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

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Agenda

• Overview of the HyspIRI data products
• L2 error decomposition
• Recent investigations
  – Radiometric corrections
  – Iterative H$_2$O path estimation
  – Aerosol estimation
HyspIRI L2 processing objectives

Accurate reflectance measurements

Without in-scene references

At any elevation

Under clear or hazy skies
HyspIRI simulated data products

AVIRIS Calibrated Radiance 677 pixel swath

x, y, z coordinates of pixel centers (Boardman)

18m nearest neighbor resampling

30m Gaussian resampling

60m Gaussian resampling

HyspIRI NEdL added

ATREM

Products:

18m, 30m, 60m optical paths for H₂O

18m, 30m, 60m radiance

18m, 30m, 60m reflectance


Courtesy Phil Dennison
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

- Oxygen A Band spectroscopy
- UV solar irradiance error
- Aerosol model inaccuracy
- UV radiometric calibration error
- Liquid, ice interference
- H₂O spectroscopy error
- No scattering term in CIBR
- Wrong optical path
- Short wavelength reflectance error
- Spikey H₂O residuals
- Coupling between absorption, scattering
- BRDF Effects
- Reflectance errors
Known Errors

In progress

Installed

- Oxygen A Band spectroscopy
- UV solar irradiance error
- Aerosol model inaccuracy
- UV radiometric calibration error
- Liquid, ice interference
- H₂O spectroscopy error
- No scattering term in CIBR
- Wrong optical path
- Short wavelength reflectance error
- Empirical radiometric correction (via cloud models)
- Multiplicative residual suppression coefficients
- 3 phase retrieval
- Spikey H₂O residuals
- Coupling between absorption, scattering
- BRDF Effects
- Reflectance errors

Fit τ
Agenda

• Overview of the HysplRI data products
• L2 error decomposition

• Recent investigations
  – Radiometric corrections
  – Iterative H₂O path estimation
  – Aerosol estimation
1. Radiometric corrections

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

![Graph showing assumed and retrieved reflectance spectra with arrows indicating the differences.](image_url)

Assumed reflectance

Retrieved reflectance

Courtesy Bo Cai Gao
Typical vegetation spectra

Before and after application of the empirical gain curve to AVIRIS L1B data.

Courtesy Bo Cai Gao
2. Reducing bias in H₂O vapor maps

Courtesy Elyse Pennington (poster at this workshop)
2. Reducing bias in H$_2$O vapor maps

Courtesy Elyse Pennington (poster at this workshop)
2. Reducing bias in H$_2$O vapor maps

Courtesy Elyse Pennington (poster at this workshop)
Better H$_2$O Vapor Maps

RGB  Initial guess  One fitting iteration  Converged
3. Bayesian estimation of aerosol parameters

\[ P(R, \theta \mid L) = P(R) \ P(\theta) \ P(L \mid \theta, R) \ Z \]
3. Bayesian estimation of aerosol parameters

\[ P(R, \theta | L) = P(R) \cdot P(\theta) \cdot P(L | \theta, R) \cdot Z \]

- Reflectance
- Aerosols
- Radiance
- Prior for reflectance, via historical data
- Prior for aerosols
- L2 algorithm
- Normalizing constant
3. Bayesian estimation of aerosol parameters

\[ P(R, \theta | L) = P(R) \cdot P(\theta) \cdot P(L | \theta, R) \cdot Z \]

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
Oxygen A Band spectroscopy
UV solar irradiance error
Aerosol model inaccuracy
UV radiometric calibration error
Liquid, ice interference
H₂O spectroscopy error
No scattering term in CIBR
Wrong optical path
Short wavelength reflectance error
Multiplicative residual suppression coefficients
Reflectance errors
Empirical radiometric correction (via cloud models)
Fit \( \tau \)
3 phase retrieval
Spikey H₂O residuals
Coupling between absorption, scattering
BRDF Effects
Thanks!

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Backup slides
L2 Surface reflectance

Solar spectrum F (modified Kurucz)

Top of atmosphere apparent reflectance $\rho$

$\rho = \frac{\pi L}{F \cos(\theta)}$

Retrieves pressure altitude, H$_2$O vapor, liquid by fitting absorption features

Gaseous transmission $T_g$

Aerosol transmission $T_d T_u$, Spherical sky albedo $s$

Path reflectance $r_a$

Aerosol particle type distribution, AOD at 550nm

Calculate molecular & aerosol scattering w/6s radiative transfer code

Reflectance spectrum

$r_s = \frac{\rho/T_g - r_a}{T_d T_u + s(\rho/T_g - r_a)}$

Residual suppression based on a reference target

Corrected reflectance spectrum
L2: The atmospheric correction component

Products:
- 18m, 30m, 60m water vapor
- 18m, 30m, 60m reflectance

Better $\text{H}_2\text{O}$ Vapor Maps

RGB  Band Ratio  Also fit liquid, ice  Iterative fitting
The ATREM Approach

Apparent reflectance

\[ r_{\text{obs}}^* (l,q,f,q_0,f_0) = p L_{\text{obs}}(l,q,f,q_0,f_0) / \left[ m_o F_0(l) \right], \]

Radiance

Path reflectance

\[ r_{\text{obs}}^* (l,q,f,q_0,f_0) = [r_{\text{atm}}^*(l,q,q_0,f_0) + t_d(l,q_0) t_u(l,q) r(l)/(1 - s(l)r(l)) ] T_g(l,q,q_0), \]

Surface reflectance

Atmospheric transmittance

Scattering terms from 6s code

\[ r = (r_{\text{obs}}^* / T_g - r_{\text{atm}}^*) / \left[ t_d t_u + s (r_{\text{obs}}^* / T_g - r_{\text{atm}}^*) \right]. \]

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 μm H₂O 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

\[ P(R, \theta | L) = P(R) \cdot P(\theta) \cdot P(L | \theta, R) \cdot Z \]
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\[
P(R, \theta | L) = P(R) \cdot P(\theta) \cdot P(L | \theta, R) \cdot Z
\]

- 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