Introduction to Imaging Spectroscopy

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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
Measurement process – 100s of parallel spectrometers
Imaging spectroscopy vs. multiband analysis

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

Images courtesy Robert O. Green, JPL
Imaging spectroscopy at JPL

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)
Lunar Trailblazer Mission

PI: Bethany Ehlmann, Caltech

Standard Lunar Trailblazer Observation
1 HVM3 cube + 1 nested LTM cube

LTM provides simultaneous temperature to understand HVM3-detected water ice, surface-bound $H_2O$ and $OH$

OH/$H_2O$ absorption (blue) at 3-µm from $M_3$ (Pieters et al., 2009)

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

HVM3 Hyper spectral @ ≤ 70 mpix
LTM Thermal Multispec @ 25 mpix

HVM3 spectra directly detect and determine the form of water

Apollo Soil + 10% Apatite metal-$OH$

Apollo Soil (w/ surf. $H_2O$)

Apollo Soil + 1% Ice

100% $H_2O$ Ice
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

Global VSWIR

Targeted VSWIR

Targeted VNIR

Hyperion (NASA Pathfinder)

HICO (ONR/NASA)

PRISMA (ISA)

AHSI (China)

HISUI (Japan, METI)

ENMAP (DRL)

EMIT (NASA)

Recommended Decadal Survey Investigation: SBG (NASA)

CHRIS/PROBA (ESA)

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)

Salton Sea
Mineral Map

50km

Courtesty NASA/JPL/Roger Clark
Cloud optical properties at high spatial resolution

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

Cloud optical properties at high spatial resolution

[Thompson et al., JGR 2016]


RGB Image

Ice Liquid Vapor
Calwater-2: David Diner, Felix Seidel

[Thompson et al., JGR. Atm. 2016]
Localized greenhouse sources

CH$_4$

AVIRIS

AVIRISng

Wavelength (nm)
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

L0: Raw Digital Numbers

L1: Orthorectified Radiance at sensor mW/nm/cm²/sr

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

L3: Maps of Geophysical Variables

Cuprite, Nevada AVIRIS 5995 Data USGS Clark & Swayne Tetracon-13 product Iron Oxides
- Nanocrystalline Hematite
- Fine-grained to medium-grained Hematite
- Large-grained Humicite
Typical data volumes

~15 Tb/day acquisition is easily possible

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

L0: 3 GB per acquisition second

L1: 3 GB per acquisition second

L2: 3 GB per acquisition second

L3: ? GB per acquisition second
Algorithms

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

Band arithmetic or dot products (trivial)
Closed form linear algebra (fast)
Iterative nonlinear optimization (slower)
*Possible external dependencies
Iterative model inversion methods

1. Predict radiance

\[ y = F(x) + \epsilon \]

\[ \chi^2(x) = (F(x) - y)^T S_\epsilon^{-1} (F(x) - y) + (x - x_a)^T S_a^{-1} (x - x_a) \]

Cost \hspace{1cm} Model match to measurement \hspace{1cm} Bayesian prior

2. Optimize state vector
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 H₂O field from [Thompson et al., Surveys in Geophys. 2019]
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

Step 1
- Aerosol optical depth $\tau$
- Aerosol type $\zeta$
- Water leaving reflectance $R_{rs}$

Step 2
- Glint-corrected $R_{rs0}$

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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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
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

\( d = \text{number of spectral channels} \)

\( C = \text{crosstrack stray light} \)

\( S = \text{spectral stray light} \)

\[
(L_{\text{meas}})_{[d \times n]} = (L_{\text{pred}} \, C^T \, S)_{[d \times n]}
\]
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:

\[
(L_{\text{pred}} \ C)^T \ S = L_{\text{meas}}
\]

\[
\begin{bmatrix}
[d \times n] & [n \times n] & [d \times d] & [d \times n]
\end{bmatrix}
\]

4. Correct future data using the following linear transformation:

\[
L_{\text{corr}} = ((C^T)^+ \ (S^T)^+ \ L_{\text{meas}}^T)^T \ T
\]

Here, \( + \) represents the Moore-Penrose inverse, e.g.

\[
C^+ = (C^T \ C)^{-1} \ C^T \quad \quad C^+ C = I
\]
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
Methods include:
- Comparisons vs. lab measurements
- Pressure altitude predictions vs. DEMs
- Surface reflectance fidelity

Results from Thompson et al., RSE 2018
Agenda

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• Deep Dive 3: Optimal Estimation for surface/atmosphere retrievals
Localized greenhouse sources
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

CH$_4$ in California

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

Elder, Thompson, et al.
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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

Site-level, lake littoral control?
\[ y = 0.021x^{-0.65} \]
\[ R^2 = 0.97 \]

Landscape, proximal wetlands/water table control?
\[ y = 0.004x^{-0.16} \]
\[ R^2 = 0.99 \]
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, $\mu$, $\Sigma$

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

$H_0 : x \sim \mathcal{N}(\mu, \Sigma)$  \hspace{1cm}  $H_1 : x \sim \mathcal{N}(\mu + \alpha t, \Sigma)$

(pure background) \hspace{1cm} (background plus target)
Algorithms for CH$_4$ detection

The matched filter is written:

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

For interpretability, the target signature $t$ is defined as the change in radiance caused by an additional unit absorption of CH$_4$ above background.

$$t = \frac{\partial x}{\partial \ell} = -\mu e^{-\kappa \ell} \kappa = -\mu \kappa$$
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 estimation (Thompson et al., 2015)
Coupling k-means background clustering with the column-wise MF provides improved robustness to background changes.
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.
Approach

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

\[ R_\alpha = (1 - \alpha)S + \alpha T \]

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

[Thompson et al., RSE 2015; Thompson et al., RSE 2018, Thompson et al., RSE 2019a, Thompson et al., RSE 2019b]
“AVIRIS Classic” imaging spectrometer, visible wavelengths

Retrieved Water vapor
[Thompson et al., Surv. Geohysics, 2018]
Conventional atmospheric correction: A sequential process

1. In advance, do RTM calculations

2. Estimate atmosphere (typically by band ratios)

Lookup table of transmission, scattering indexed by H₂O, etc.

3. Algebraic Inversion

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

measurement

reflectance

Radiance Spectrum

Reflectance Spectrum
Global spectroscopy missions are an atmospheric correction challenge

Annual average AOD

Thompson et al., (in review)
Global spectroscopy missions are an atmospheric correction challenge.
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**
The “forward problem”

State vector

\[ \mathbf{x} \in \mathbb{R}^N \]

\[ \mathbf{x} = [ \text{Surface parameters} \\
\quad \ldots \\
\quad \text{Atmosphere parameters} \\
\quad \ldots \\
\quad \text{Instrument parameters} \\
\quad \ldots ] \]

Forward model

\[ F(\mathbf{x}) : \mathbb{R}^N \rightarrow \mathbb{R}^M \]

Measurement

\[ \mathbf{y} \in \mathbb{R}^M \]

\[ \mathbf{y} = [ \text{Calibrated at-aperture radiance measurements} ] \]
The “inverse problem”

**Measurement**

\[ y \in \mathbb{R}^M \]

\[ y = \begin{bmatrix} \text{Calibrated at-aperture} \\ \text{radiance measurements} \end{bmatrix} \]

**Inversion algorithm**

\[ R(y) : \mathbb{R}^M \rightarrow \mathbb{R}^N \]

**Estimated state vector**

\[ \hat{x} \in \mathbb{R}^N \]

\[ \hat{x} = \begin{bmatrix} \text{Estimated surface parameters} \\ \ldots \\ \text{Estimated atmosphere parameters} \\ \ldots \\ \text{Estimated instrument parameters} \end{bmatrix} \]
Maximum A Posteriori solution

\[ p(x|y) = \frac{p(y|x)p(x)}{p(y)} \]
Maximum A Posteriori solution

\[ p(x|y) = \frac{p(y|x)p(x)}{p(y)} \]

The Maximum A Posteriori estimation is equivalent to the optimization:

\[ \chi^2(x) = (F(x) - y)^T S^{-1}_\epsilon (F(x) - y) + (x - x_a)^T S_a^{-1} (x - x_a) \]

... we can solve it by conjugate gradient descent.
Maximum A Posteriori estimation

\[ p(x|y) \]

\[ x_i \]

\[ \hat{S} \]

\[ x \]

\[ x_{\text{init}} \]

\[ x_0 \]

\[ x_1 \]
Conventional atmospheric correction: A sequential process

1. In advance, do RTM calculations

2. Estimate atmosphere (typically by band ratios)

3. Algebraic Inversion

\[ \rho_{obs} = \rho_a + \frac{T \rho_s}{1 - S \rho_s} \]

Lookup table of transmission, scattering indexed by H$_2$O, etc.
Iterative simultaneous estimation of atmosphere and surface

1. Predict radiance

\[ y = F(x) + \epsilon \]

\[ \chi^2(x) = (F(x) - y)^T S_{\epsilon}^{-1} (F(x) - y) + (x - x_a)^T S_a^{-1} (x - x_a) \]

Cost  Model match to measurement  Bayesian prior

2. Optimize state vector
Case study
[Thompson et al., Remote Sensing of Environment 2018]

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

Ivanpah Playa

From Thompson et al., RSE 2018.
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 $\text{H}_2\text{O}$ absorption coefficients
- $\text{H}_2\text{O}$, 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
Reflectance estimate vs. in situ


**Ivanpah Radiance**

**Green Artificial Turf Radiance**

**Red Artificial Turf Radiance**

**Ivanpah Reflectance**

**Green Artificial Turf Reflectance**

**Red Artificial Turf Reflectance**

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Posterior uncertainty compared to actual discrepancies


Remote retrieval: converged solution

Remote retrieval: heuristic initialization
High aerosol loading in India campaign
High aerosol loading in India campaign

“Averaging Kernels” for $\text{H}_2\text{O}$, and absorbing and scattering aerosol particles

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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)

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Combined estimate of $H_2O$ vapor, AOT, surface reflectance and temperature.
Maximum A Posteriori vs. MCMC

MCMC samples
MAP solution and linearized uncertainty
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
Coastal ecosystems: wetland vegetation

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

<table>
<thead>
<tr>
<th>In Situ Points</th>
<th>Correct Points</th>
<th>Percent Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nelumbo</td>
<td>50</td>
<td>92.0</td>
</tr>
<tr>
<td>Polygonum punctatum/Forbs</td>
<td>19</td>
<td>52.6</td>
</tr>
<tr>
<td>Colocasia</td>
<td>18</td>
<td>72.2</td>
</tr>
<tr>
<td>Salix nigra/Forest</td>
<td>30</td>
<td>76.7</td>
</tr>
<tr>
<td>Grasses</td>
<td>16</td>
<td>50.0</td>
</tr>
</tbody>
</table>

Nelumbo lutea  Senesced Nelumbo/Floating Vegetation
Colocasia esculenta  Senesced Nelumbo/Mudflat
Polygonum punctatum/Forbs  Phragmites australis
Submerged Vegetation  Other Grasses
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
Dimensionality estimates must account for measurement noise.

Laplacian Eigenmap code via Kye Taylor, Mathworks file exchange.
High Intrinsic Dimensionality
Variability due to measurement noise vs. unknown state parameters

Total observation noise

\[ S_\varepsilon = S_y + K_b S_b K_b^T \]

Measurement noise (instrument effects)
- Photon noise
- Read noise
- Dark current noise

Jacobian WRT unknowns

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

1. Radiance at sensor

2. Reflectance at surface

3. Ecosystem fractional cover maps

Vansda, India 9 Feb 2016

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Geologic maps for the EMIT mission

Surface Reflectance (Salton Sea, CA)
Salton Sea
Mineral Map

50km

Courtesy NASA/JPL/Roger Clark
Coincident multi-aircraft measurement

AVIRIS-C
NASA ER-2 aircraft

WCM-2000, FCDP, 2DS
DOE G-1 AAF aircraft

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In situ corroborates remote data

In situ and remote measurements coincident within 10 minutes

AVIRIS-C remote absorption path, EWT\textsubscript{liquid} / EWT\textsubscript{al}

AAF WCM-2000 in situ measurements (LWC/TWC)

- Liquid
- Mixed
- Ice

Line 7, Line 8, Line 9, Line 10, Line 11
In situ and remote measurements coincident within 10 minutes

AVIRIS-C Remote Effective Water Thickness due to Ice, $E_{\text{Ice}}$

Liquid

Ice

Mixed

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In situ and remote measurements coincident within 10 minutes

2DS Particle imager

Liquid

Ice

Mixed

Liquid

Line 7

Line 8

Line 9

Line 10

Line 11

AVIRIS-C Remote Effective Water Thickness due to Ice, EWT_Ice

AAF FCDP and 2DS Effective Particle Radius, μm
Remote sensing of cloud phase

RGB Image  
08/28/2019  
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Ice  Liquid  Vapor  Pressure Altitude
Example of $b_b$ endmember library

Wavelength (nm)

$b_b$

0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
400 450 500 550 600 650 700 750 800
Example of $K_d$ endmember library
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
Procedure

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

\[ R_{rs0} = R_{inf} + (A - R_{inf}) e^{-2K_dH} \]

Optimize via Levenberg Maquardt, minimizing:

\[ \text{Error}(x) = (R_{rs0} - R_{rs0}^*) + \alpha_{bb590} (\mu_{bb590} - \mu_{bb590}^*) + \alpha_{kd450} (\mu_{kd450} - \mu_{kd450}^*) + \alpha_{kd590} (\mu_{kd590} - \mu_{kd590}^*) + \alpha_H (\mu_H - H^*) \]

Statistical priors to constrain the other free parameters

Model fit vs. measurement

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Procedure

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

\[ R_{rs0} = R_{inf} + \left(R_b - R_{inf}\right) e^{-2K_d H} \]

- \( R_{rs0} \): Benthic reflectance
- \( R_{inf} \): Reference reflectance
- \( R_b \): Benthic reflectance
- \( K_d \): Attenuation coefficient
- \( H \): Depth

\[ bb / (2K_d) \]

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Procedure

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

\[ R_{rs0} = R_{inf} + (R_b - R_{inf}) e^{-2K_d H} \]

**Problem: underdetermined**

\( K_d, \ bb, \) and \( R_b \) yield \((3N + 1)\) parameters for just \( N \) measurements
Posit the relation [Maritorena et al., 1994]:

\[ R_{rs0} = R_{inf} + (R_b - R_{inf}) e^{-\frac{2K_d H}{bb / (2K_d)}} \]

**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)

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

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Hochberg et al., Remote Sensing of Environment 2003
Thompson et al., Remote Sensing of Environment 2017
Water-leaving Reflectance

Rb

Benthic Cover

Depth

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Airborne (2020 - 2024): S-MODE
PI: Tom Farrar, WHOI
Orbital (2021 – 2022): EMIT

Spaceborne Imaging Spectroscopy

Particle Emission and Transport

Radiative Forcing

Wet and Dry Deposition

Ecosystems and Snow Hydrology Models

Arid Dust Source Region

Ocean Biology Models

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Salton Sea
Mineral Map

50km

Courtesy NASA/JPL/Roger Clark

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Airborne VSWIR data collected by the Carnegie Airborne Observatory