



Jet Propulsion Laboratory  
California Institute of Technology

# HyspIRI-like VSWIR L2 processing: Investigations, Advances, Products

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Dar. A. Roberts<sup>4</sup>, Phil Dennison<sup>5</sup>, Sarah Lundein<sup>1</sup>

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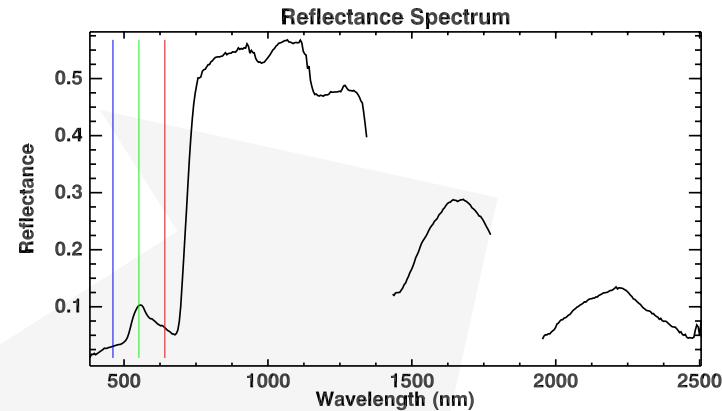
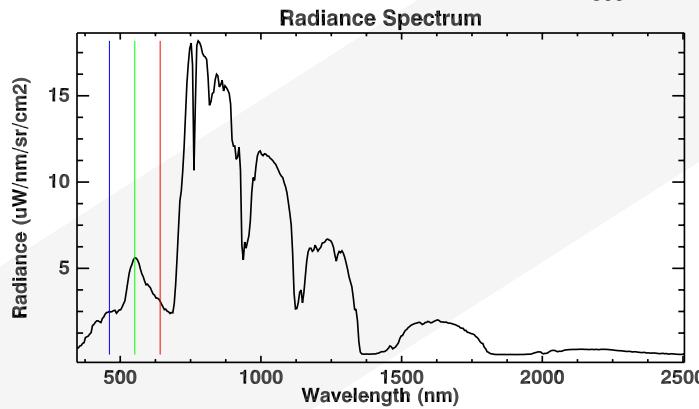
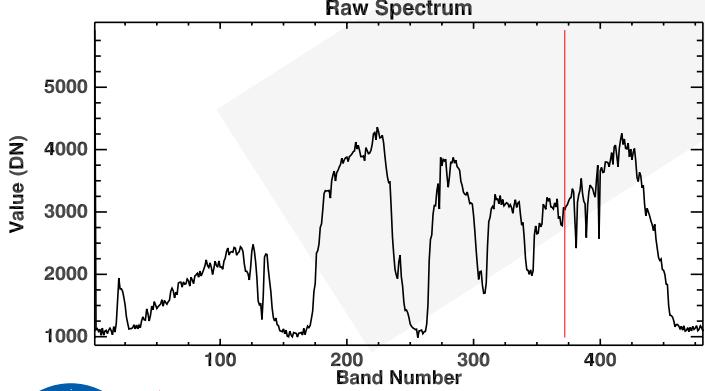
# Agenda

- Overview of the HyspIRI data products
- L2 error decomposition
- Recent investigations
  - Radiometric corrections
  - Iterative  $\text{H}_2\text{O}$  path estimation
  - Aerosol estimation



# HyspI RI L2 processing objectives

Accurate reflectance measurements

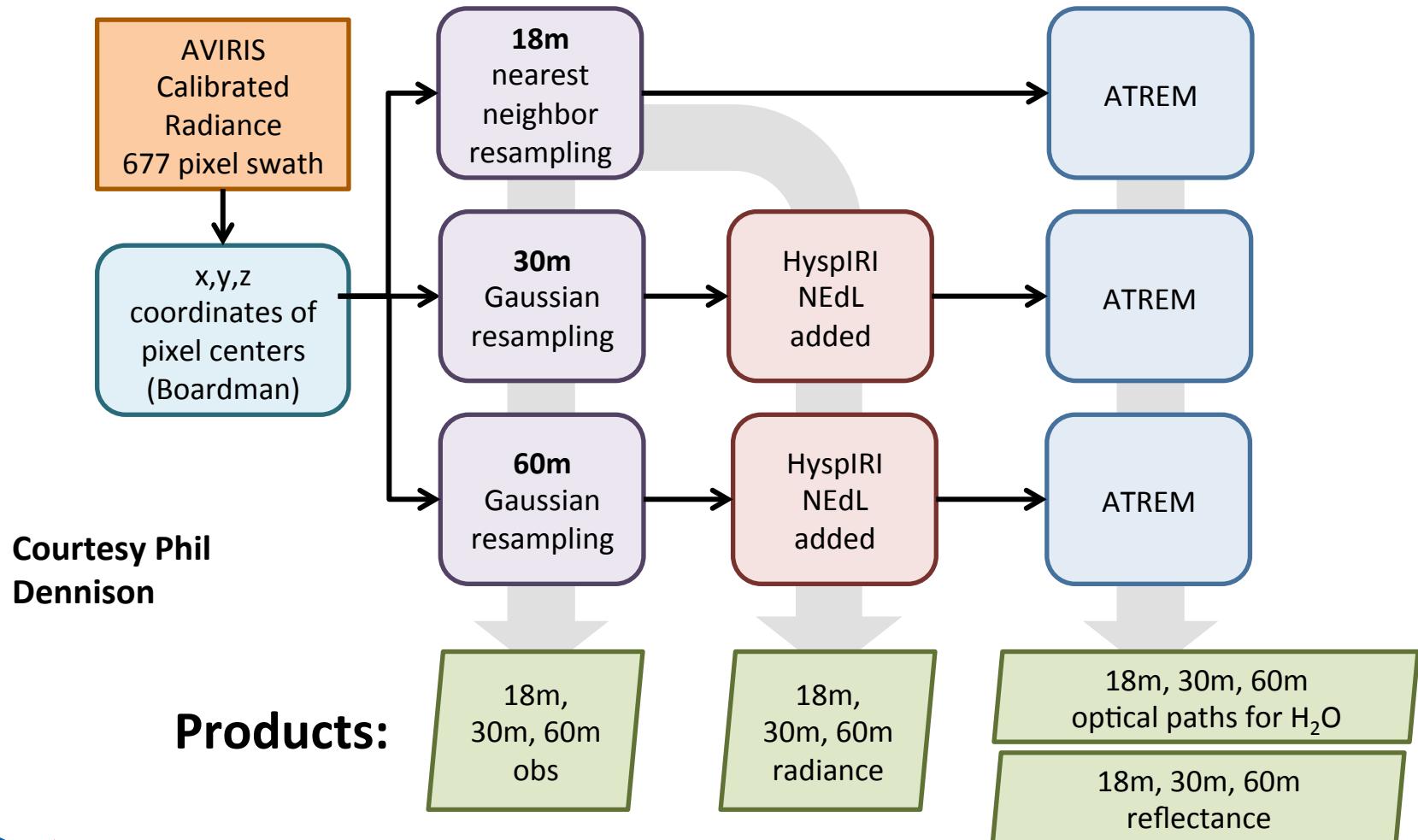


At any elevation

Without in-scene references  
Under clear or hazy skies



# HyspIRI simulated data products

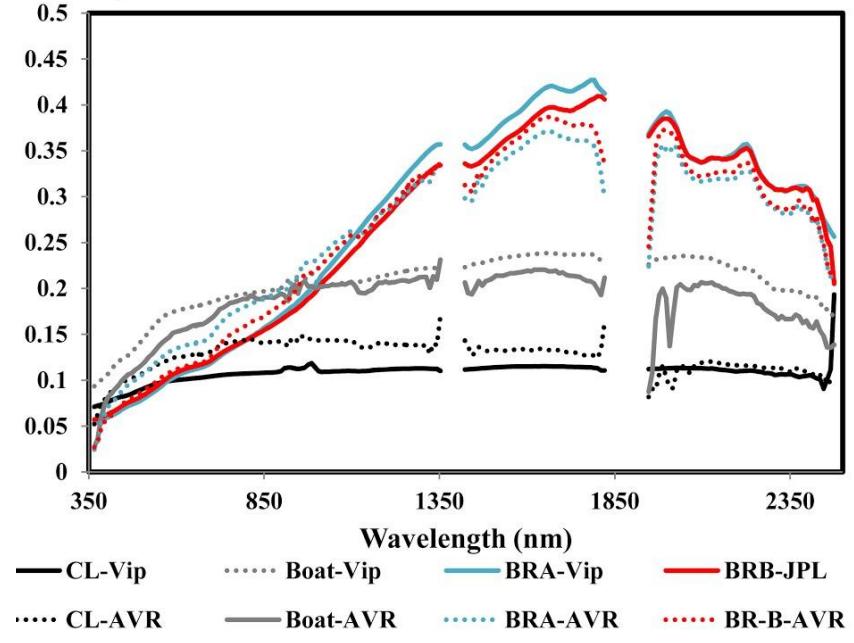
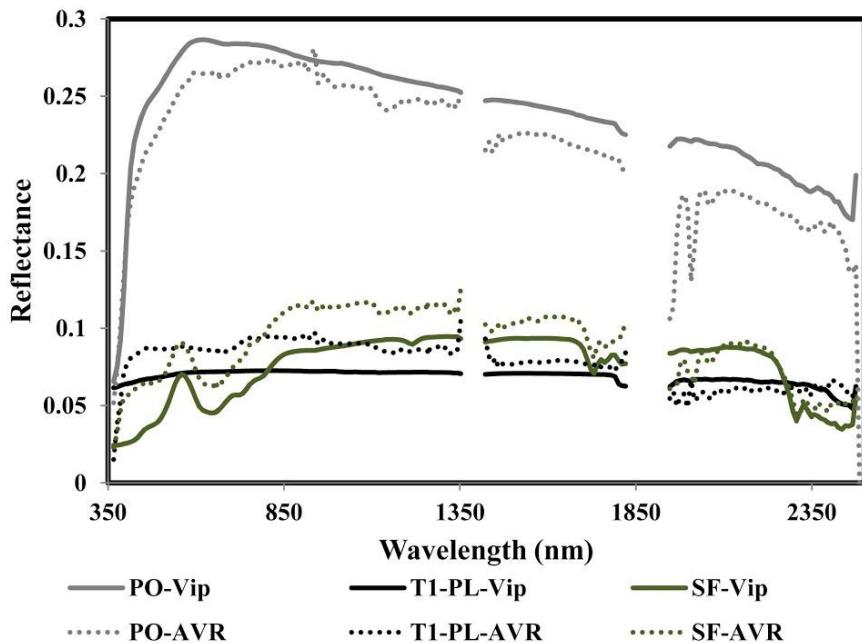


[http://aviris.jpl.nasa.gov/data/AV\\_HyspIRI\\_Prep\\_Data.html](http://aviris.jpl.nasa.gov/data/AV_HyspIRI_Prep_Data.html)



# Ground truth validation targets

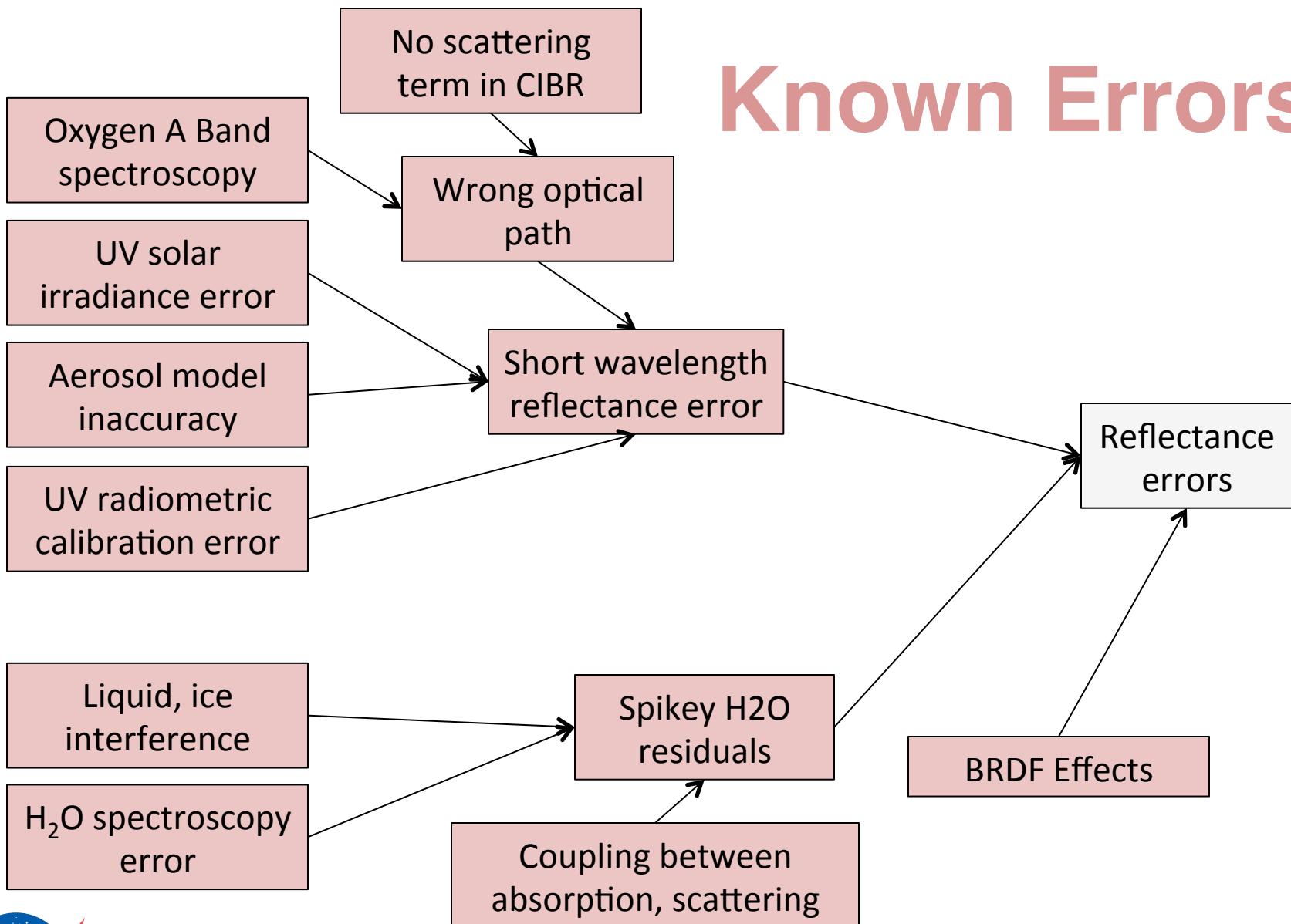
- Dark targets too bright, bright targets too dark
- This suggests uncorrected scattering is a major offender
- Accuracy degrades somewhat at short wavelengths
- Water vapor maps (not shown) still show some “vegetation bias”



Courtesy Dar Roberts



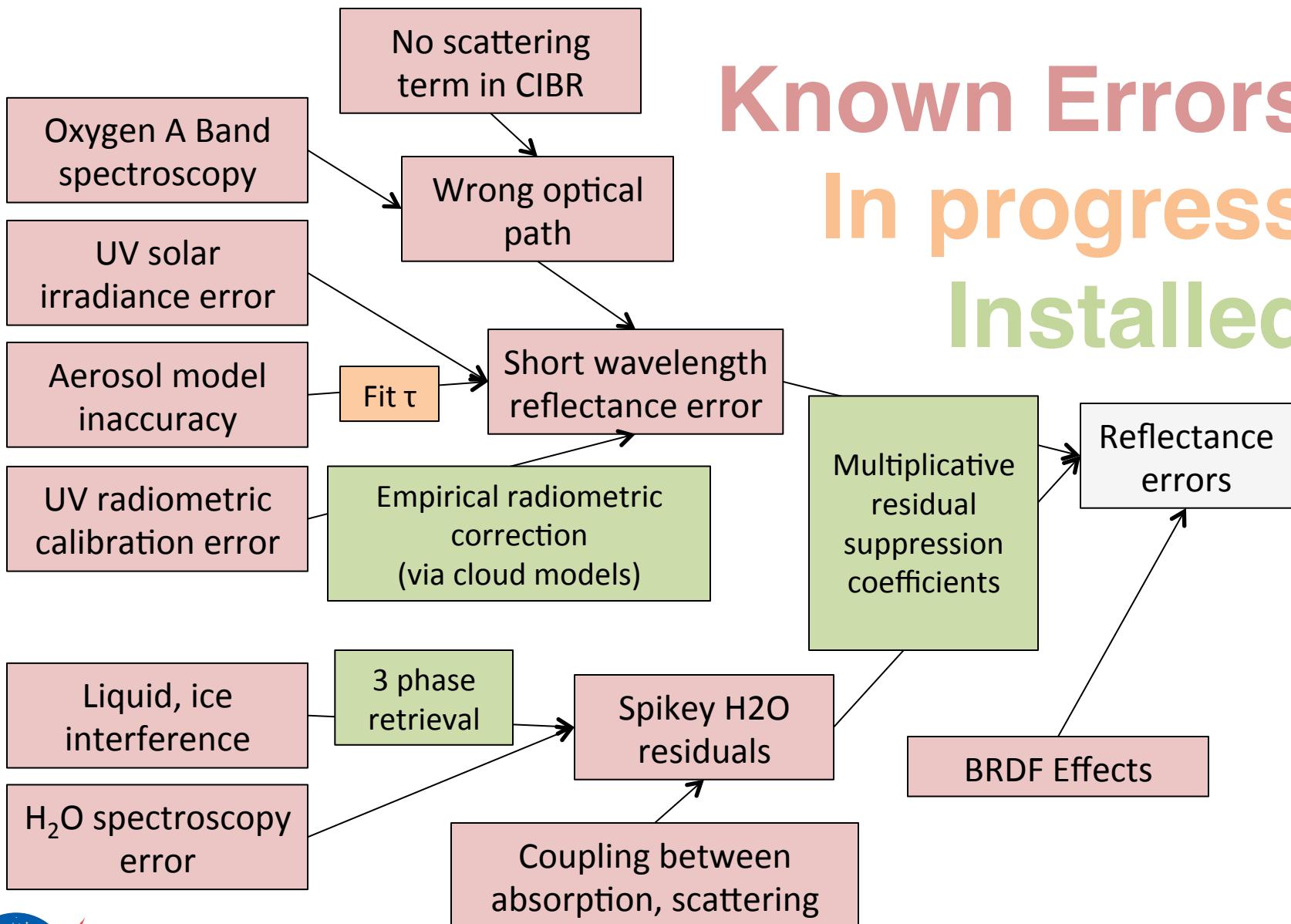
# Known Errors



# Known Errors

## In progress

## Installed



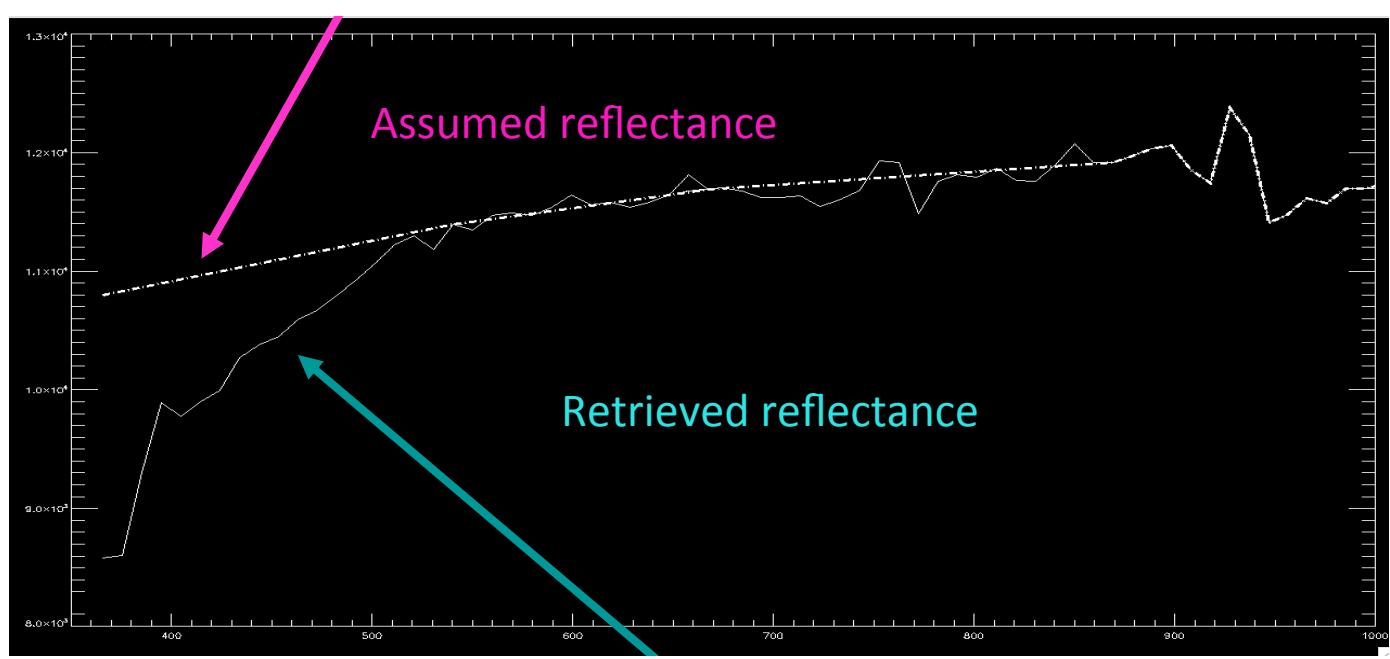
# Agenda

- Overview of the HyspIRI data products
- L2 error decomposition
- **Recent investigations**
  - Radiometric corrections
  - Iterative  $\text{H}_2\text{O}$  path estimation
  - Aerosol estimation



# 1. Radiometric corrections

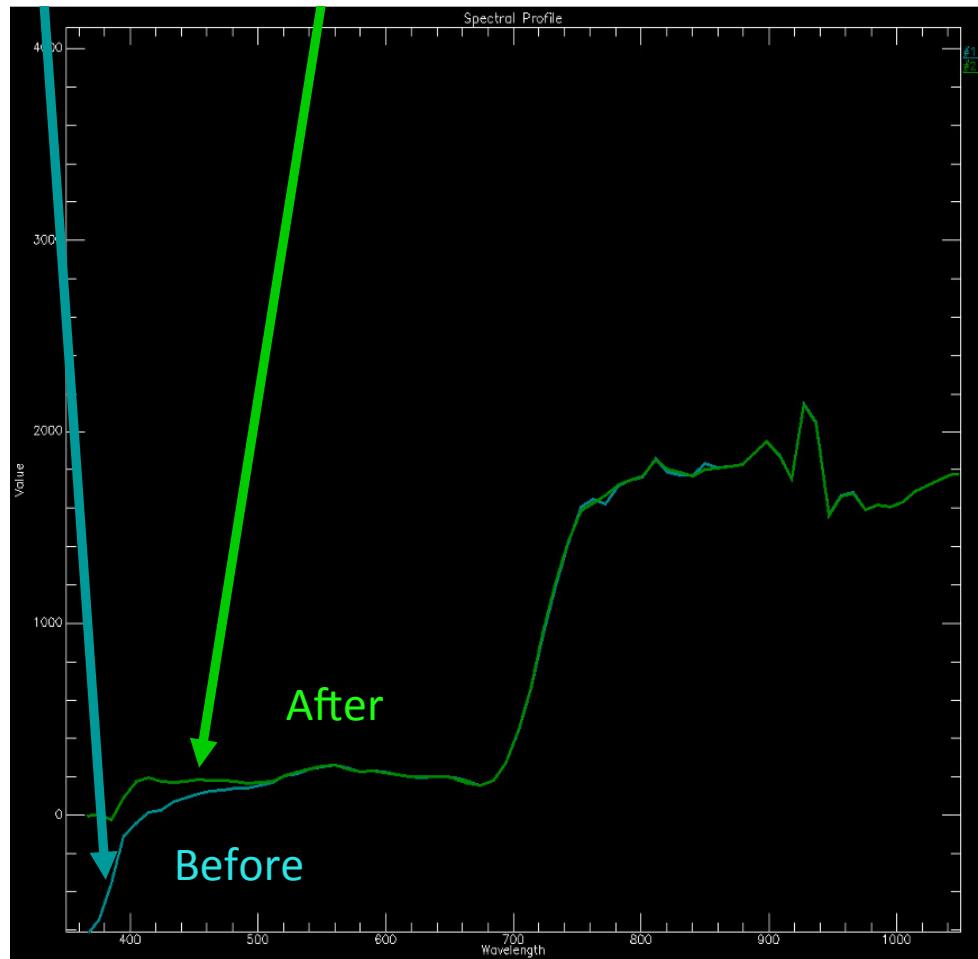
- Clouds are assumed smooth in the UV.
- This leads to a radiometric gain estimate



Courtesy Bo Cai Gao



# Typical vegetation spectra

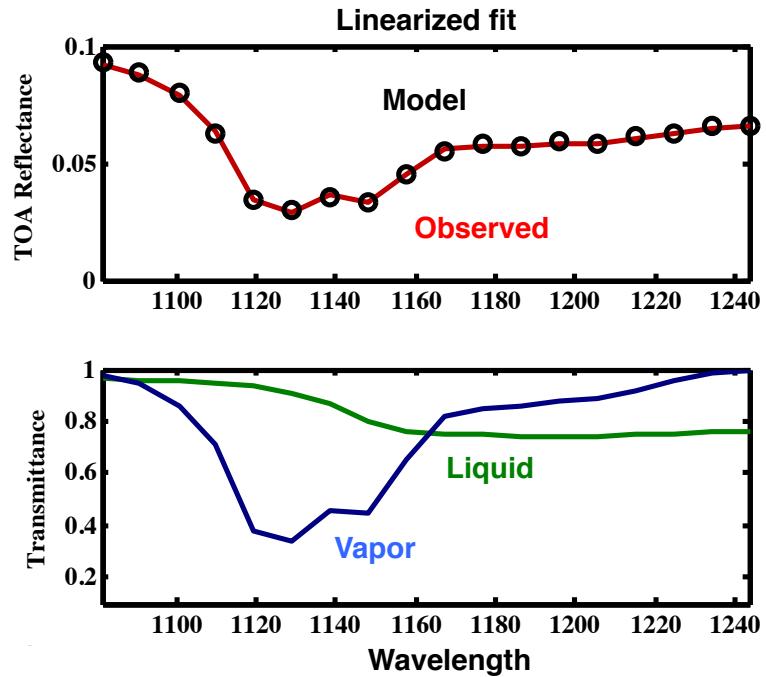


Courtesy Bo Cai Gao



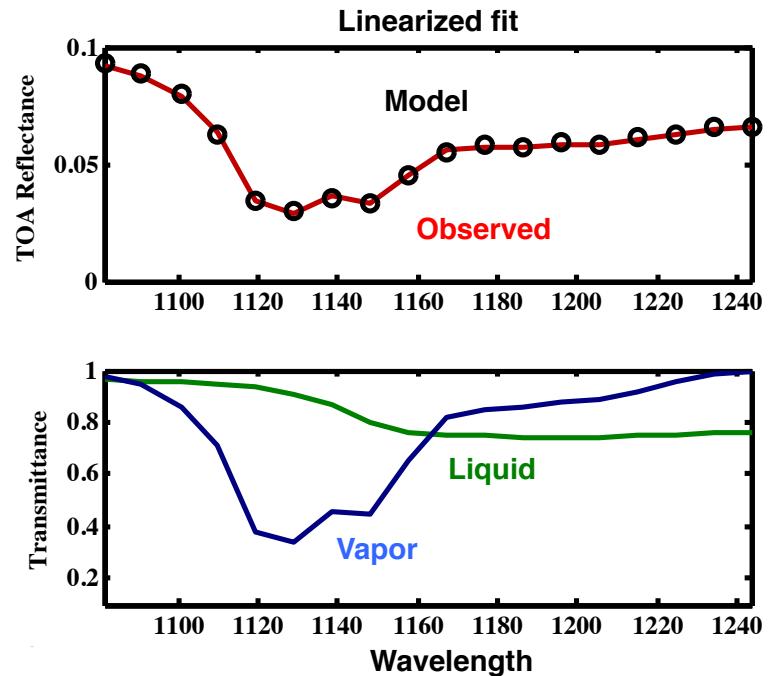
# 2. Reducing bias in H<sub>2</sub>O vapor maps

Courtesy Elyse Pennington  
(poster at this workshop)

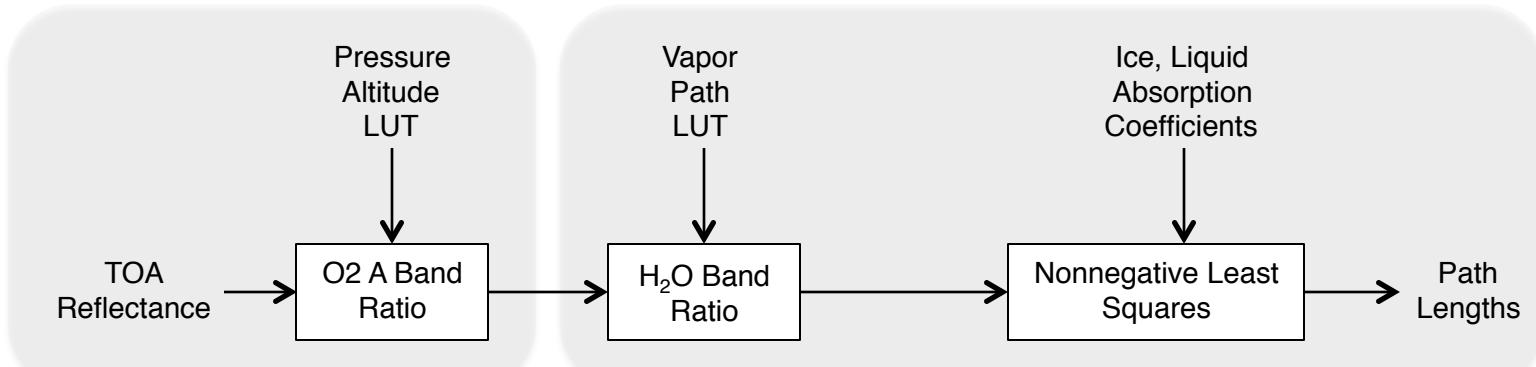


# 2. Reducing bias in H<sub>2</sub>O vapor maps

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## Pressure Altitude Retrieval



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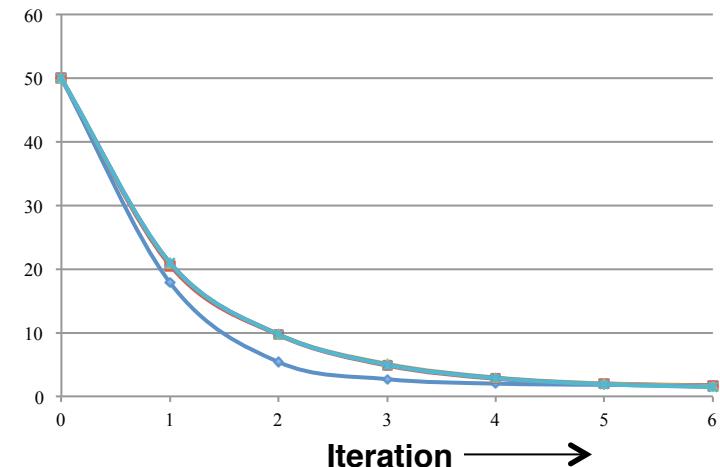
## H<sub>2</sub>O Retrieval



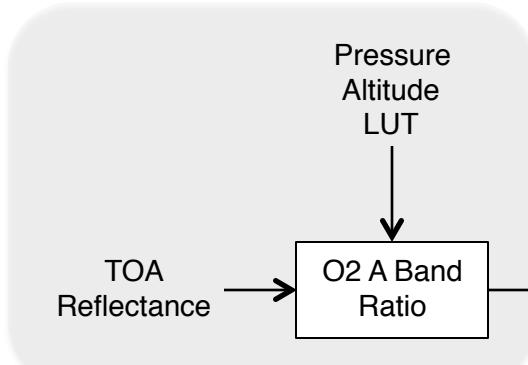
# 2. Reducing bias in $\text{H}_2\text{O}$ vapor maps

Courtesy Elyse Pennington  
(poster at this workshop)

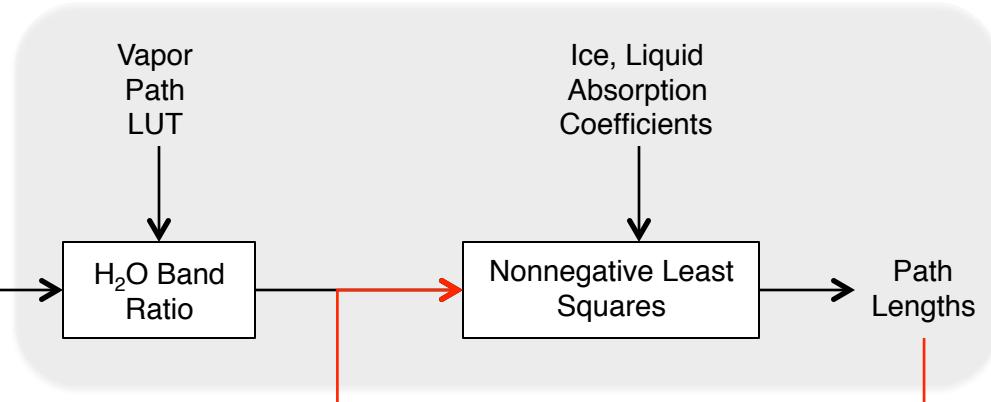
## Melting Snow with Vegetation



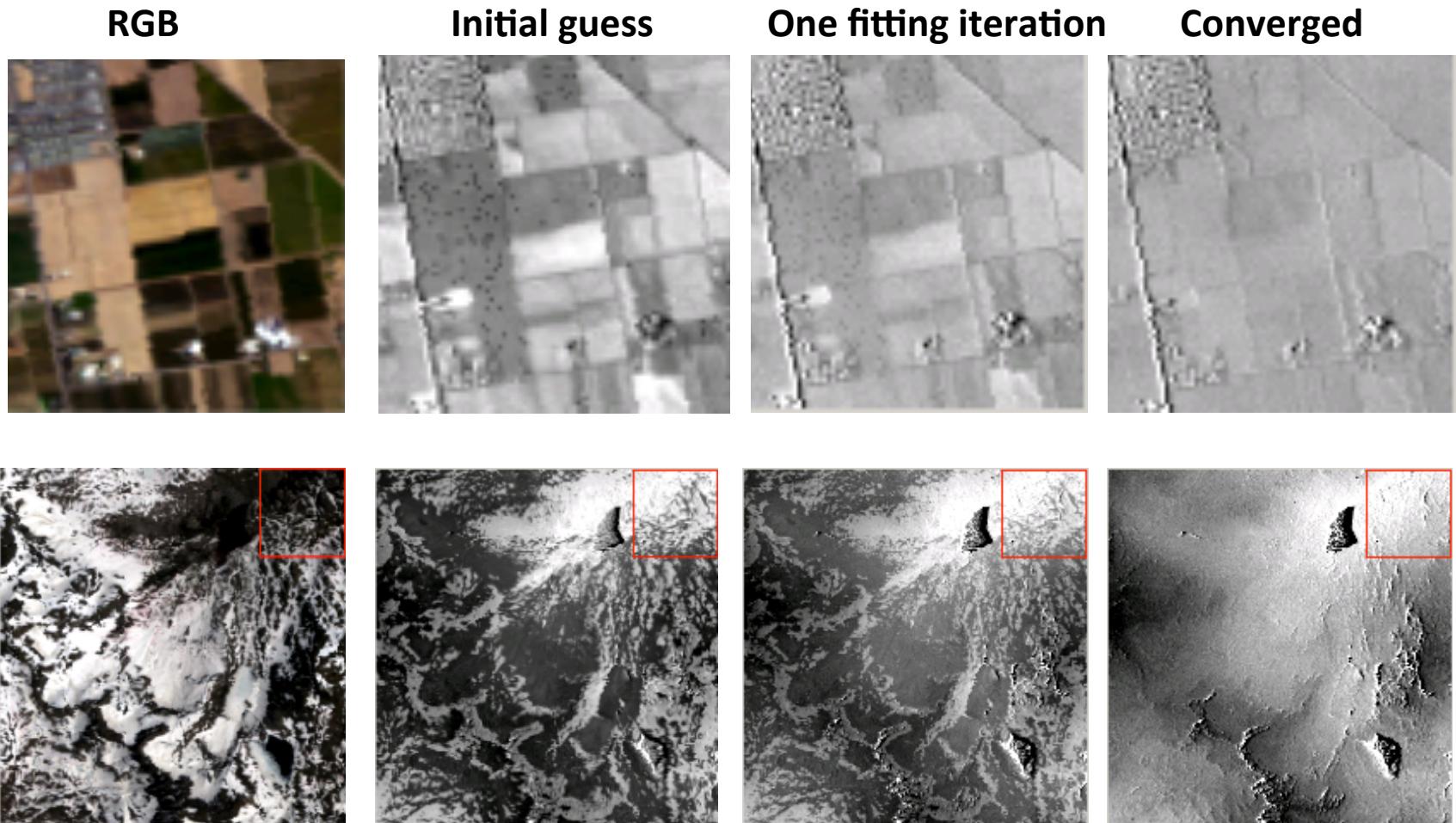
### Pressure Altitude Retrieval



### H<sub>2</sub>O Retrieval

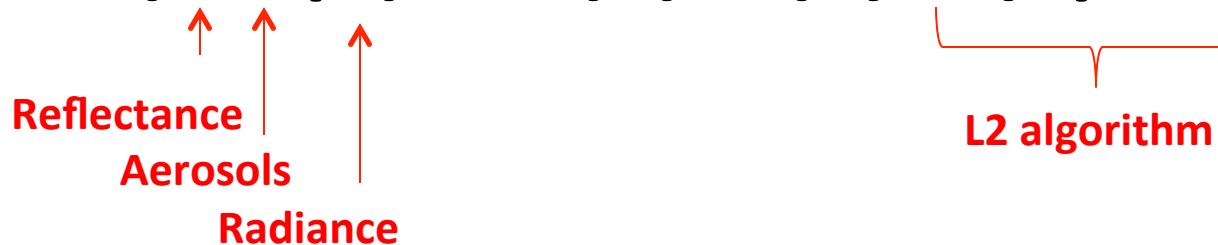


# Better H<sub>2</sub>O Vapor Maps



### 3. Bayesian estimation of aerosol parameters

$$P(R, \theta | L) = P(R) P(\theta) P(L | \theta, R) Z$$



### 3. Bayesian estimation of aerosol parameters

$$P(R, \theta | L) = P(R) P(\theta) P(L | \theta, R) Z$$

↑      ↑      ↑  
Reflectance      Aerosols      Radiance  
Prior for reflectance, via historical data  
Prior for aerosols  
L2 algorithm  
Normalizing constant



# 3. Bayesian estimation of aerosol parameters

$$P(R, \theta | L) = P(R) P(\theta) P(L | \theta, R) Z$$

↑      ↑      ↑           ↑           ↑           ↑  
Reflectance      Aerosols      Radiance      Prior for      reflectance,      Prior for      L2 algorithm      Normalizing  
Aerosols                     via historical      aerosols                constant  
Radiance      data

1. In advance, model the distribution of valid surface reflectances (Gaussian Mixture Model)
2. At runtime, generate reflectance *hypotheses* based on many aerosol parameters
3. Calculate the probability of each hypothesis



# 3. Bayesian estimation of aerosol parameters

Original image, Yosemite rim fire f130913

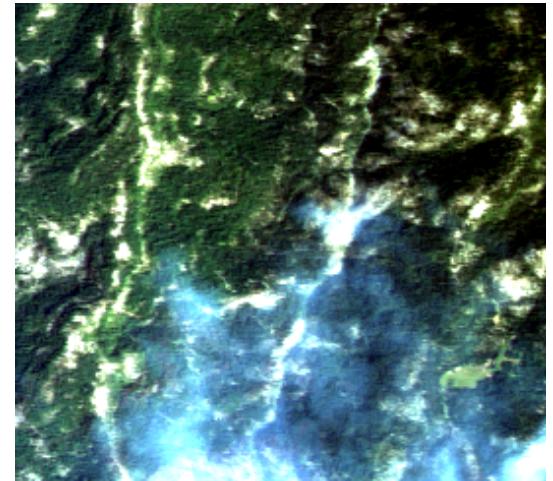


Corrected

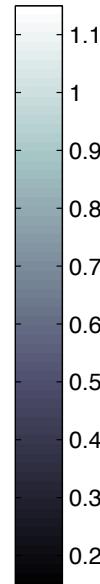
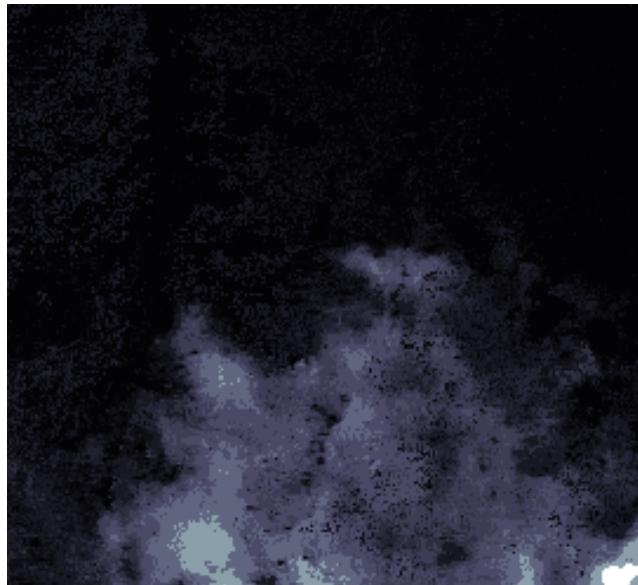


# Retrieved Aerosol Optical Depth

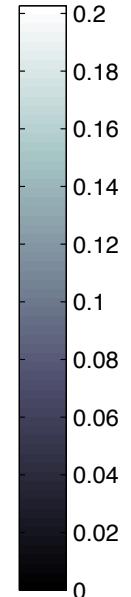
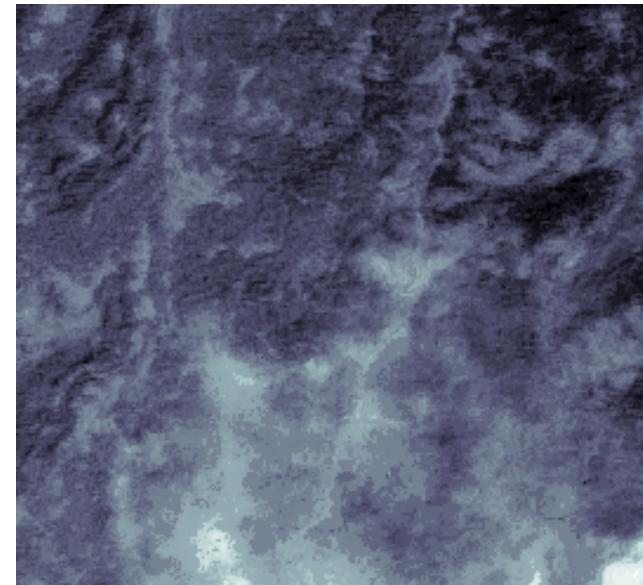
The retrieval has highest confidence over dark vegetated regions. It has lower confidence inside smoke, or over bright bare surfaces.



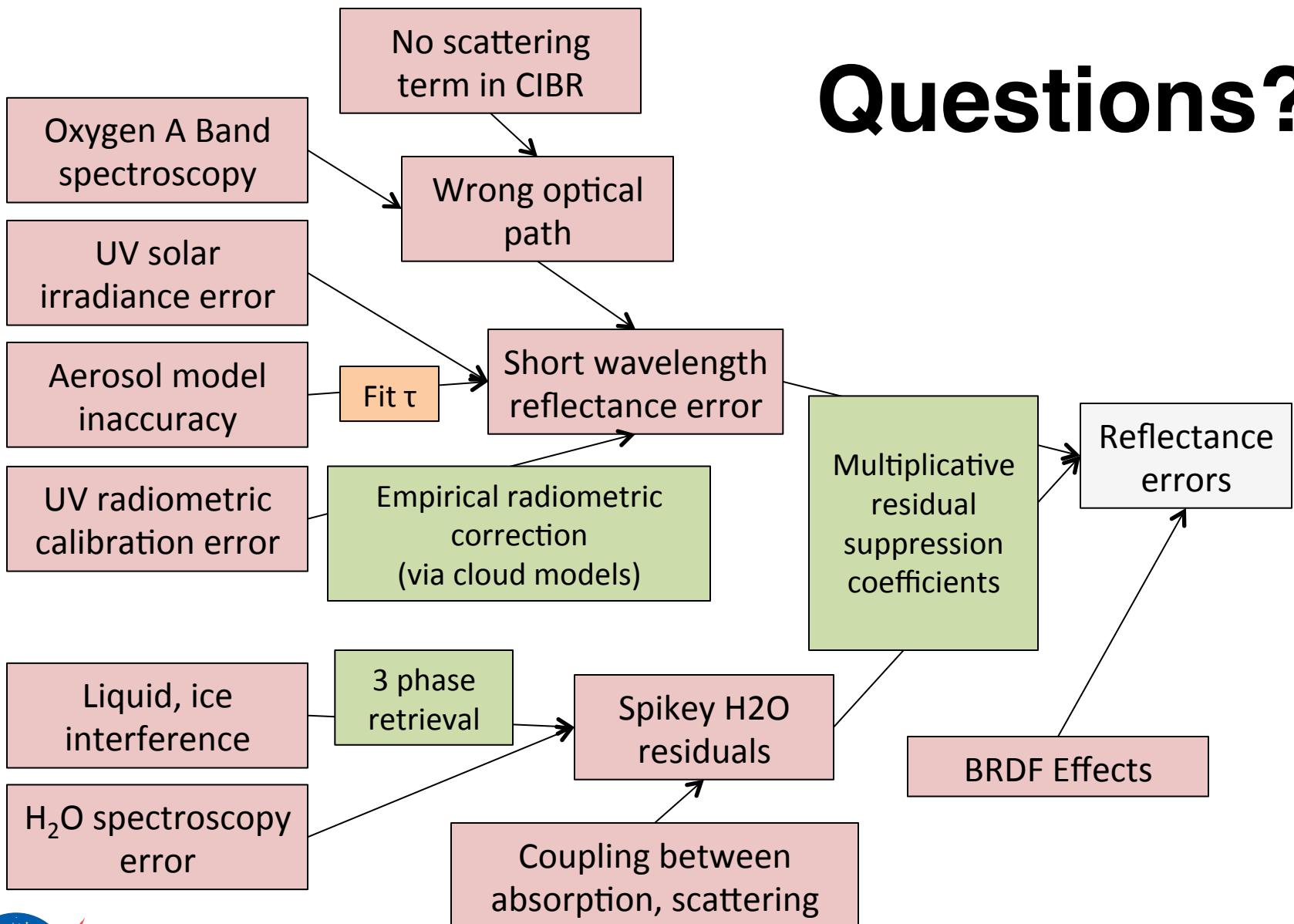
Most probable AOD



Posterior Standard Deviation



# Questions?

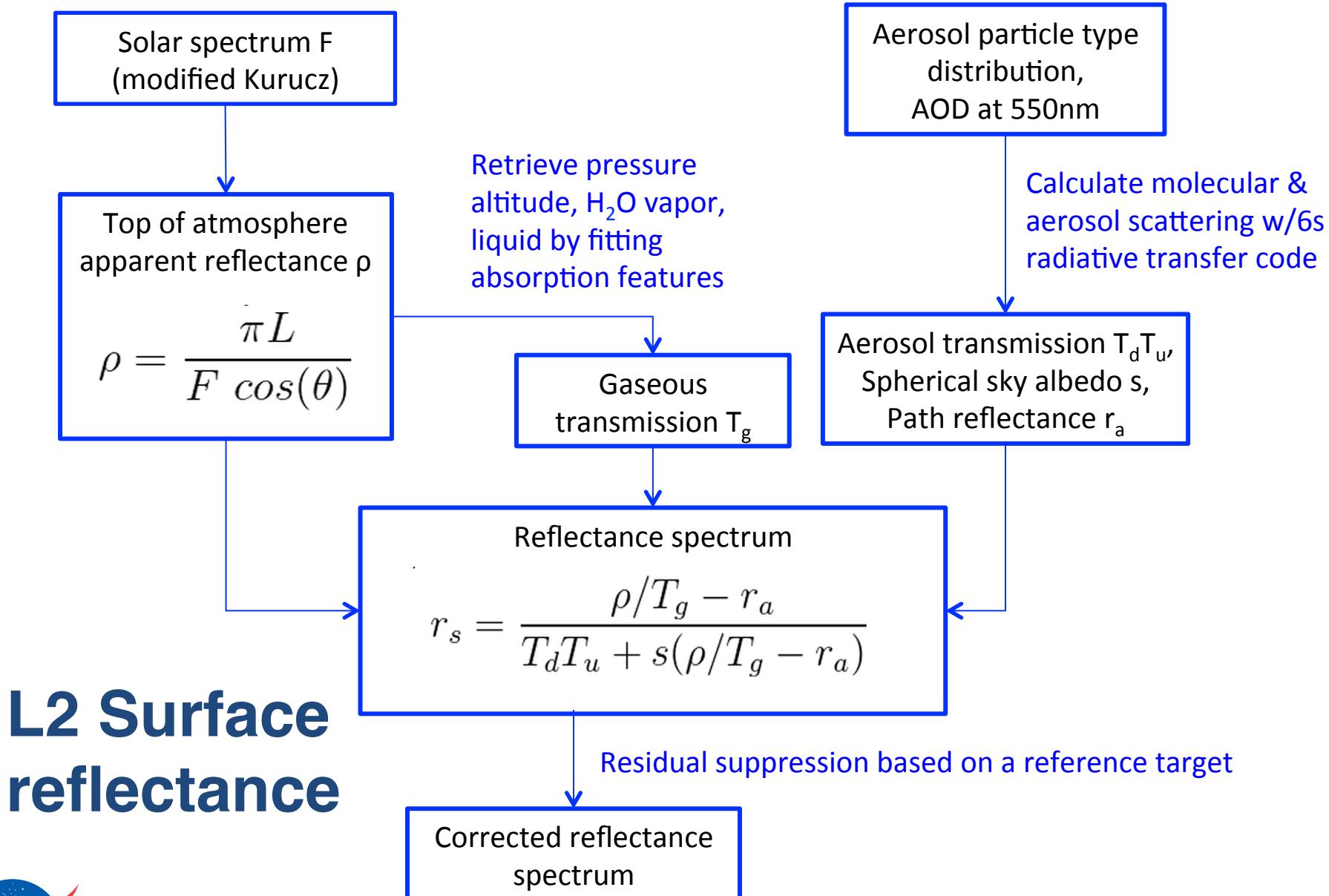


# Thanks!

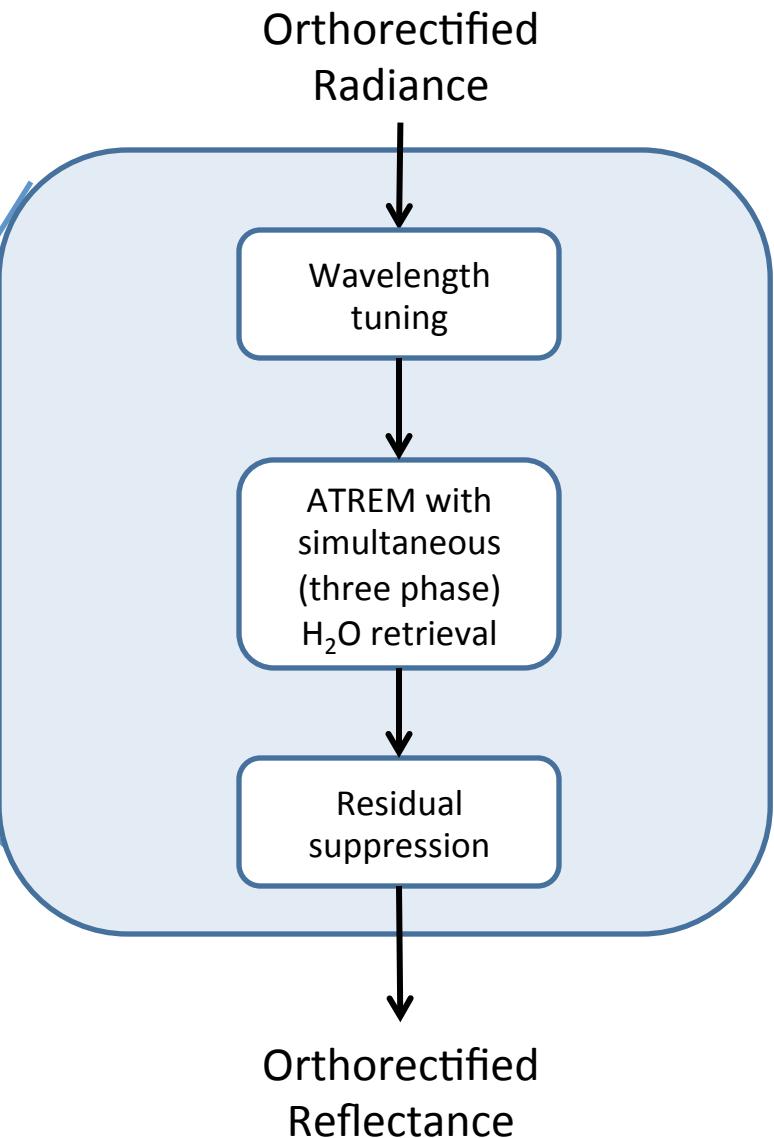
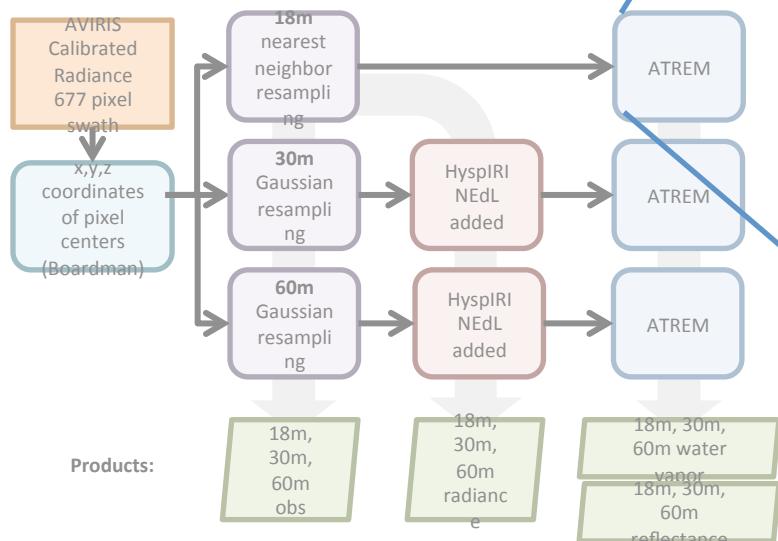
Ian McCubbin, Didier Keymeulen, Brian Bue, Sarah Lundein,  
Mark Helmlinger, Scott Nolte and the AVIRIS team...

This research has been performed at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration. NASA programmatic support through ESTO and Terrestrial Ecology programs is gratefully acknowledged.

# Backup slides



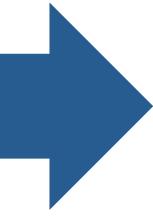
# L2: The atmospheric correction component



[http://aviris.jpl.nasa.gov/data/AV\\_HypsIPI\\_Prep\\_Data.html](http://aviris.jpl.nasa.gov/data/AV_HypsIPI_Prep_Data.html)



# Better H<sub>2</sub>O Vapor Maps



RGB



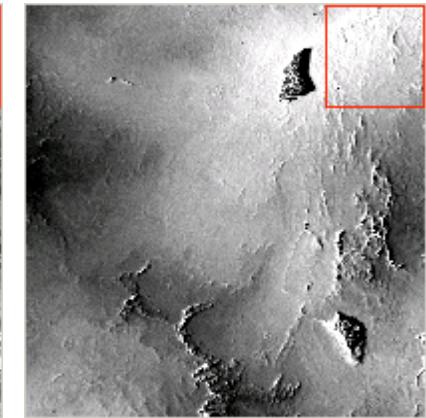
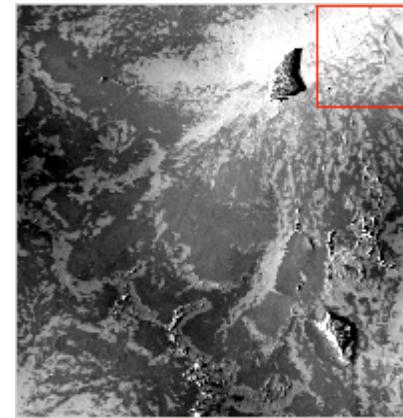
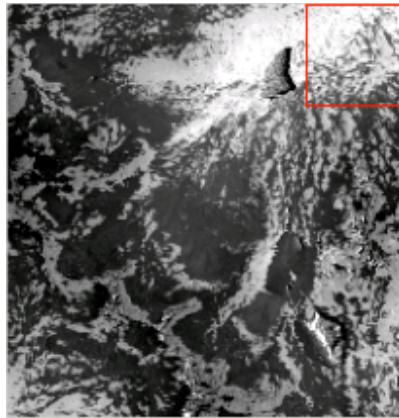
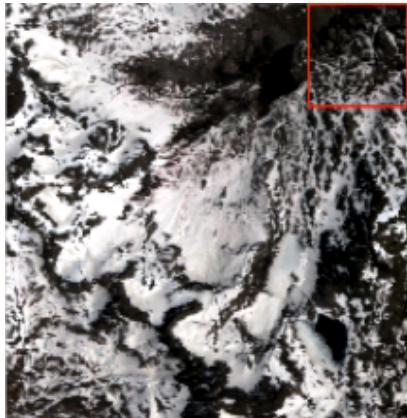
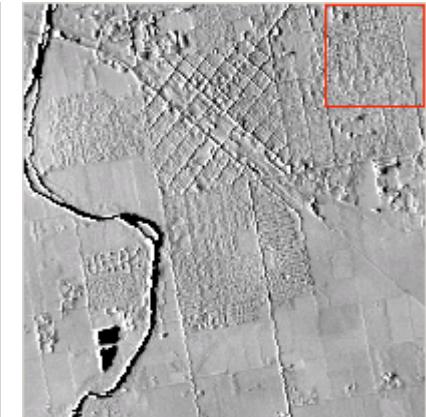
Band Ratio



Also fit liquid, ice



Iterative fitting



# The ATREM Approach

Apparent reflectance

Radiance

Solar flux

$$r^*_{obs}(l, q, f, q_o, f_o) = p L_{obs}(l, q, f, q_o, f_o) / [m_o F_o(l)],$$

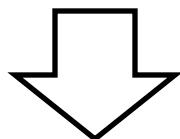
Path  
reflectance

Surface  
reflectance

Atmospheric  
transmittance

$$r^*_{obs}(l, q, f, q_o, f_o) = [r^*_{atm}(l, q, q_o, f_o) + t_d(l, q_o) t_u(l, q) r(l) / (1 - s(l)r(l))] T_g(l, q, q_o),$$

Scattering terms  
from 6s code

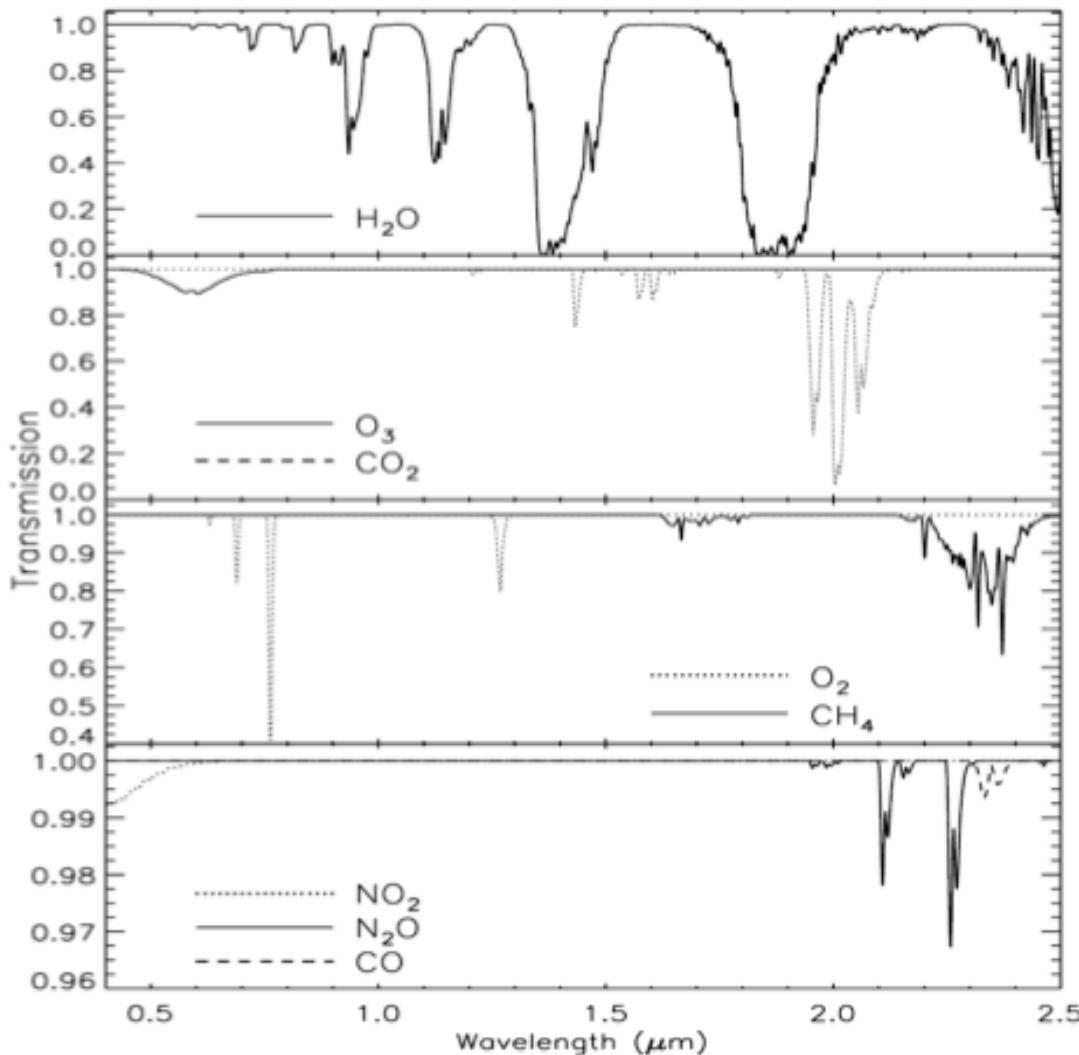


$$r = (r^*_{obs}/T_g - r^*_{atm}) / [t_d t_u + s (r^*_{obs}/T_g - r^*_{atm})].$$

From [Gao and Green 2010]



# Typical transmittance



Absorption is modeled for 7 gases

ATREM retrieves water vapor for each pixel using 0.94 and 1.14  $\mu\text{m}$   $\text{H}_2\text{O}$  band depths

Vertical profiles use 20-layer atmospheres

[Gao and Green 2010]



# 3. Bayesian estimation of aerosol parameters

1. In advance, model the distribution of valid surface reflectances (here a Gaussian Mixture Model)
2. At runtime, generate reflectance hypotheses based on different aerosol parameters
3. Calculate the probability of each hypothesis

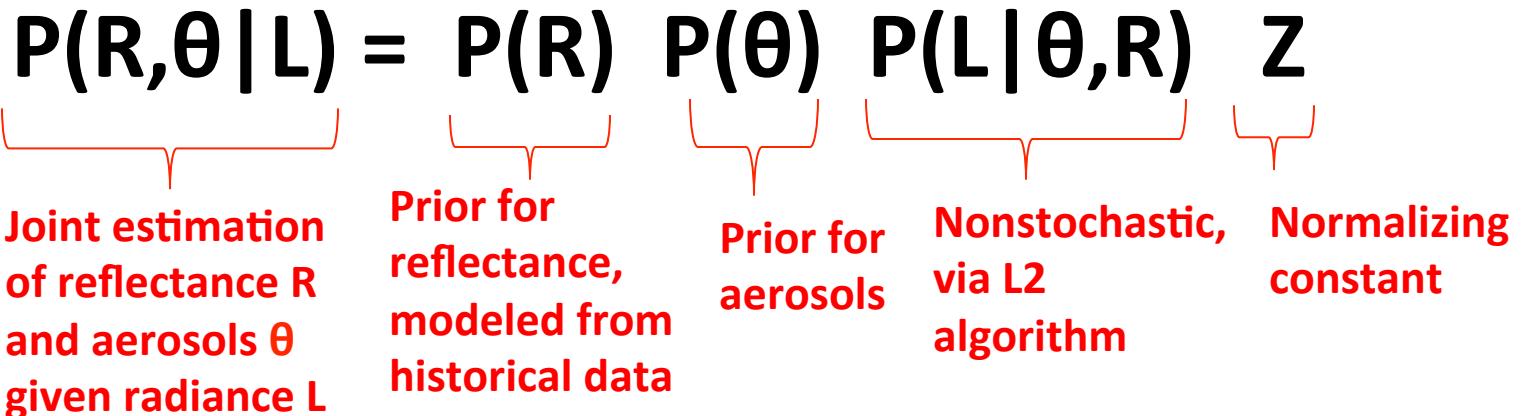
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Joint estimation of reflectance  $R$  and aerosols  $\theta$  given radiance  $L$

Prior for reflectance, modeled from historical data

Prior for aerosols

Nonstochastic, via L2 algorithm

Normalizing constant

