Jet Propulsion Laboratory
California Institute of Technology

Improving atmospheric correction across the Indian subcontinent: Initial project results

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Vijay Natraj[1]
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Robert O. Green[1]
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With thanks to Rahul Nigam[2], BK Bhattacharya[2], and Arundhati Misra[2]

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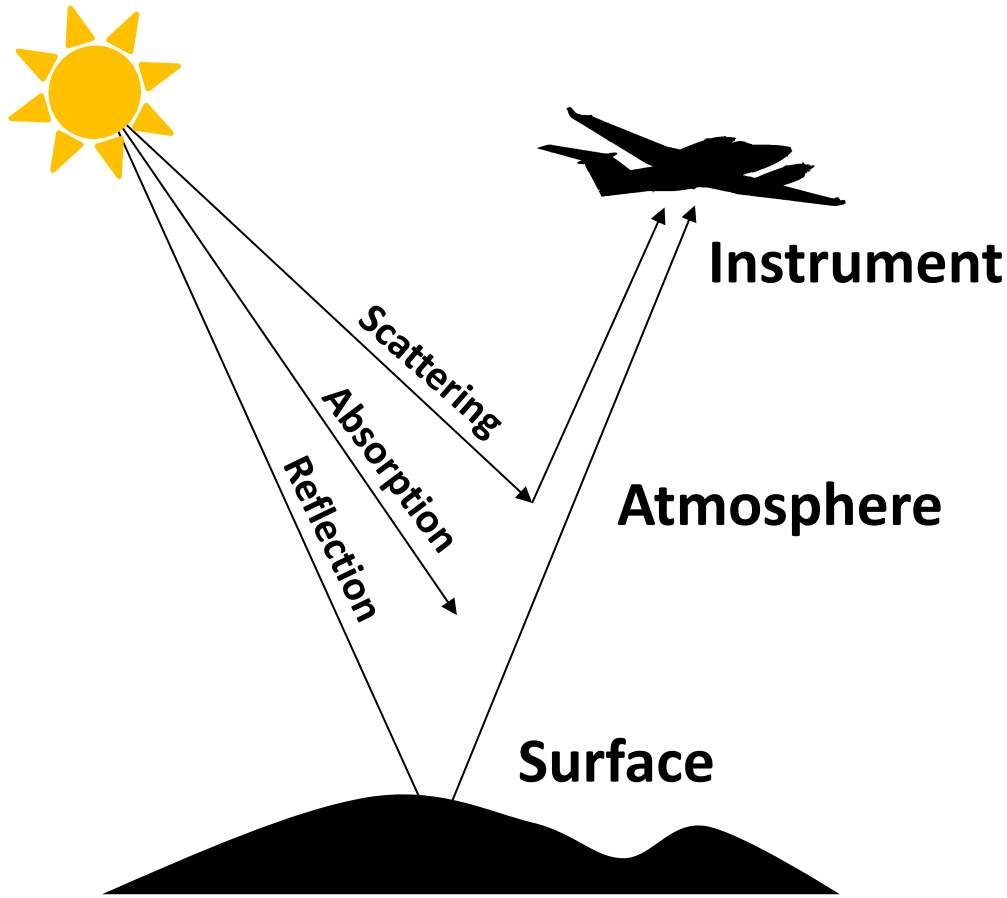
Agenda

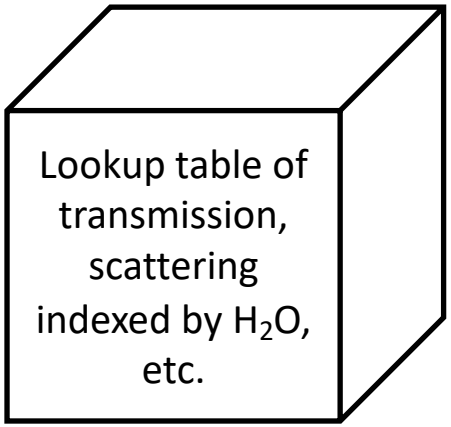
1. Algorithms and approach: *Optimal Estimation*

2. Field validation experiment

3. Nonlinear solutions and India results

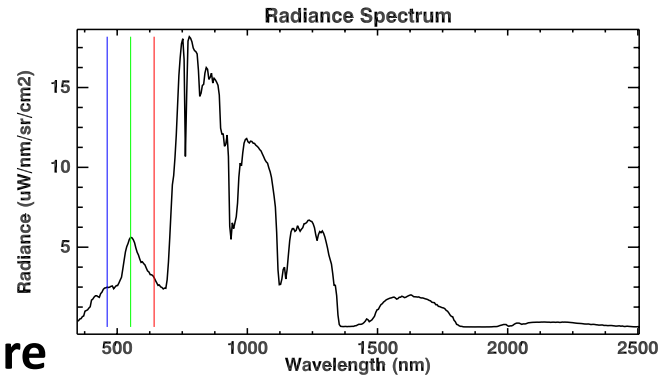


Conventional atmospheric correction: A sequential process



1. In advance, do RTM calculations

Conventional atmospheric correction: A sequential process



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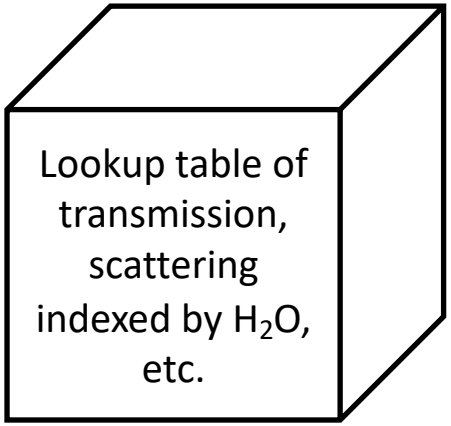

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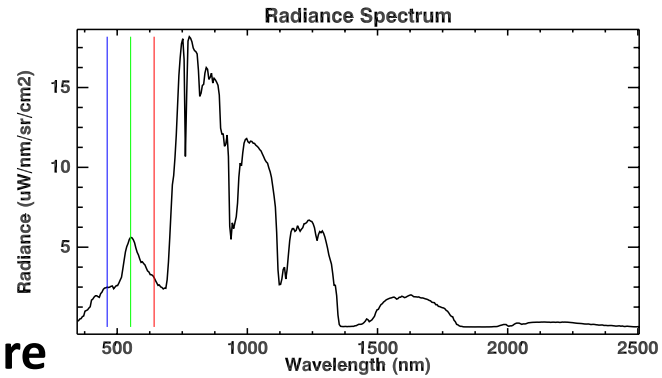

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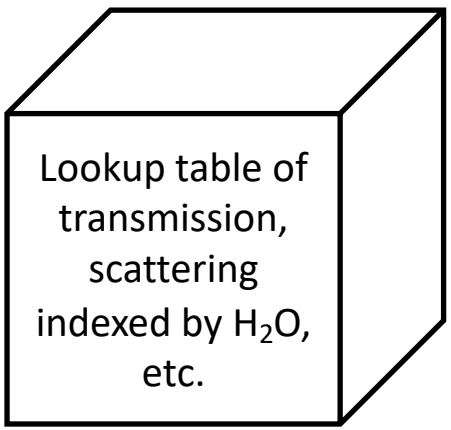
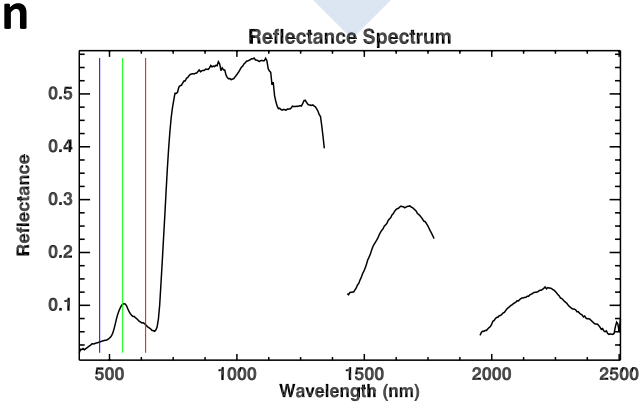


1. In advance, do RTM calculations

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

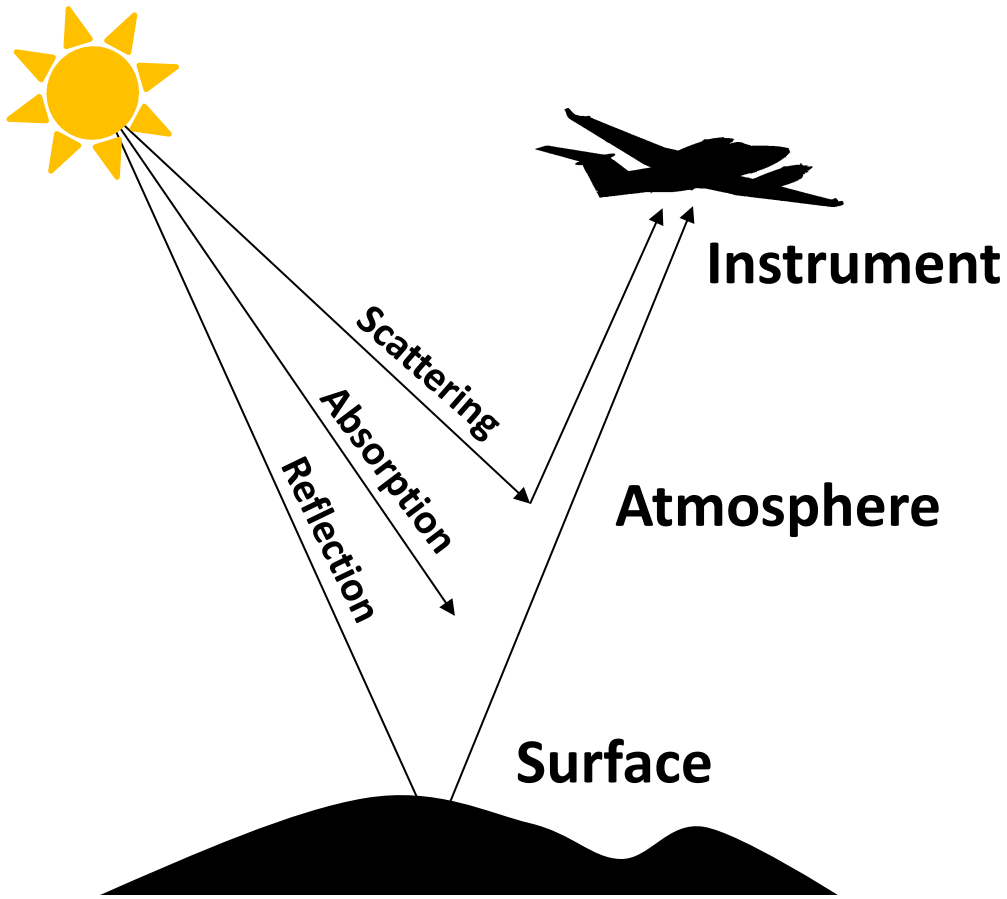
3. Algebraic Inversion



Alternative: a combined model

Optimal estimation (Rodgers, 2000) has been used for decades in NASA's atmospheric sounding (OCO-2, AIRS, TES, et cetera).

Here we extend it to VSWIR imaging spectroscopy



Optimal Estimation advantages

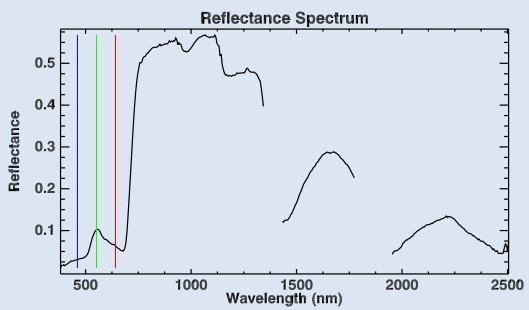
- **Improved accuracy -** a true spectroscopic retrieval to exploit information distributed across the spectrum
- **Statistical rigor** incorporates and weights information appropriately using measurement and prior information
- **Uncertainty propagation** can incorporate instrument uncertainty, inform downstream analyses and synthesis
- **Flexible state vectors** that might be more robust for difficult observing conditions
- **Elegant, conceptually simple 1-step estimation**

The “forward problem”

State vector

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

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



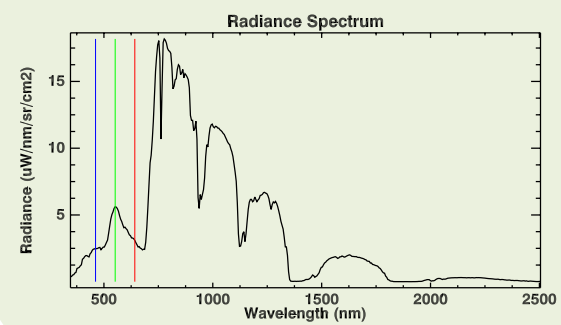
Forward model

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

Measurement

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

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

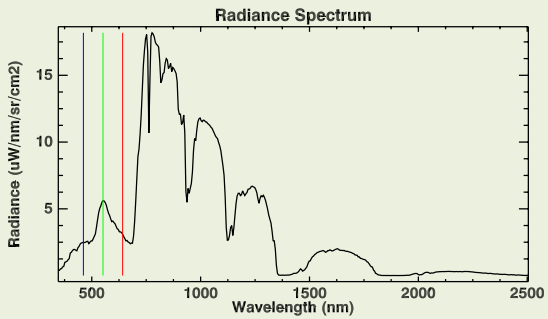


The “inverse problem”

Measurement

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

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



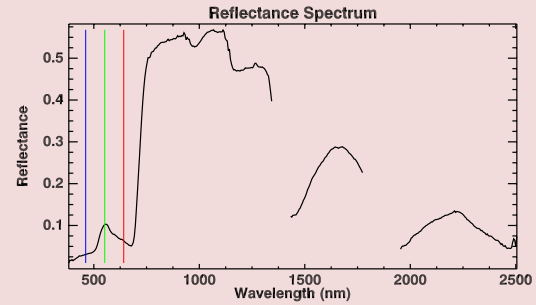
Inversion algorithm

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

Estimated state vector

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

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



Maximum *A Posteriori* solution

State vector Measurement

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

Maximum *A Posteriori* solution

State vector Measurement

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

Reduces to the optimization:

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

… solve it by conjugate gradient descent.

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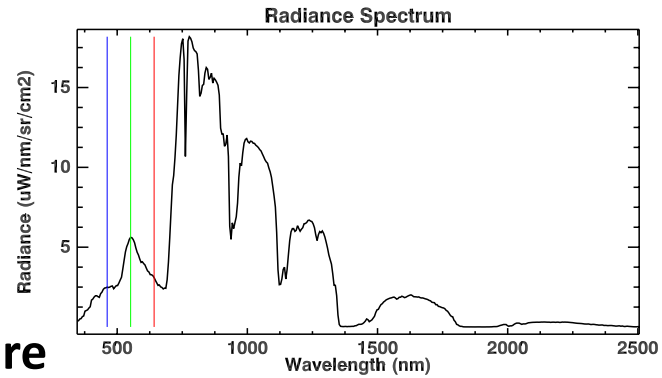

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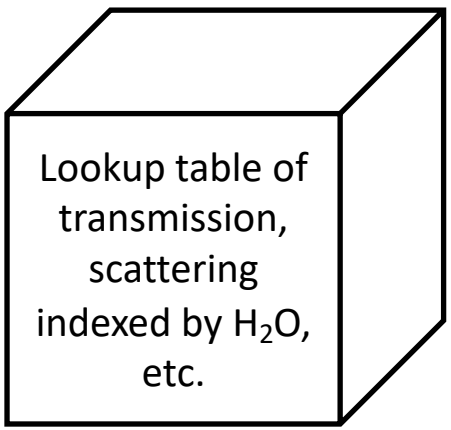

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measurement

reflectance

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

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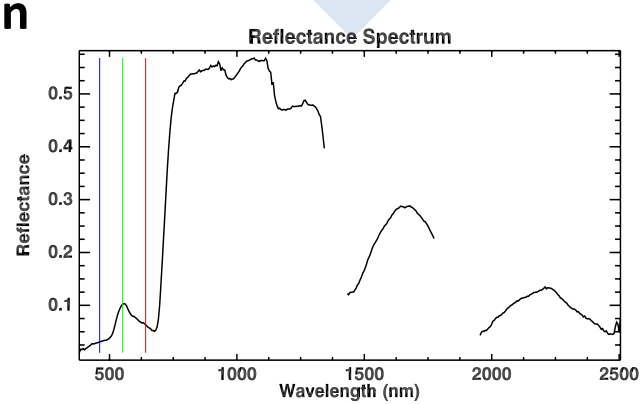

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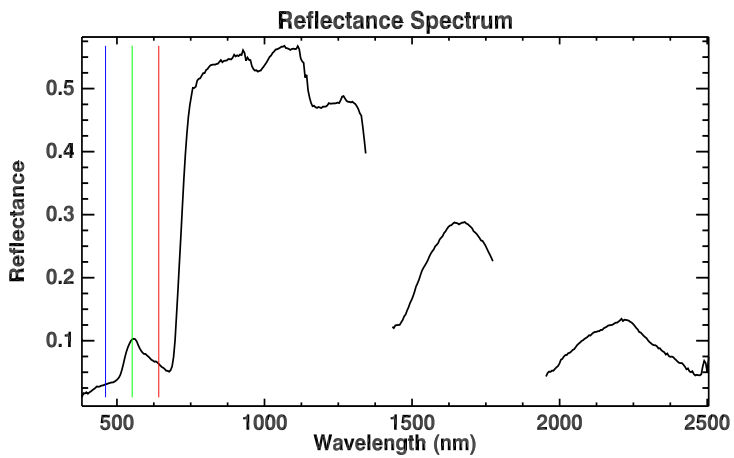
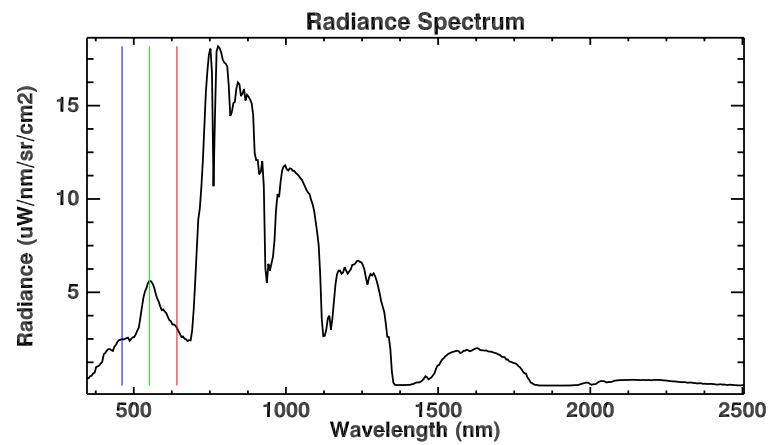
Iterative simultaneous estimation of atmosphere and surface

1. Predict radiance

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





2. Optimize state vector

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

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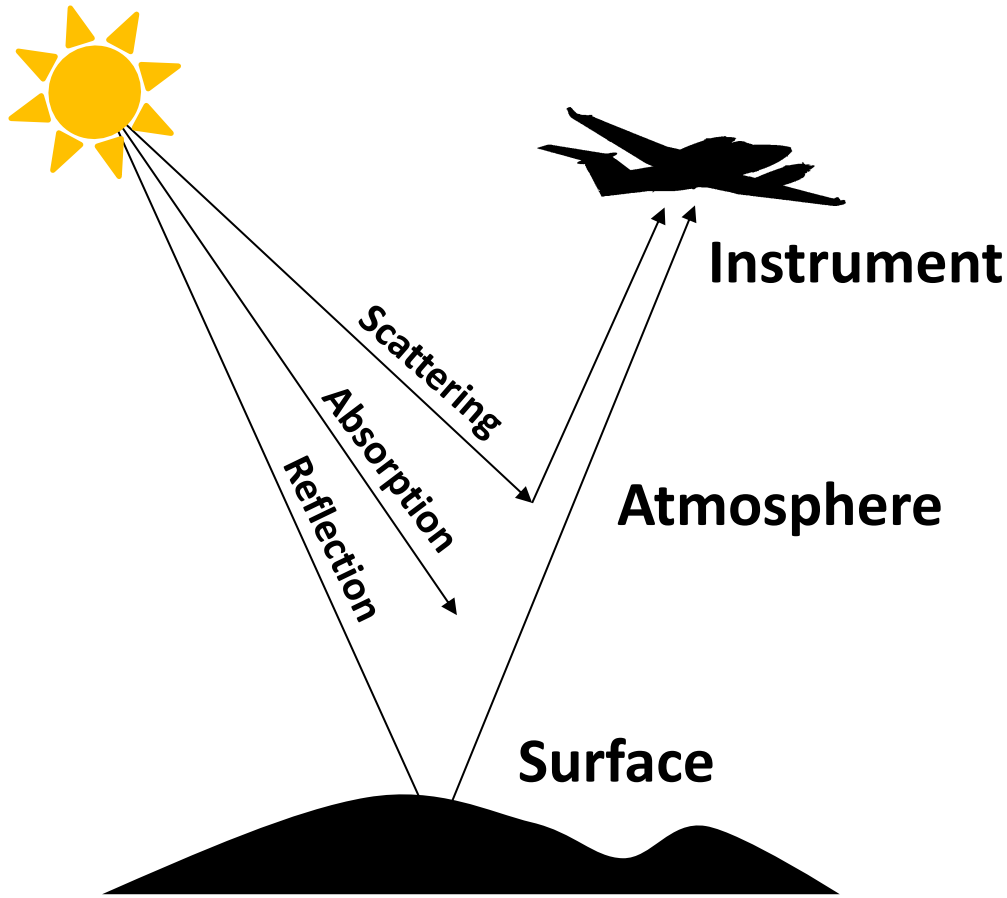
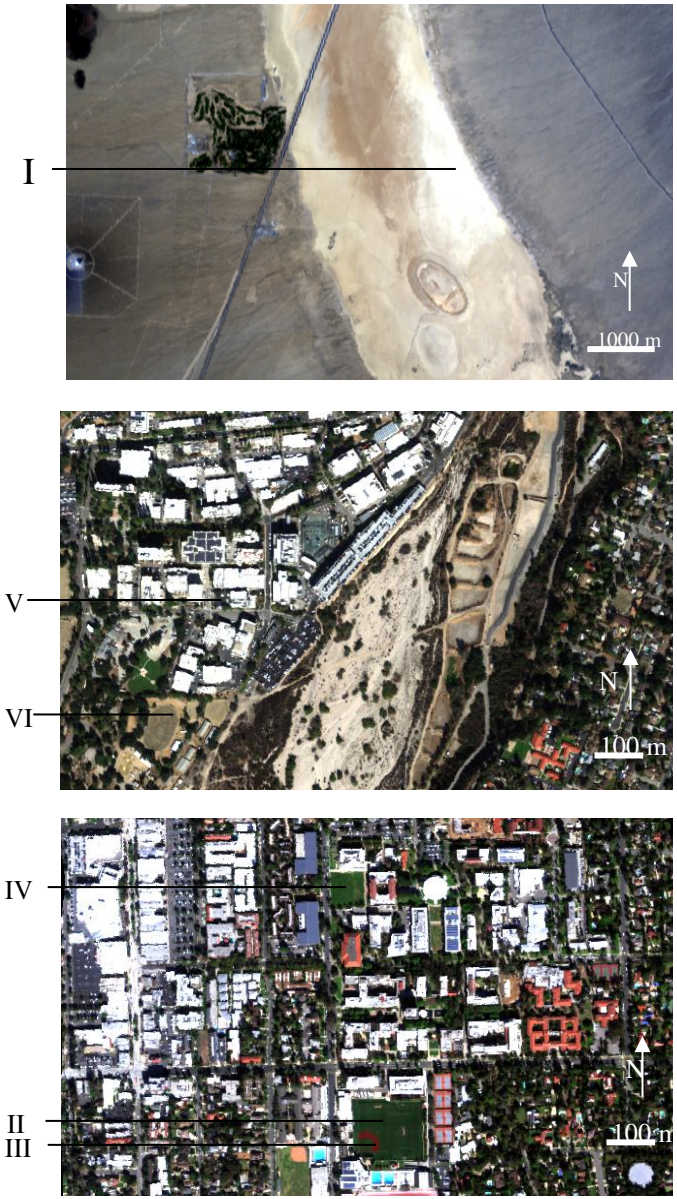
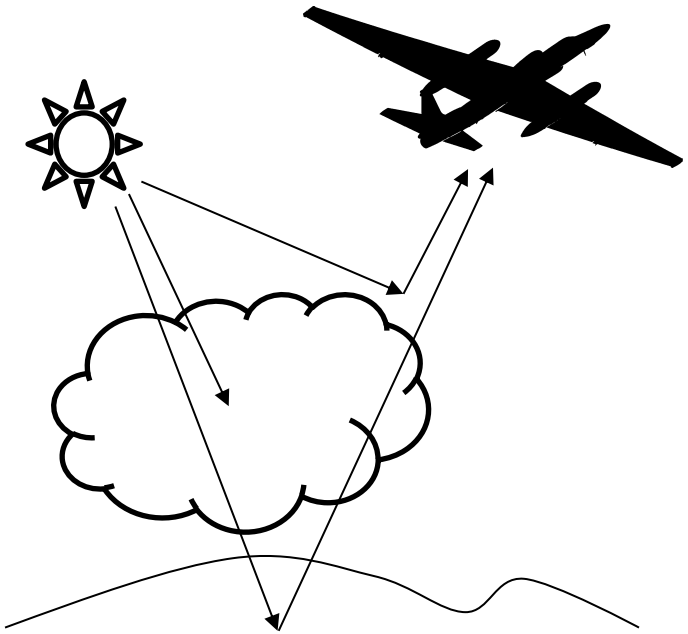


Imaging spectroscopy case study

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

- In-situ Reagan sunphotometers and ASD spectrometers
- *Maximum a posteriori* retrieval via optimal estimation formalism
- Full uncertainty accounting for atmosphere, instrument, surface



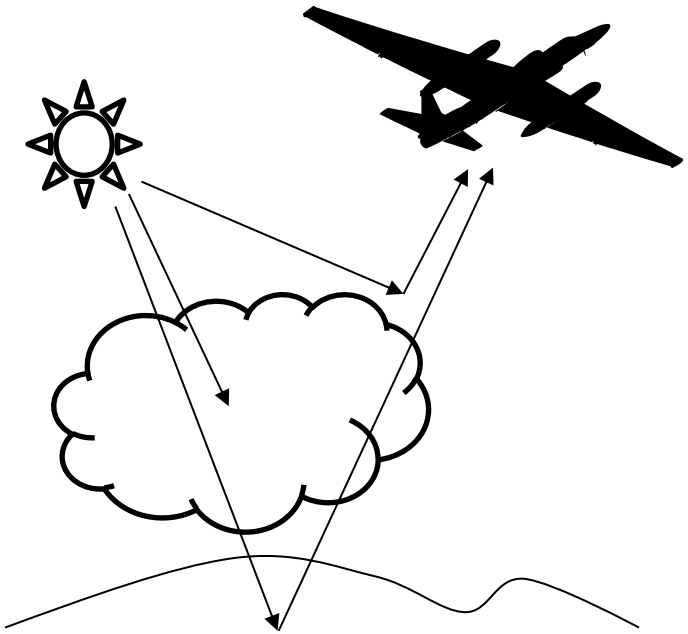


Instrument: AVIRIS-NG

Atmosphere: MODTRAN 6.0 RTM

Model components

Surface: Multi-component Multivariate Gaussians



Model components

Pre-defined

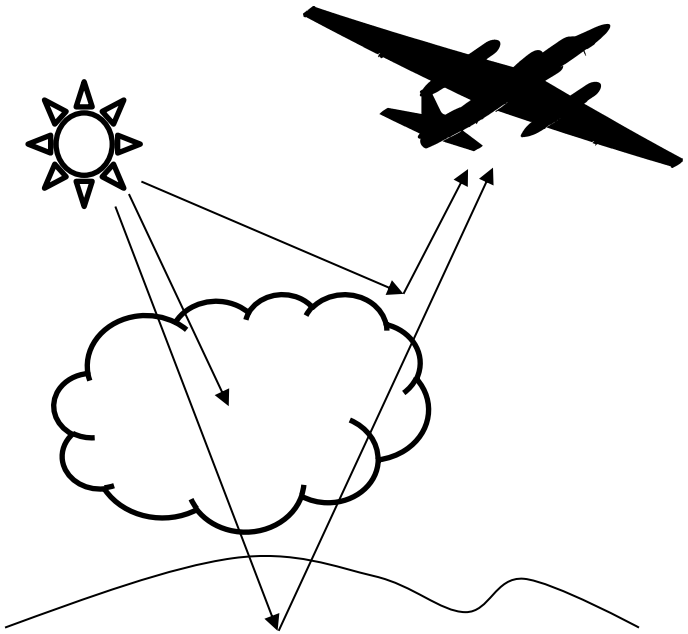
Instrument: AVIRIS-NG

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

Atmosphere: MODTRAN 6.0 RTM

- DISORT MS, Correlated-k
- Rural aerosol model

Surface: Multi-component Multivariate Gaussians



Model components

Pre-defined

Statistical, fit to data

Instrument: AVIRIS-NG

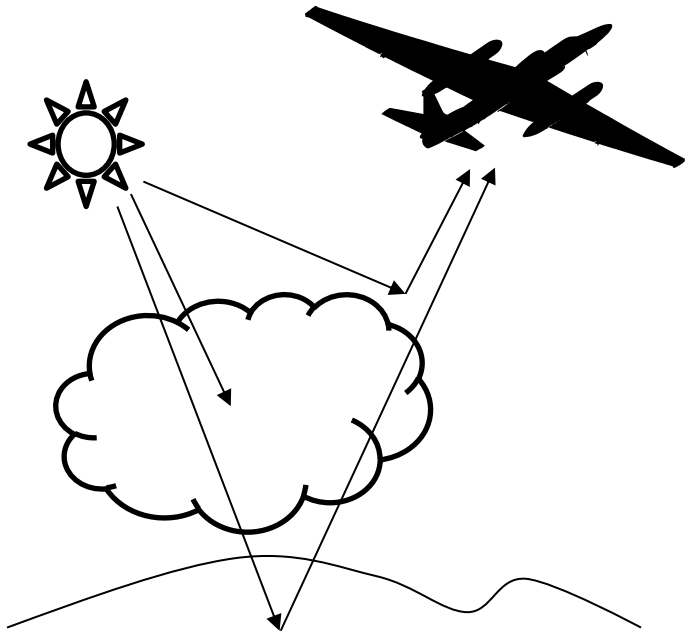
- Instrument model with Wavelength- and signal-dependent SNR
- Photon shot & read noise
- Uncorrelated calibration uncertainty
- Systematic calibration / RT uncertainty

Atmosphere: MODTRAN 6.0 RTM

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

Surface: Multi-component Multivariate Gaussians

- Prior based on universal library, highly regularized to permit accurate retrieval of arbitrary shapes



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

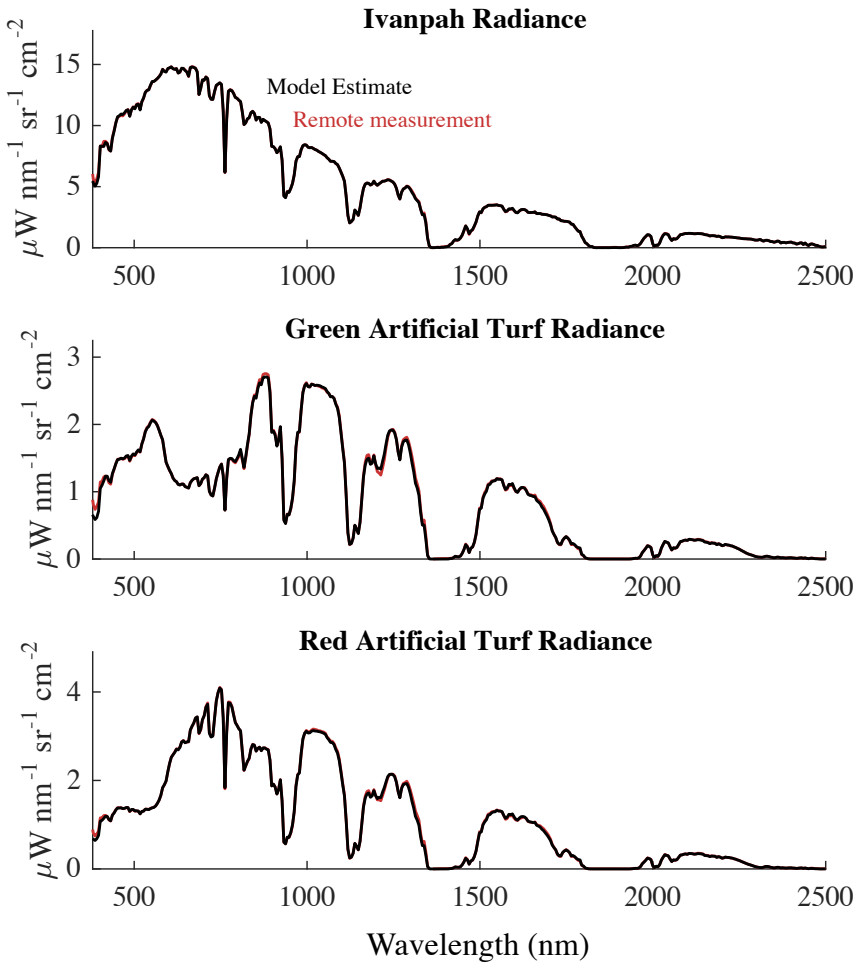
- DISORT MS, Correlated-k
- Rural aerosol model
- broad prior uncertainties
- Unmodeled unknowns, including H_2O absorption coefficients
- H_2O, AOD retrieved

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

Radiance model vs. measurement

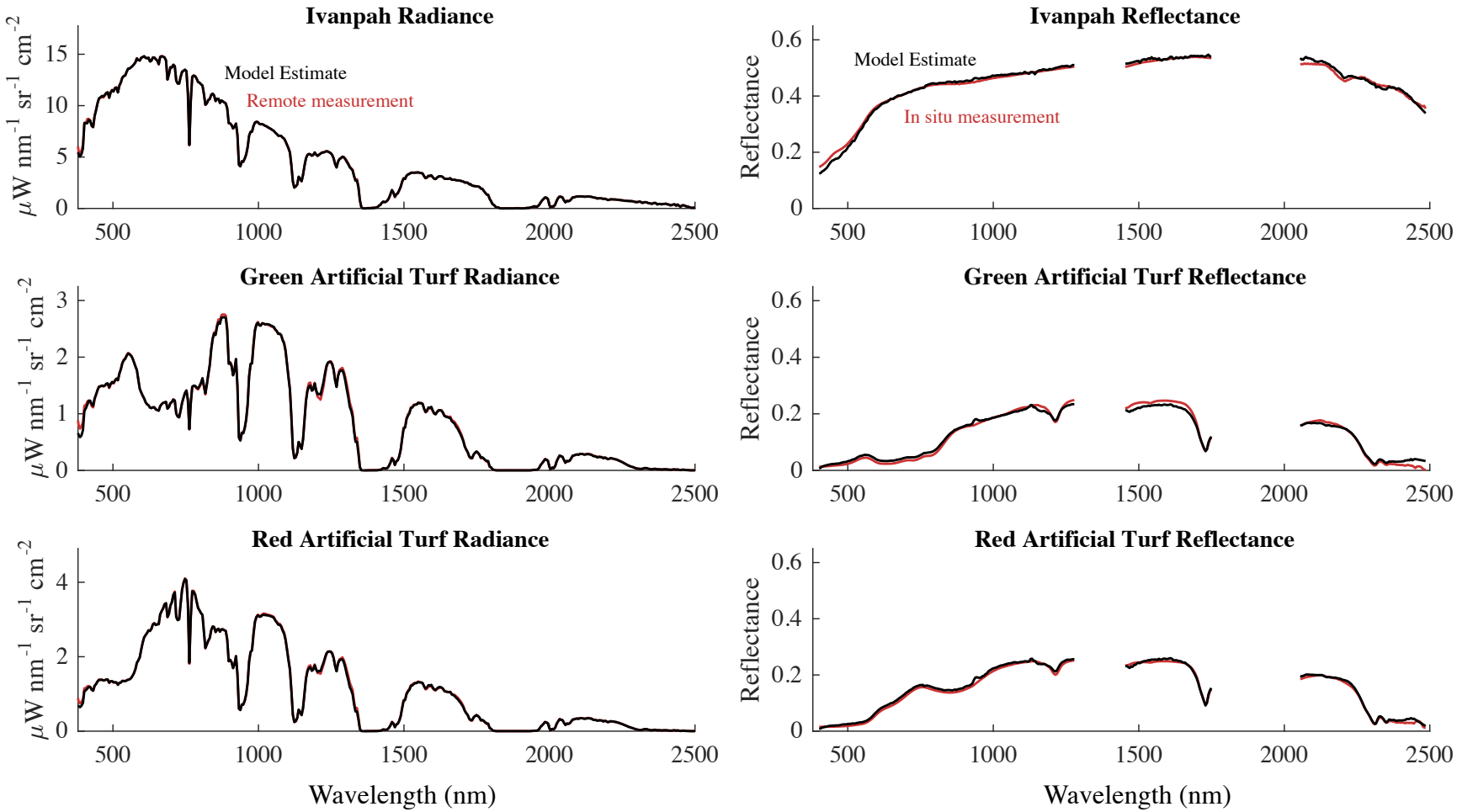
[Thompson et al., *Remote Sensing of Environment* 2018]



Wavelength (nm)

Reflectance estimate vs. in situ

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

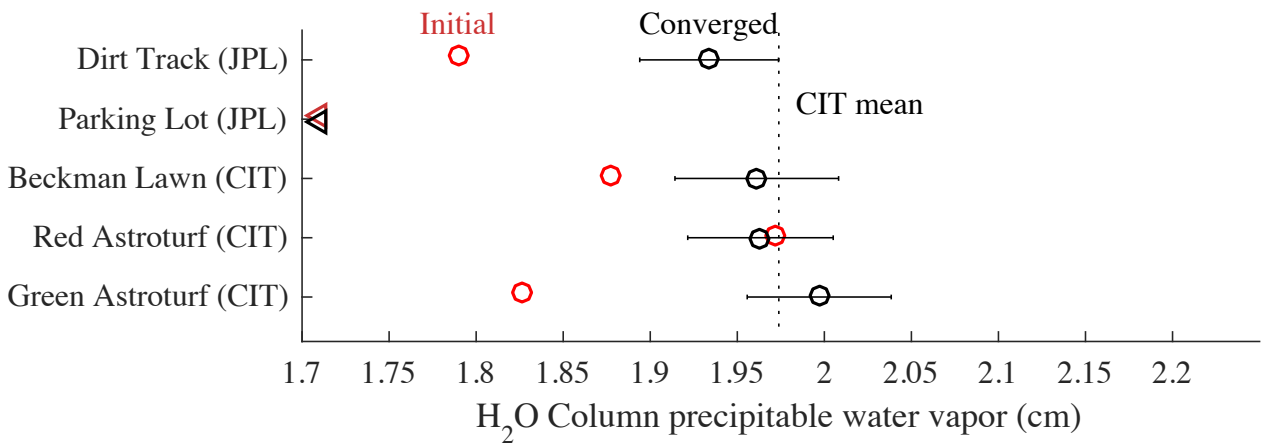


Performance

Surface reflectance fidelity

			$\hat{\rho}_s$ Mean Error			$\hat{\rho}_s$ Spectral Angle		
	Feature	**Site**	**Initial**	**Algebraic**	**Posterior**	**Initial**	**Algebraic**	**Posterior**
I.	Ivanpah Playa[1]	Ivanpah	0.0077	0.0079	**0.0075**	0.0215	0.0212	**0.0199**
II.	Green Artificial Turf	CIT	0.0097	0.0098	**0.0092**	0.0961	0.1185	**0.0687**
III.	Red Artificial Turf	CIT	0.0085	0.0080	**0.0064**	0.0779	0.0777	**0.0339**
IV.	Lawn Grass	CIT	0.0110	0.0115	**0.0104**	0.0593	0.0611	**0.0369**
V.	Parking Lot	JPL	0.0055	0.0056	**0.0054**	0.1016	0.1024	**0.0918**
VI.	Dirt Track	JPL	0.0221	0.0200	**0.0195**	0.0455	0.0502	**0.0338**

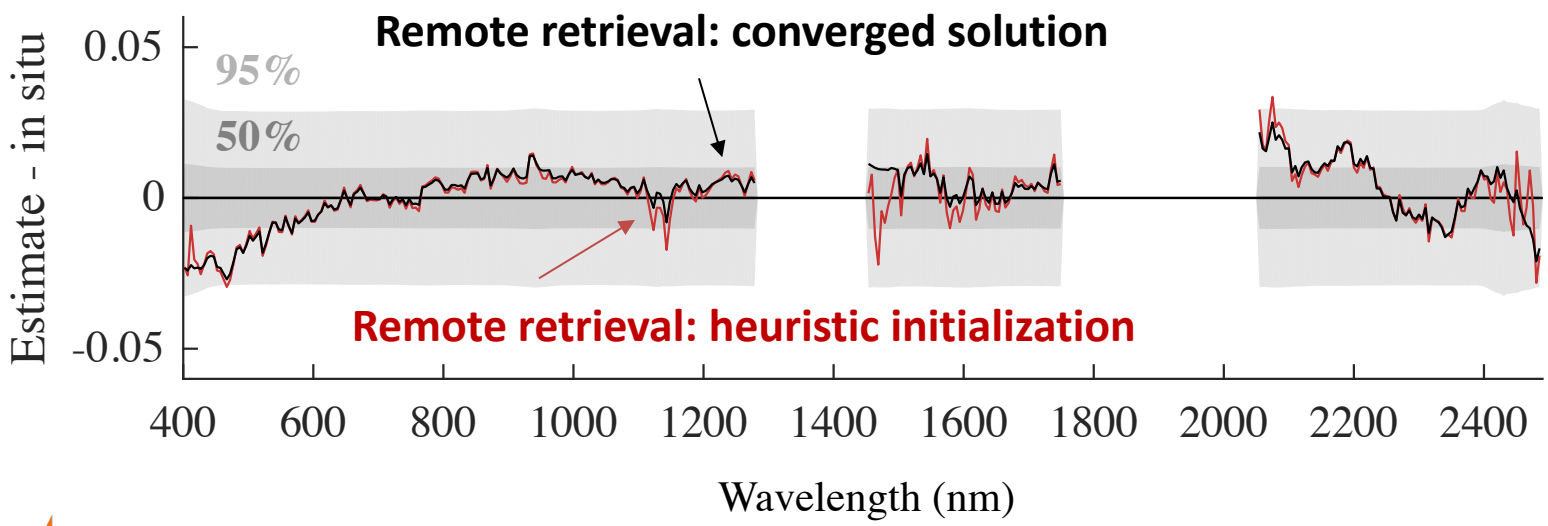
H_2O consistency



From Thompson et al., RSE (in review)

Posterior uncertainty compared to actual discrepancies

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



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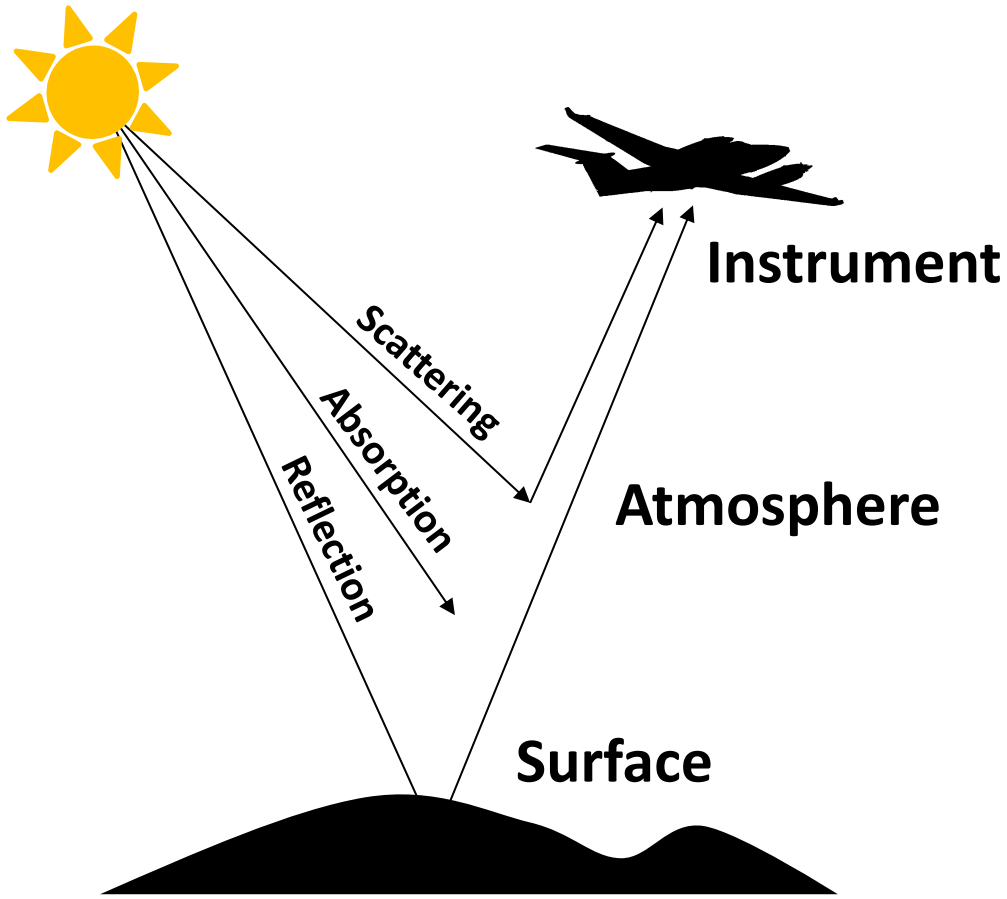


Karnataka test procedure

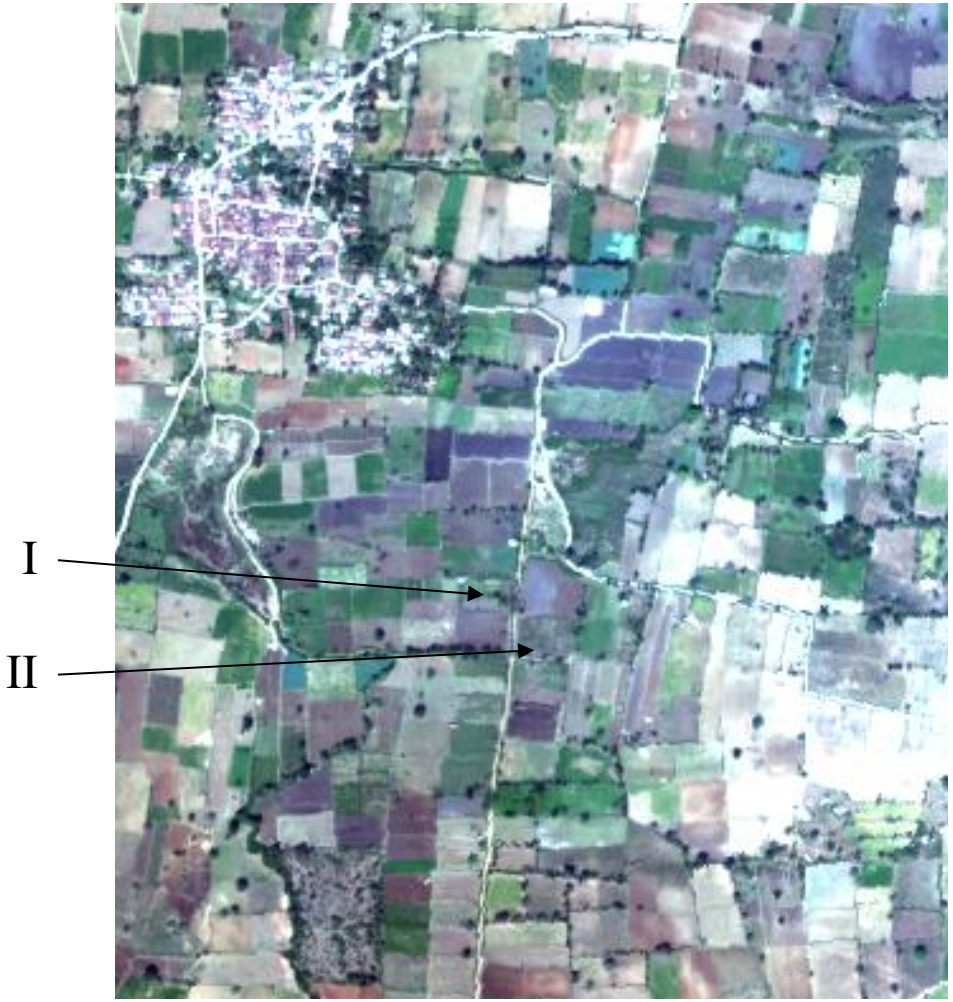
An AVIRIS-NG overflight took place on 10 January 2016, with an in-situ team measuring crop canopy reflectance and atmospheric AOD

The top-of-canopy reflectance measurements excluded soil around and between the plants, which was significant at 8m GSD.

Consequently we constructed nonnegative geographic mixing models using existing libraries of soil and NPV spectra

We elected two in-situ spectra for that had good model reconstructions

ang20160110t074559 (RGB)



MCMC Sampling

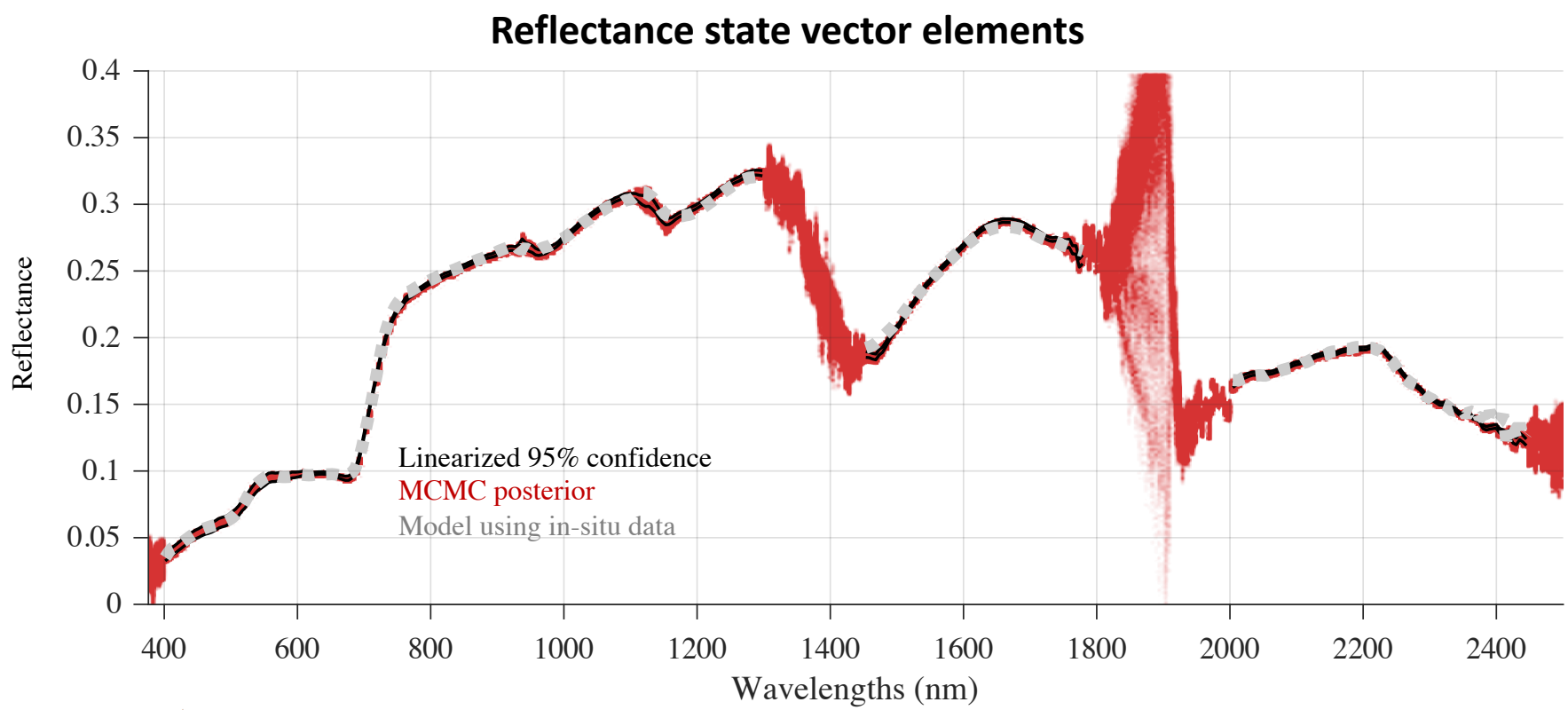
OE Uncertainties are calculated in closed form using local linearity assumptions.

To characterize the error more precisely, we sample directly from the posterior distribution using Markov Chain Monte Carlo sampling.

We use a Metropolis-Hastings formalism with a proposal distribution based on the linearized posterior error predictions.

Karnataka example

Overall, alignment with ground truth is quite good.
Linearized estimates are a good proxy for the MCMC posterior.



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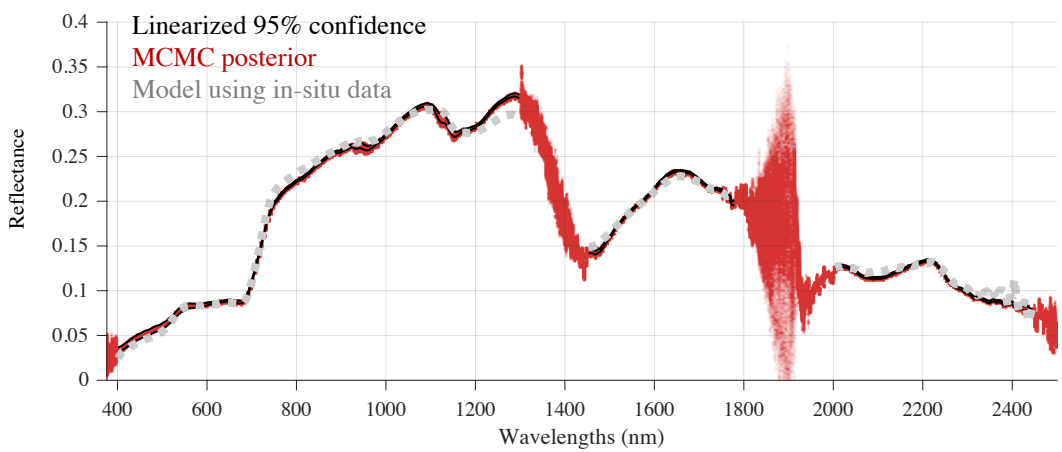
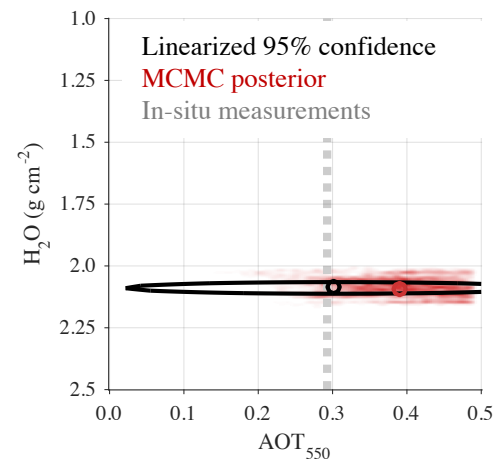
Karnataka test results

Reflectance state vector elements

Atmospheric state vector elements

I





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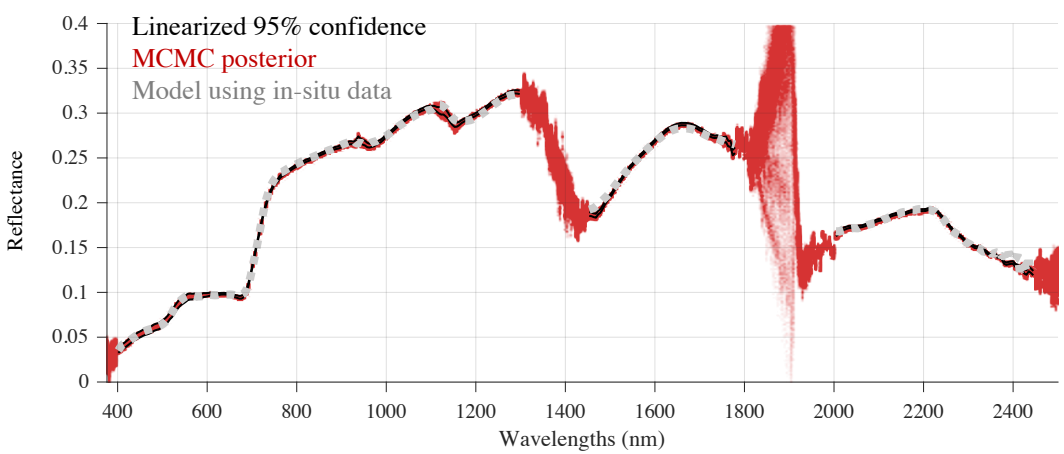
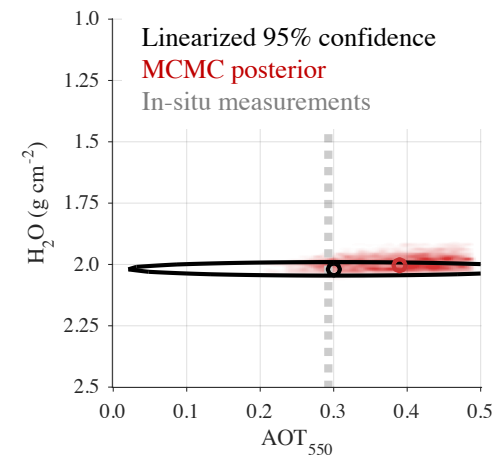




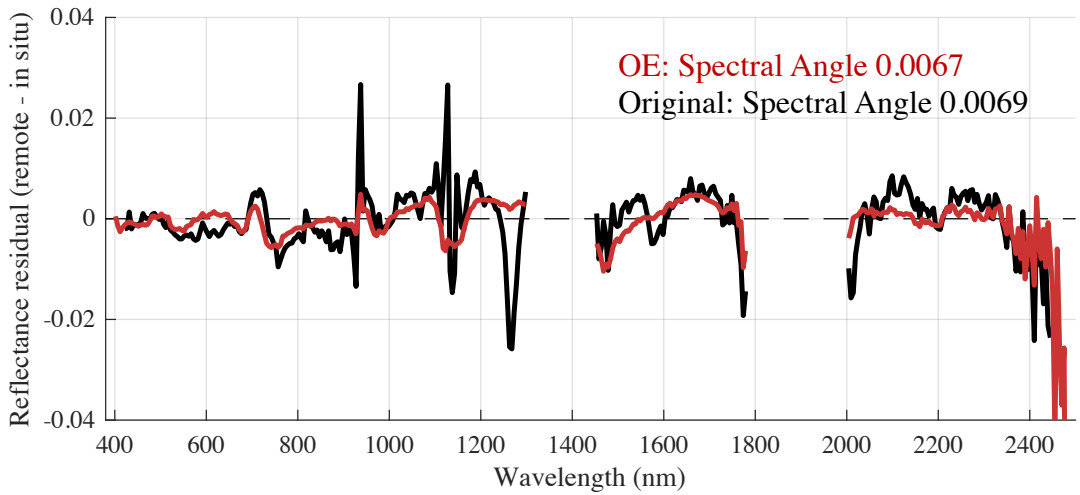
Karnataka test results

We compare new results with the standard L2 atmospheric correction methods

Spectral angles indicate the fidelity of the spectral shape match to the in situ model

Lower scores are better

I



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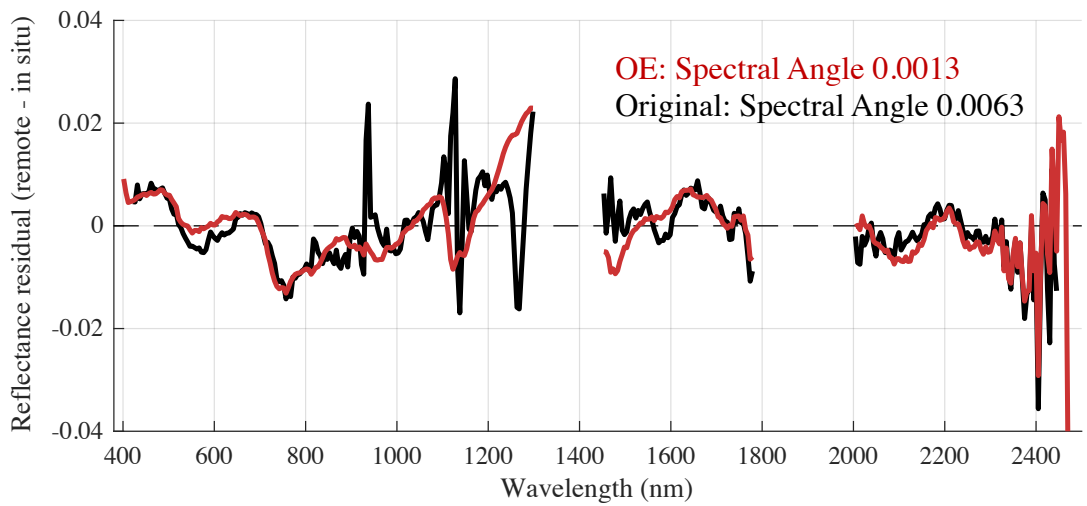
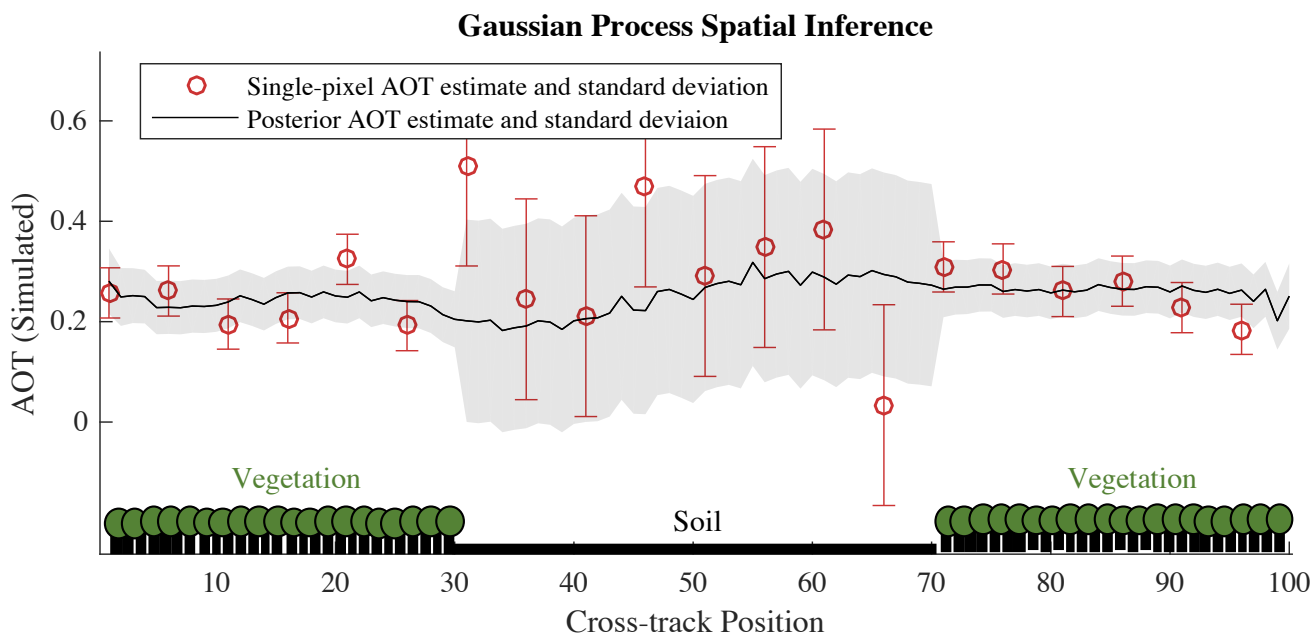


Next steps

- Assessment of atmospheric residuals and AOD on all India sites
- Spatial inference of smooth atmospheric fields via Gaussian Process Priors



Code and examples are available online

https:/github.com/isofit/isofit

New collaborators and contributors are welcomed

Thanks!

The AVIRIS-NG Team, including Sarah Lundeen, Brian D. Bue, Winston Olson-Duvall, John Chapman, and others

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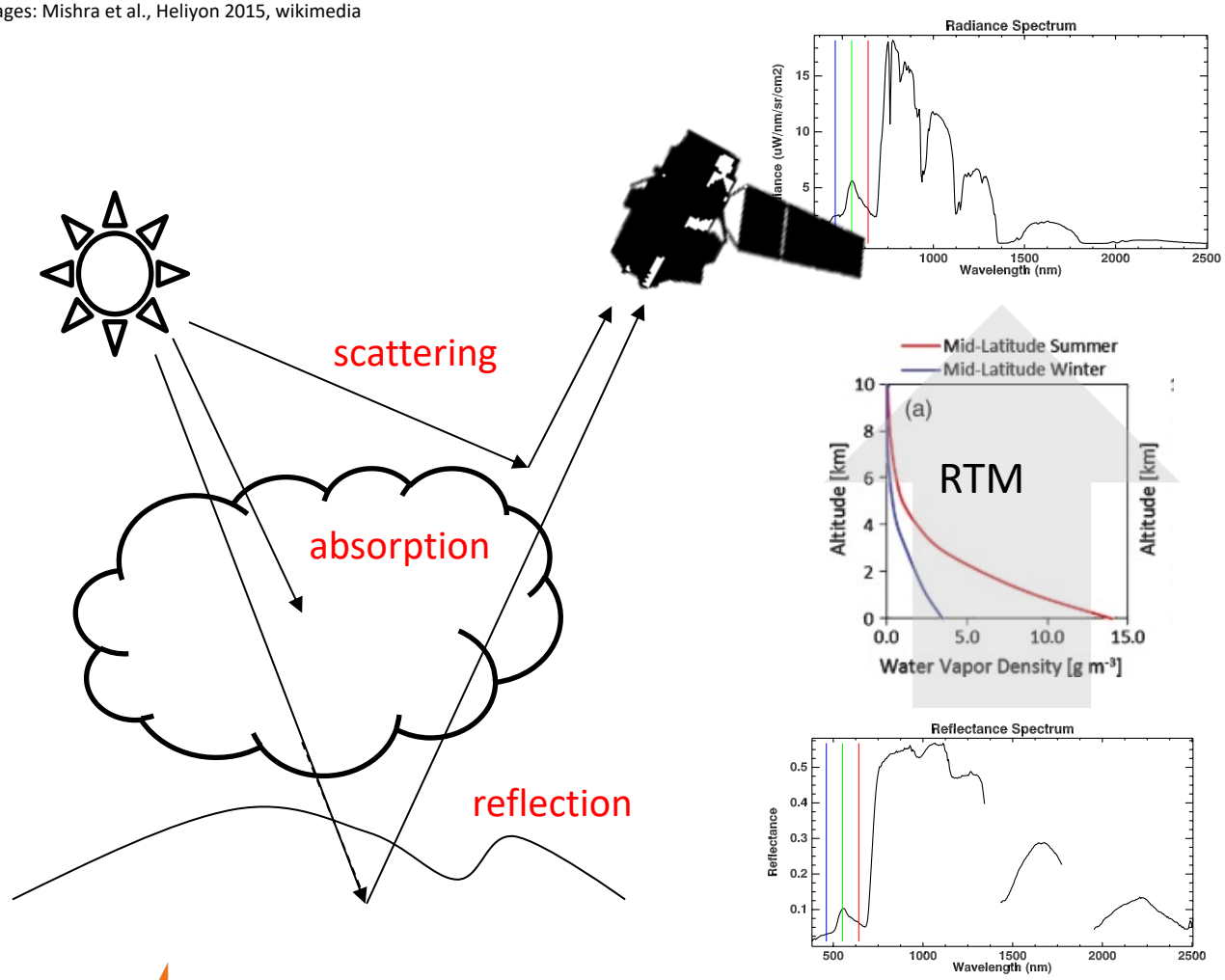
Backup

Speeding up the forward model

images: Mishra et al., Heliyon 2015, wikimedia



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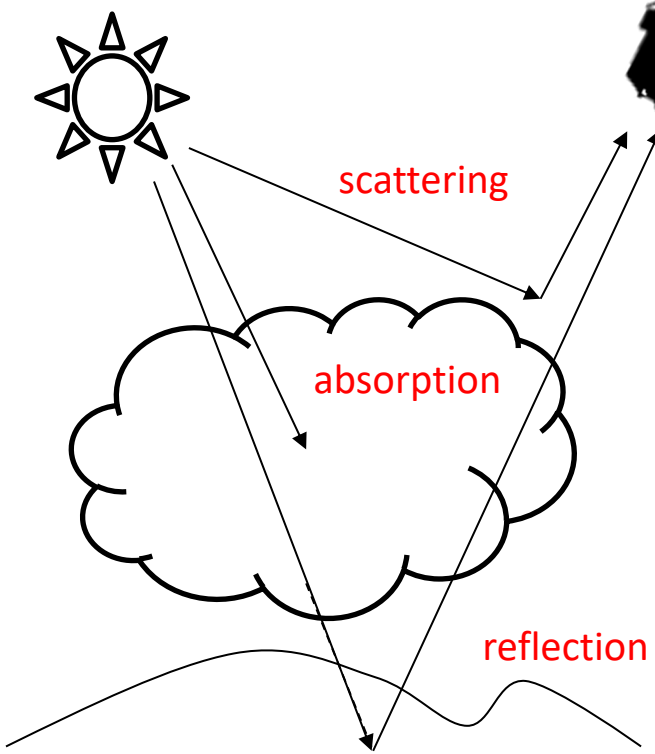
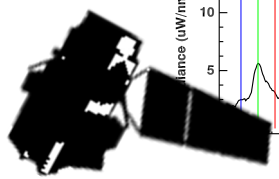
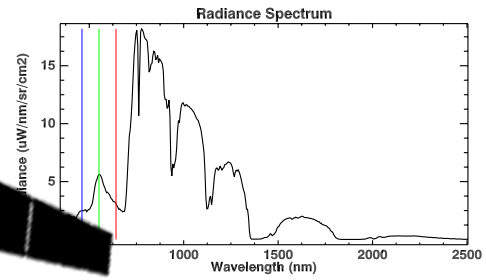
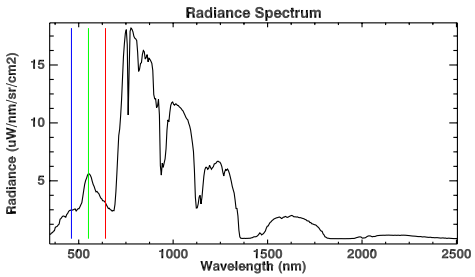
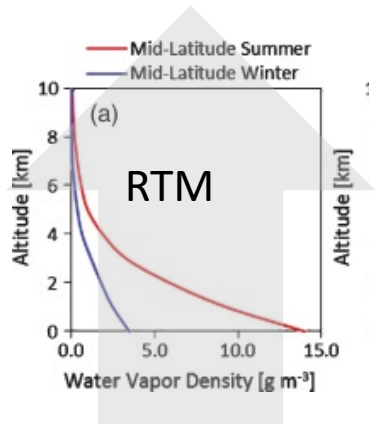
images: Mishra et al., Heliyon 2015, wikimedia

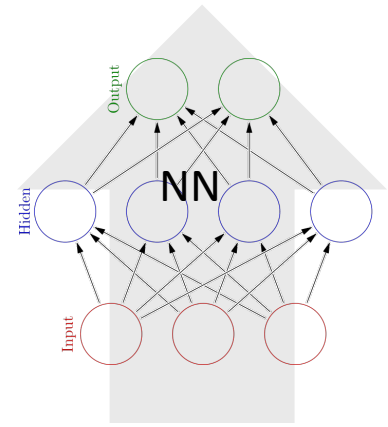


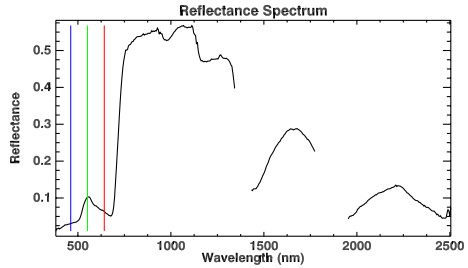


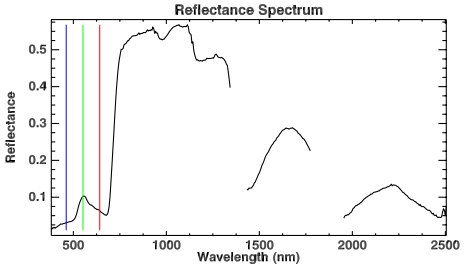






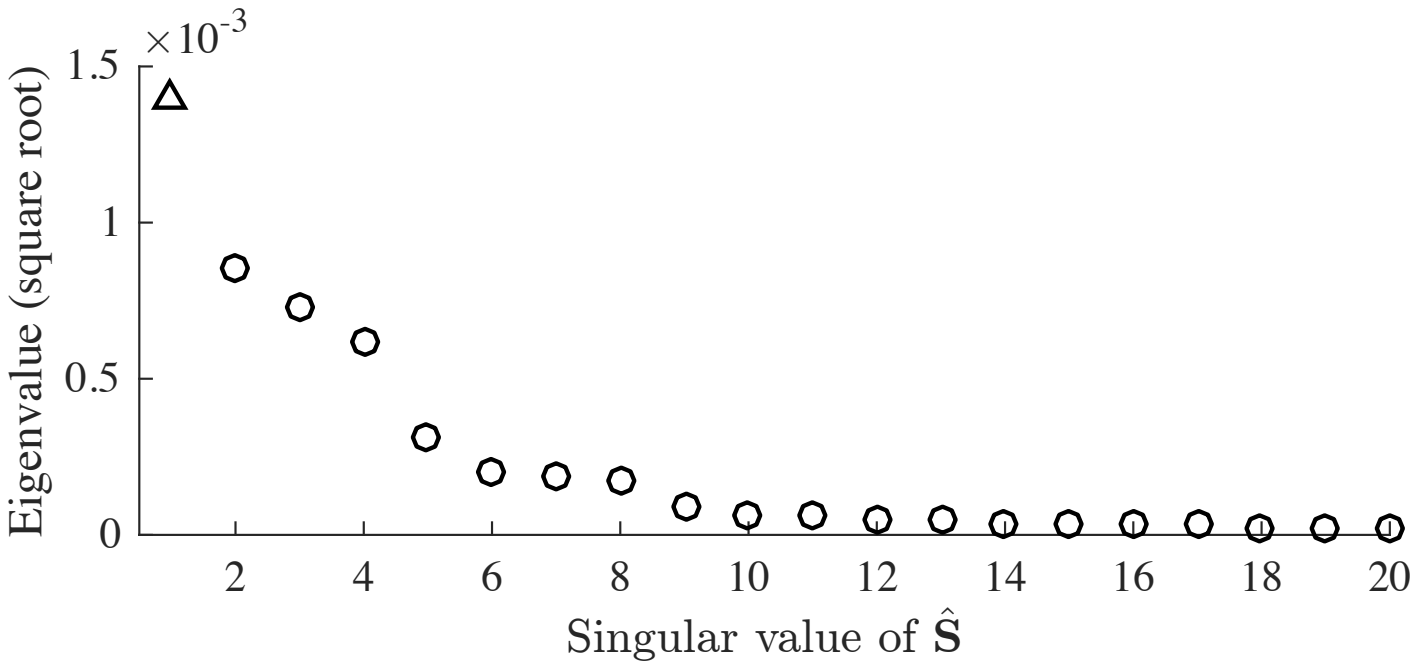






Operational Considerations: Data Volume of Uncertainties

It is not necessary to distribute the full error covariances for each spectrum– a few eigenvalues are enough.

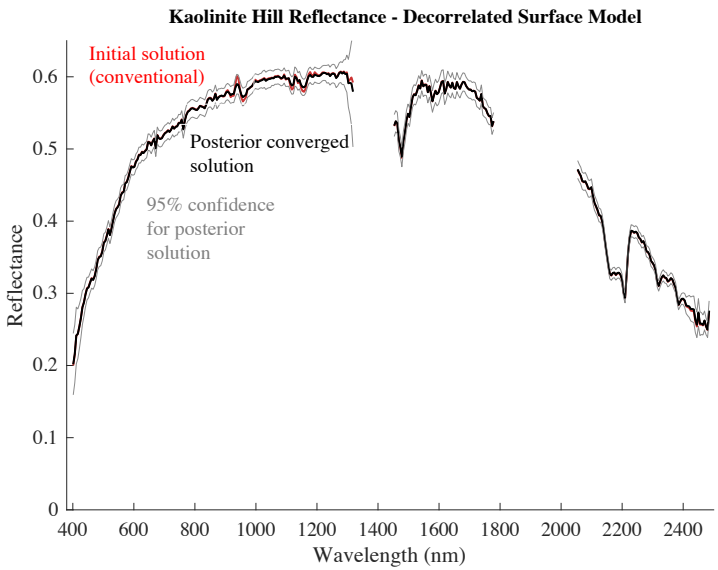


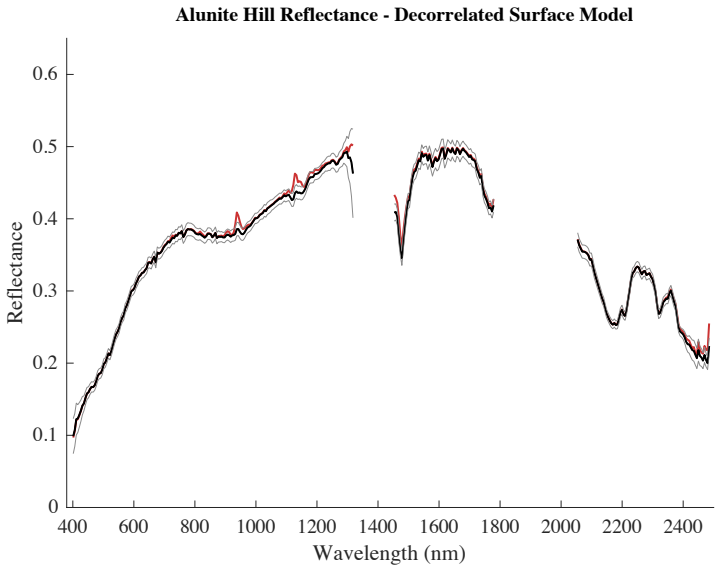
Operational Considerations: Smoothing error

General purpose products (i.e. for broad distribution) can use unconstrained surfaces, decorrelating wavelengths outside atmospheric intervals to:

- Preserve the numerical proportion between neighboring wavelengths, facilitating downstream calculation of gain corrections or PLSR coefficients
- Eliminate any chance of “missing” unanticipated features
- Preserve the ability to calculate uncertainties

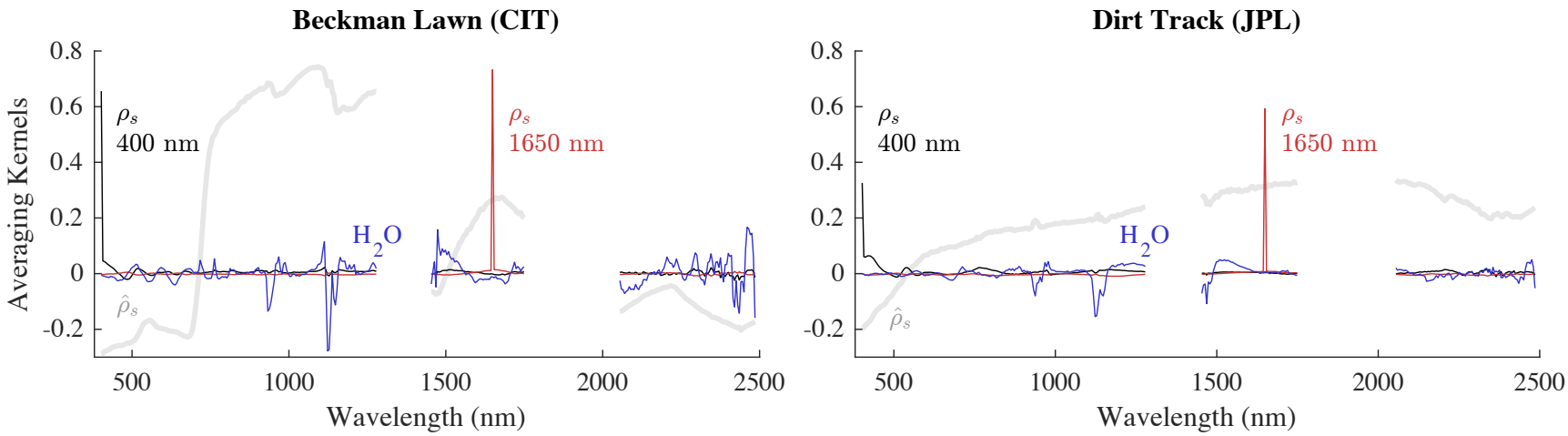
Investigators could still use custom surface models for specific studies





“Averaging Kernels”

Rows of the A matrix show sensitivity of the retrieval to different elements of the true state



E.G. The H_2O estimate transparently leverages information across the VSWIR spectrum (though mostly in the strong absorption features)

From Thompson et al., RSE (in review)

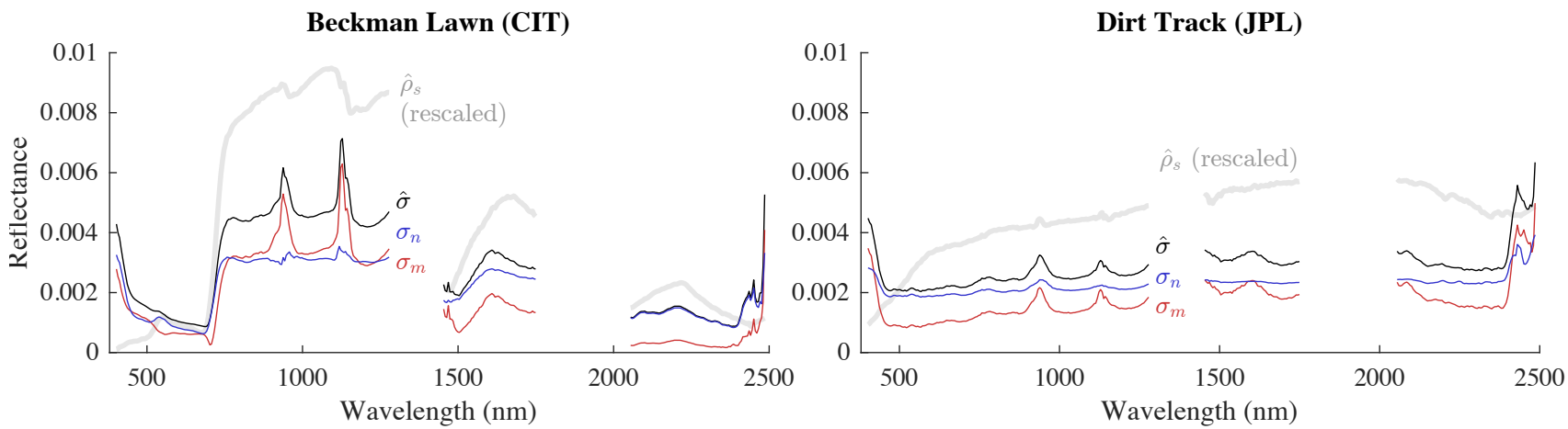
Posterior Error decomposition

$$\hat{\mathbf{S}} = \mathbf{G}\mathbf{S}_\epsilon\mathbf{G}^T + (\mathbf{I}-\mathbf{A})\mathbf{S}_a(\mathbf{I}-\mathbf{A})^T$$

$$= \mathbf{S}_n + \mathbf{S}_m$$

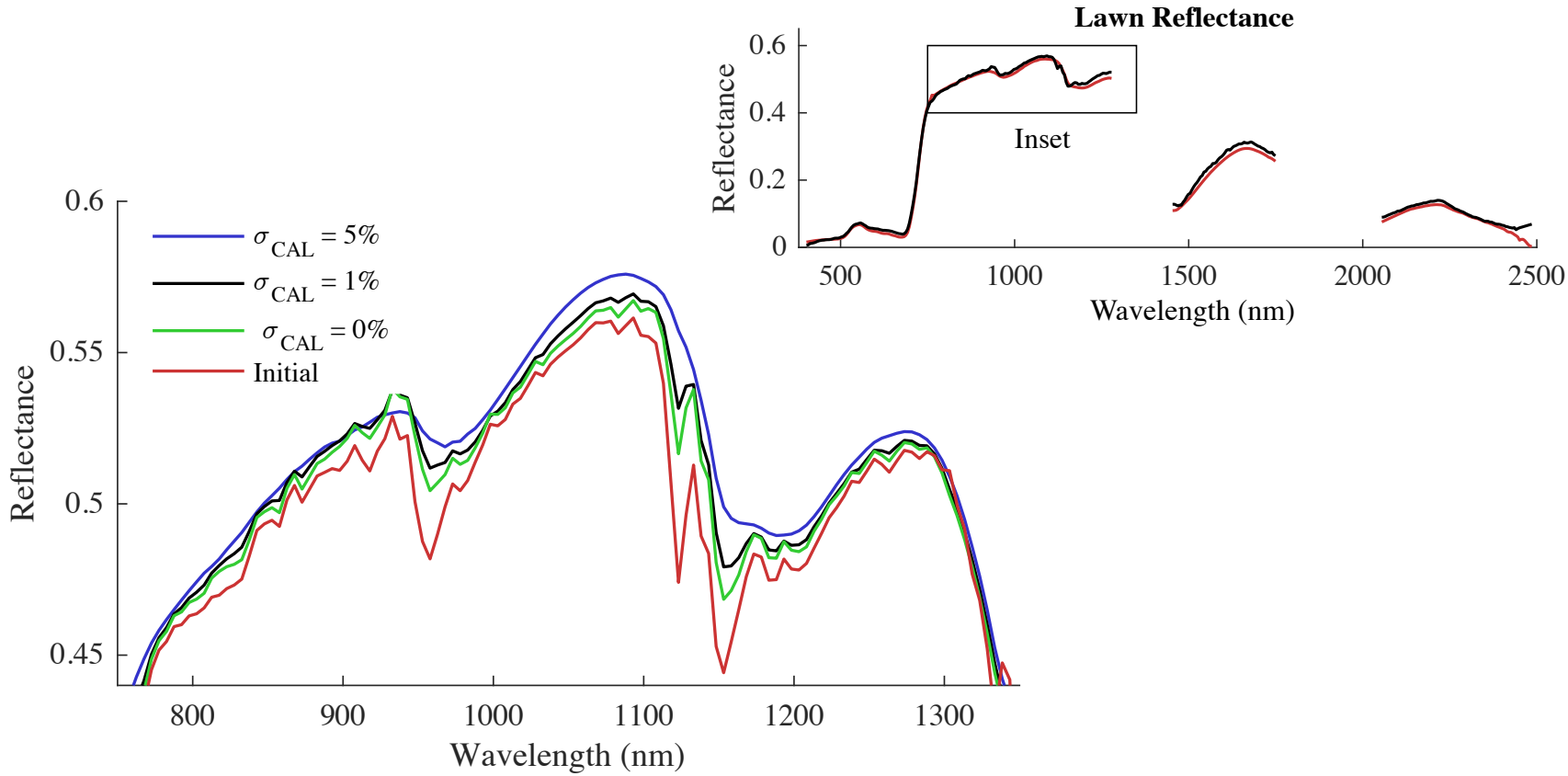
Uncertainty due to observation noise

Uncertainty due to resolution of the retrieval



From Thompson et al., RSE (in review)

How do modeling assumptions affect reflectance retrievals?

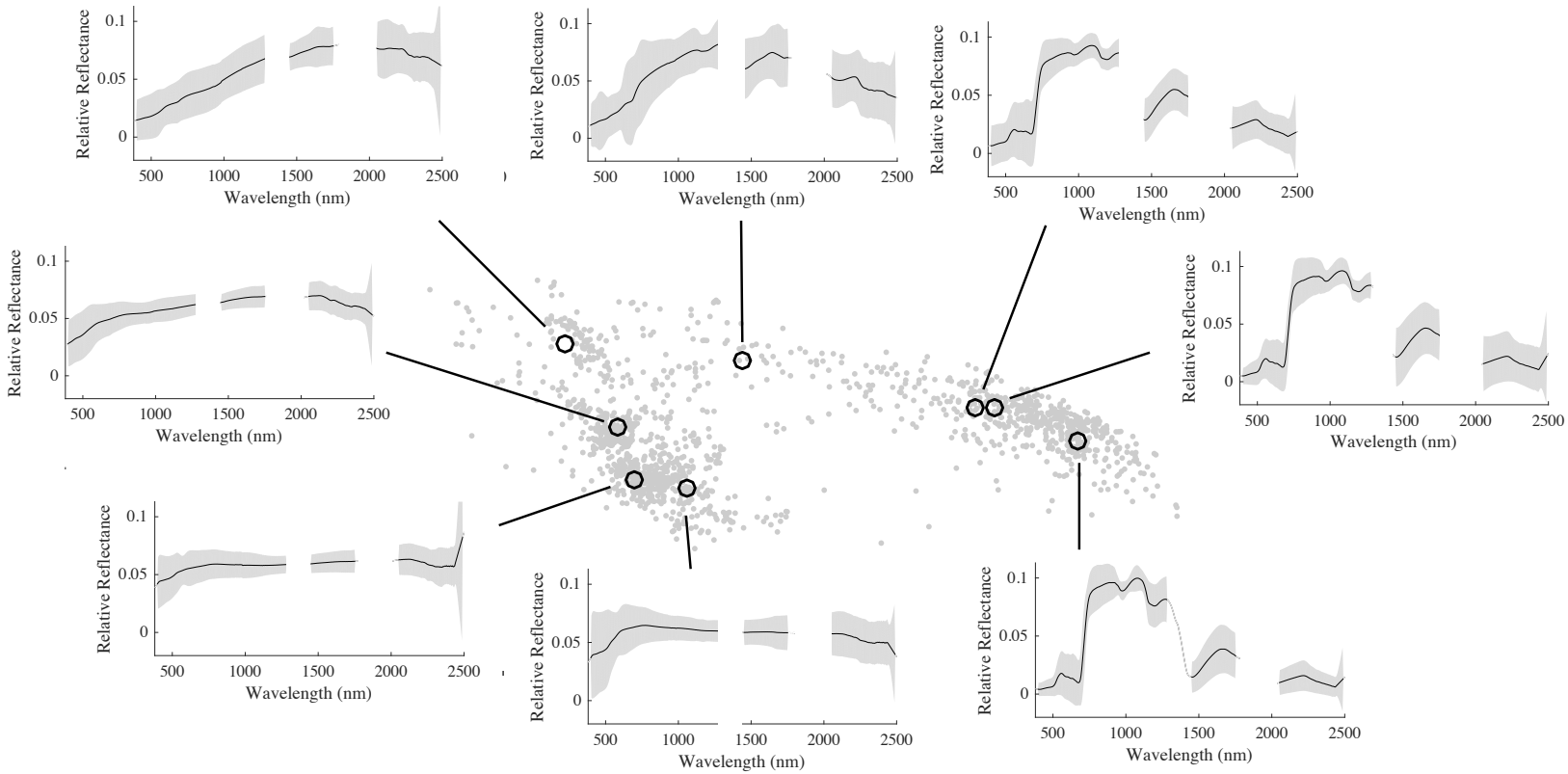


From Thompson et al., RSE (in review)

Case	Original-RSE	OE-RSE	Original-SA	OE-SA
I	0.034	0.035	0.0069	**0.0067**
II	0.030	0.014	0.0063	**0.0031**

Surface reflectance model

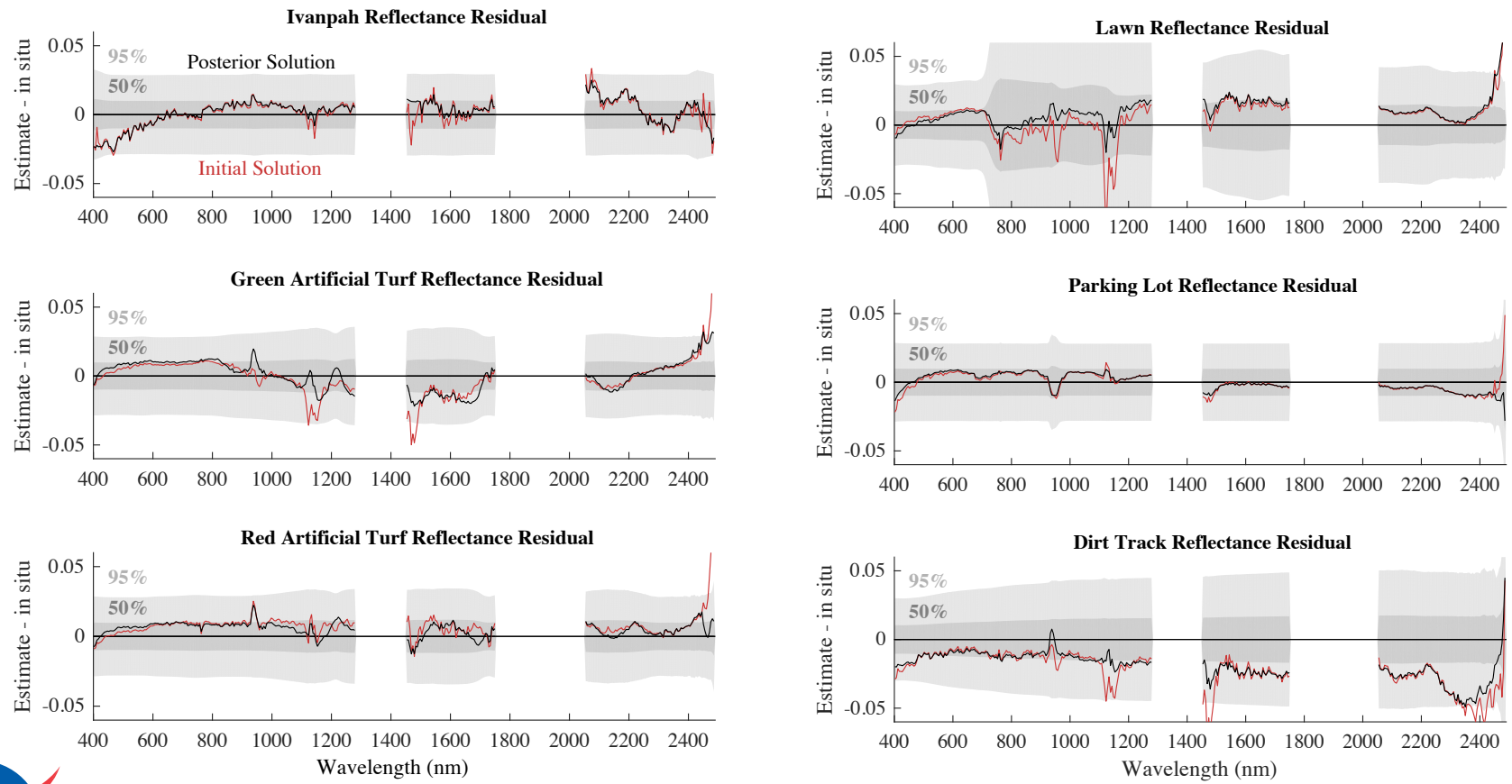
A Mixture of Gaussians, trained on a diverse library spectra courtesy EcoSIS, Dar Roberts (Santa Barbara) and Phil Dennison (University of Utah).



From Thompson et al., RSE (in review)

Posterior uncertainty compared to actual discrepancies

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



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