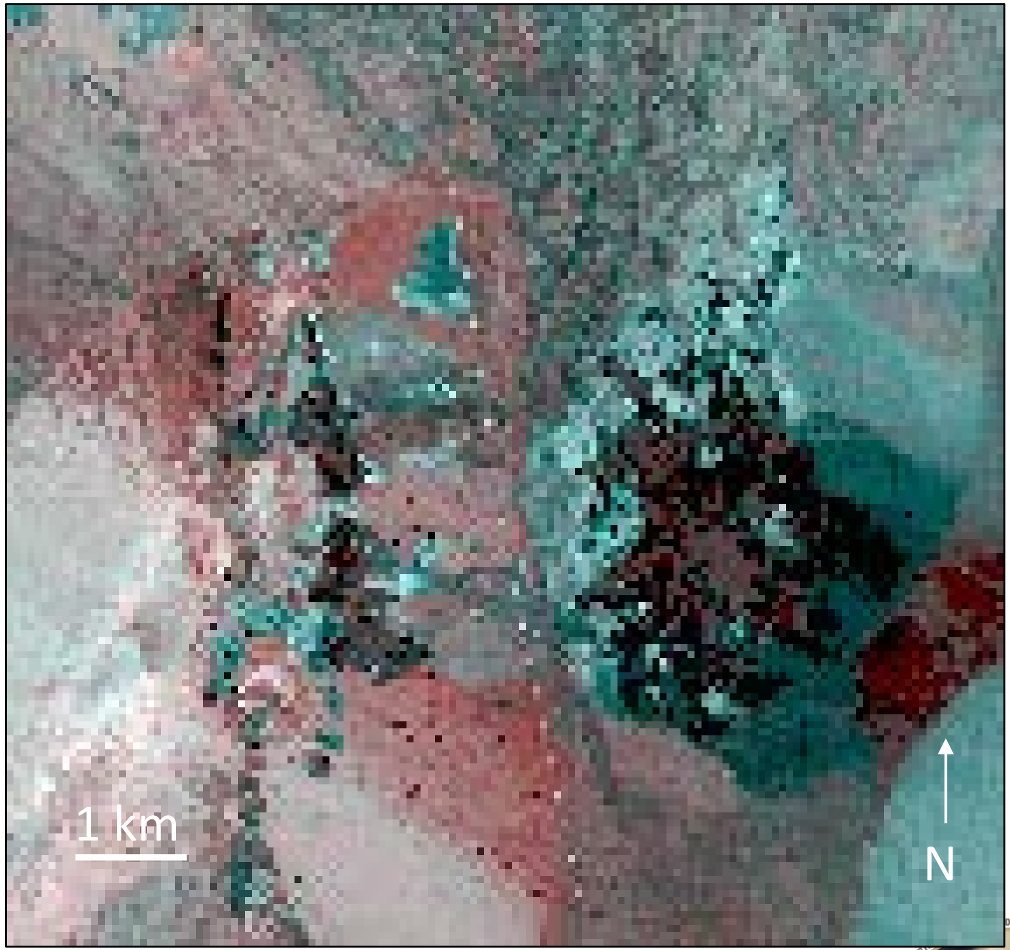
… test all minerals, and pick the highest probability

Example maps: iron oxides

Estimated Feature Depth

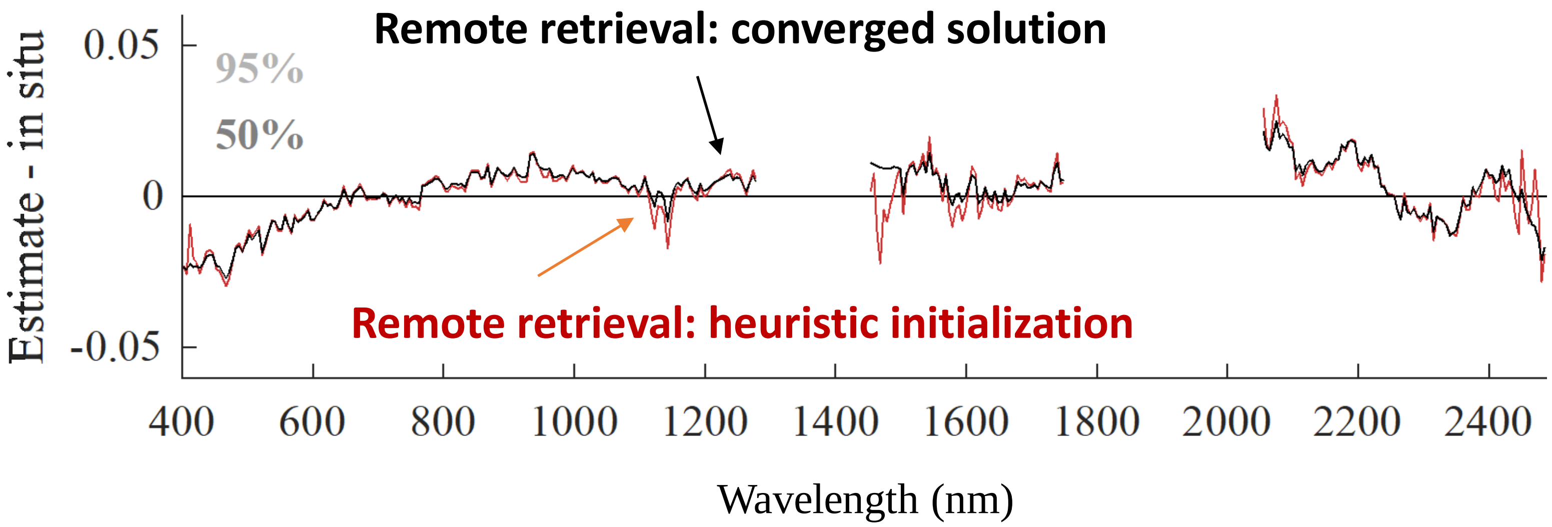


Negative Log Likelihood (Model Error)



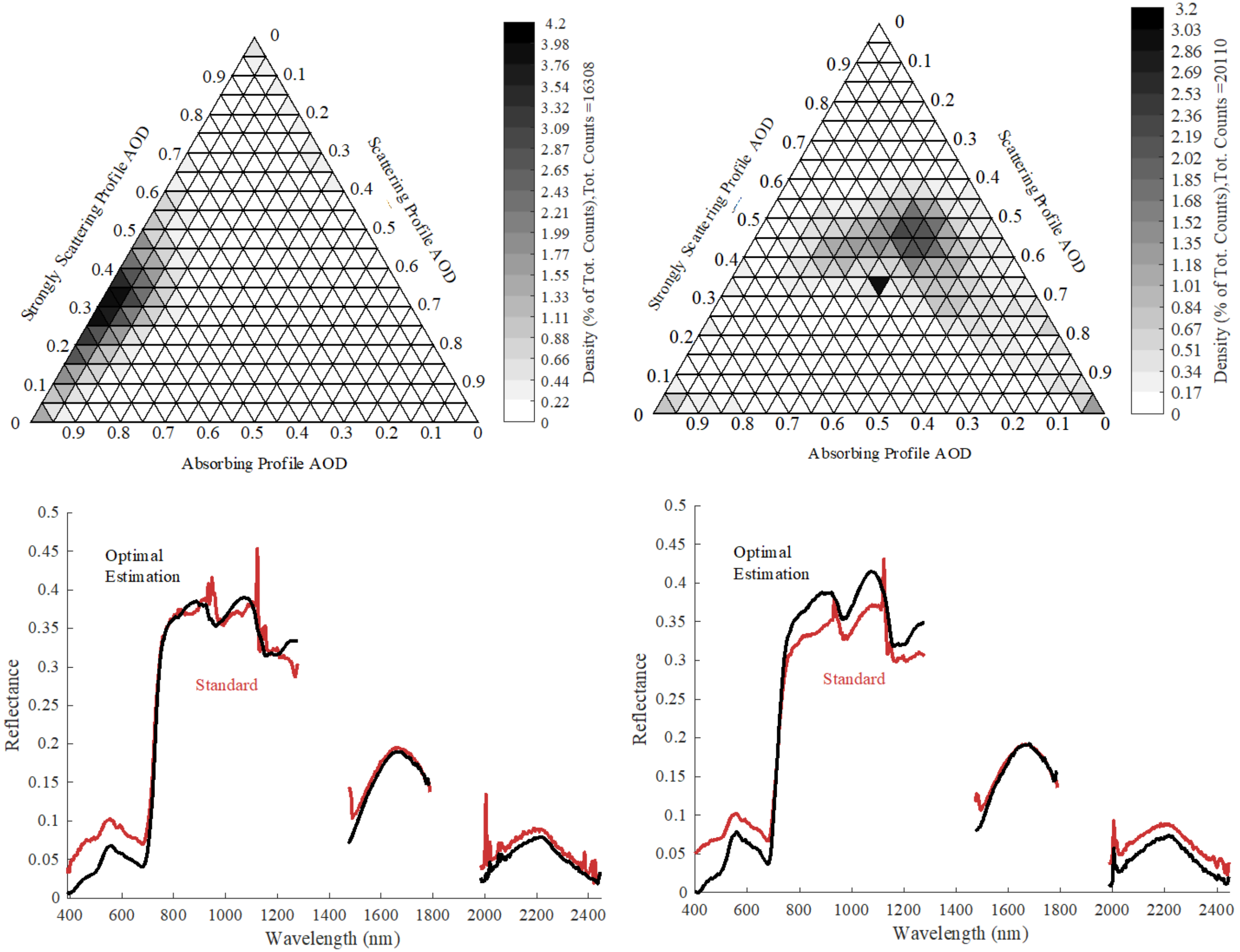
Posterior uncertainty compared to actual discrepancies

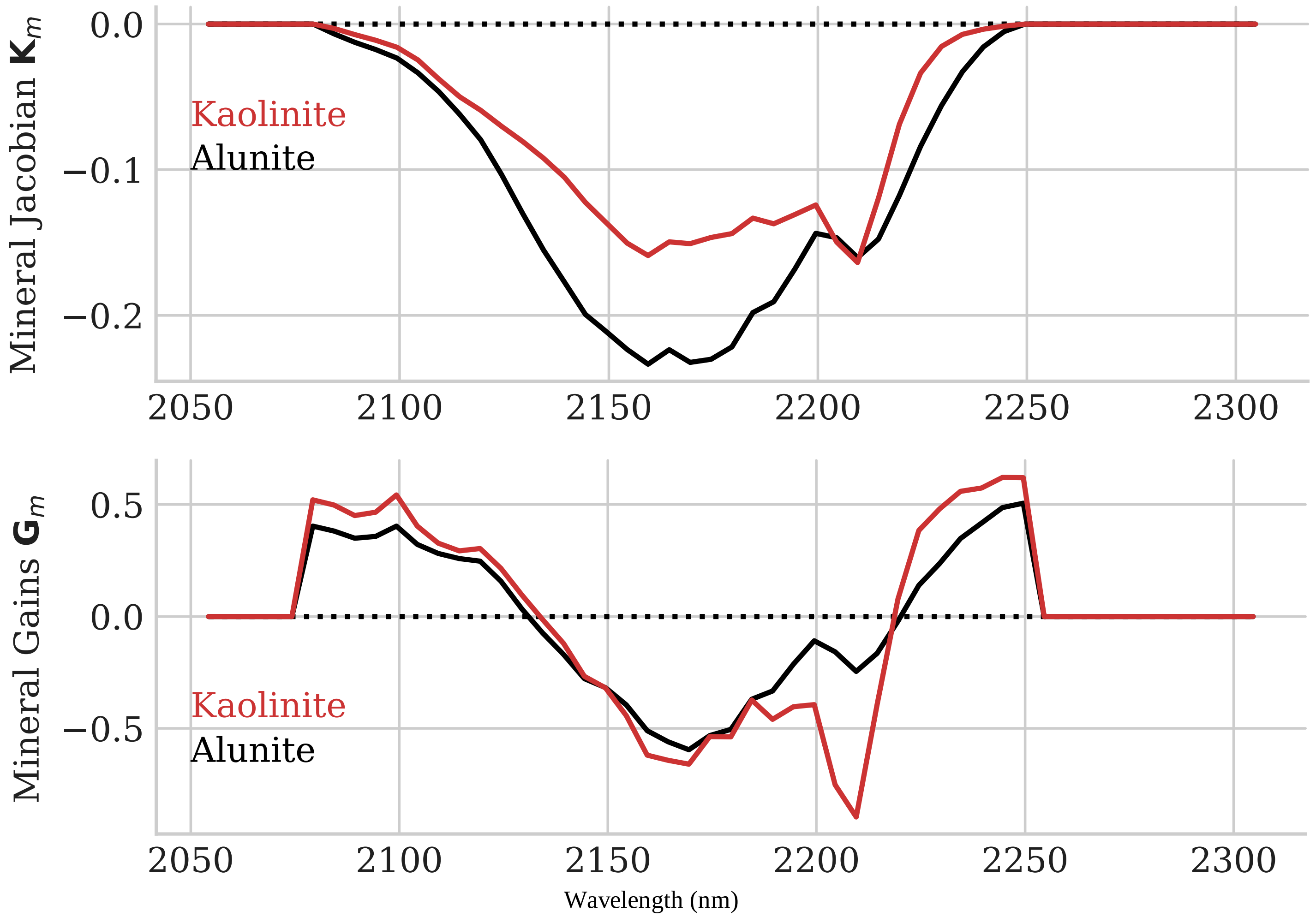
[Thompson et al., *Remote Sensing of Environment* 2018]



High aerosol loading in India campaign

[Thompson et al., Remote Sensing of Environment, 2019]

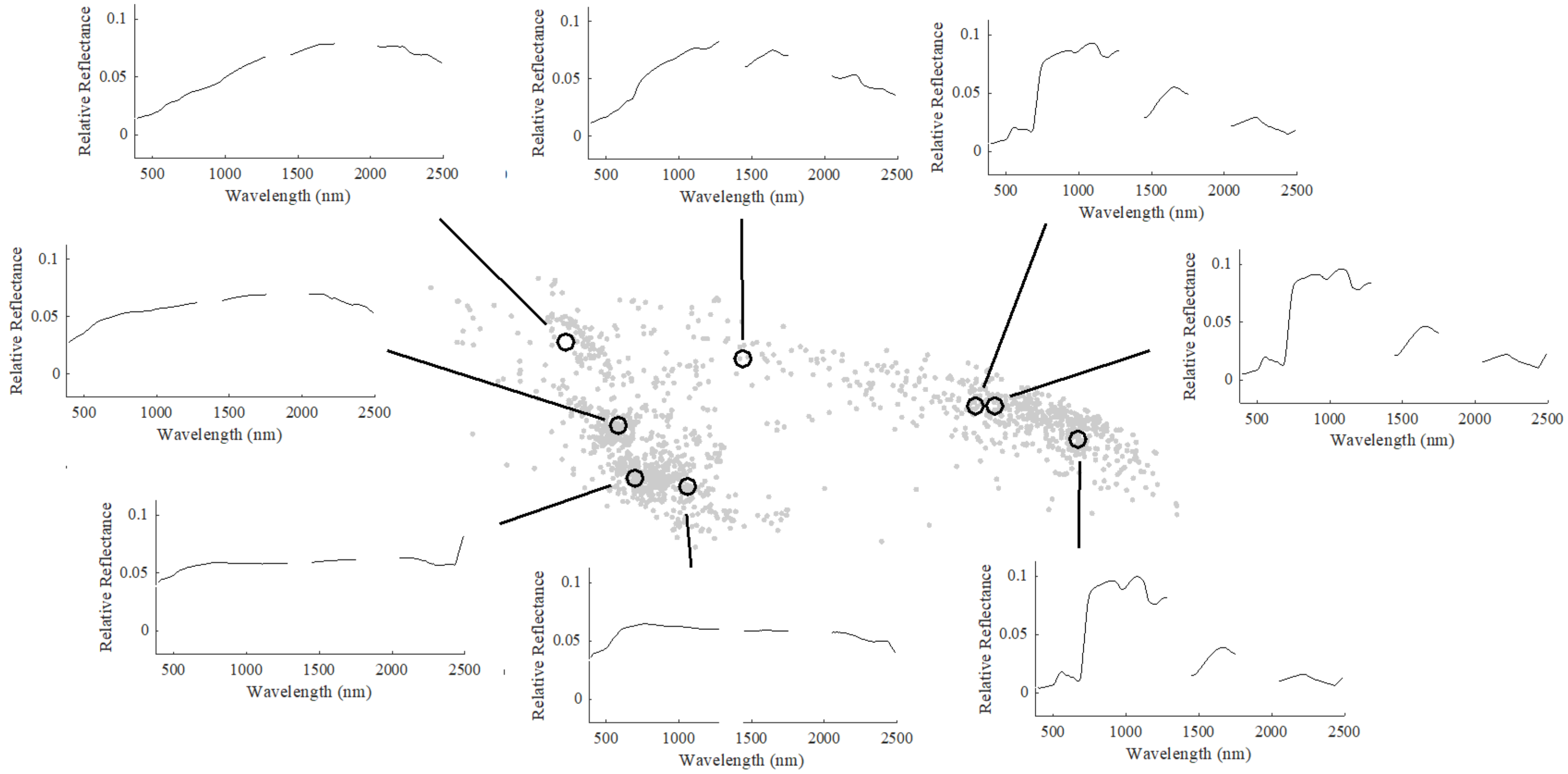




Mineral Jacobian $\mathbf{K}_m$
0.0
−0.1
−0.2
Kaolinite
Alunite
2050
2100
2150
2200
2250
2300
Mineral Gains $\mathbf{G}_m$
0.5
0.0
−0.5
Kaolinite
Alunite
2050
2100
2150
2200
2250
2300
Wavelength (nm)

Universal surface reflectance priors

A collection of multivariate Gaussians, trained on a diverse library spectra and further regularized to enable retrieval of arbitrary surface shapes not previously observed



From Thompson et al., RSE (2018, 2019a, 2019b)