2015 Summer Course

on Optical Oceanography and Ocean Color Remote Sensing

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Shallow-water Remote Sensing

Delivered at the Darling Marine Center,
University of Maine
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Who Cares About Shallow Waters?

- Military needs maps of bathymetry and bottom classification in denied-access areas for amphibious operations; water clarity maps for optical mine finding and diver operations

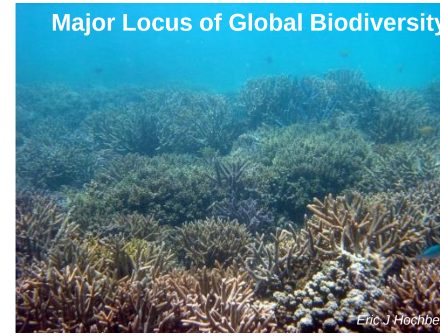
- Ecosystem managers need to map and monitor bottom type and water quality for management of coral reefs, sea grass beds, kelp forests, fisheries, and recreation
  - episodic (hurricane effects, harmful algal blooms, pollution events)
  - long-term (global climate change, anthropogenic changes from coastal land usage)

- Maps needed at 1-10 meter spatial scales (not kilometers), sometimes within ~1 day of image acquisition, repeat on demand

CORAL: COral Reef Airborne Laboratory

Coral Reef Background

Importance

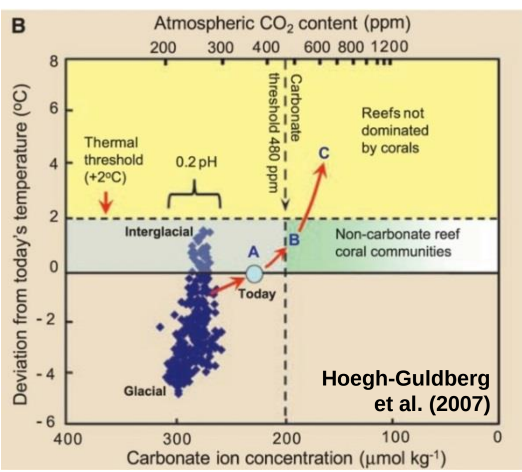


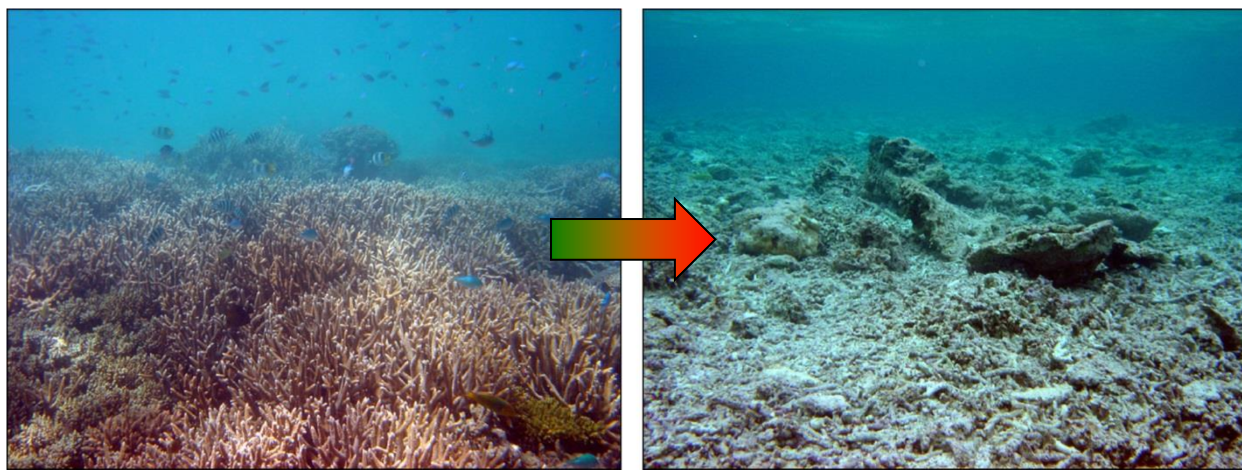
Coral reef ecosystem goods & services valued at ~$400 billion annually

Coral reefs do not influence the short-term global carbon cycle, but...

Concern

...they are among the first ecosystems to respond critically and dramatically to climate change.





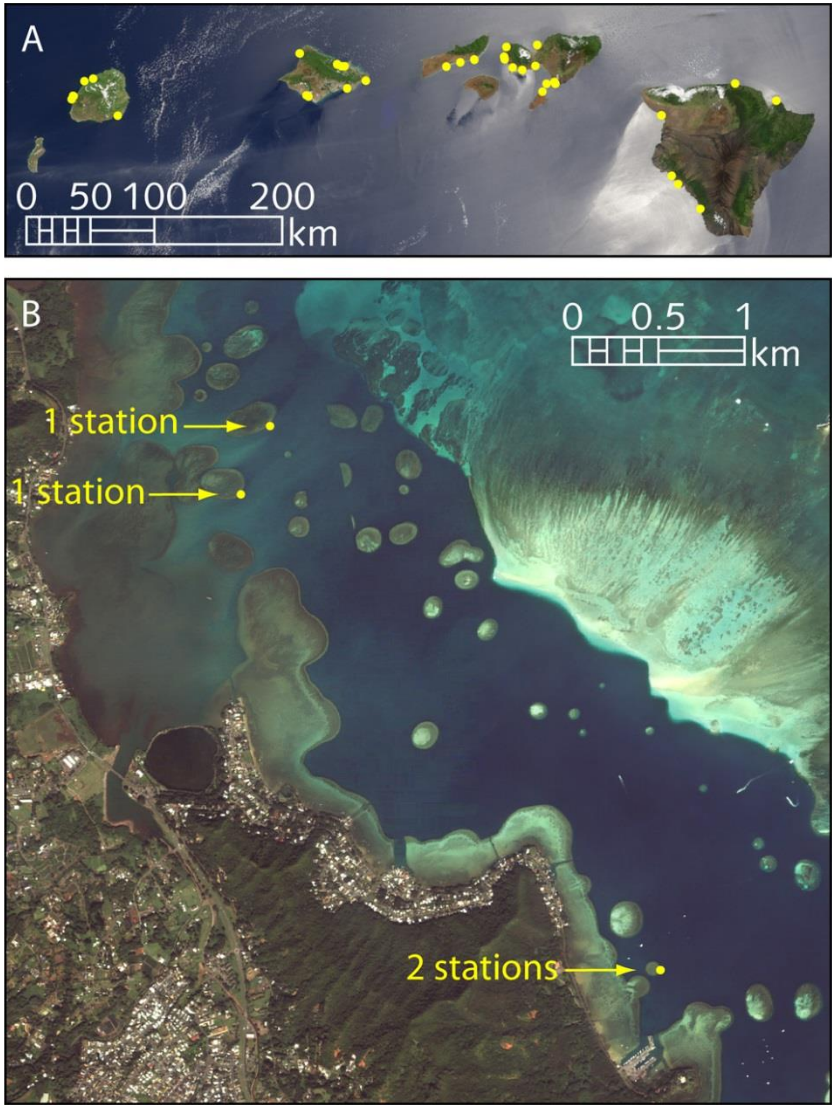
Ocean warming and acidification may exacerbate local impacts, leading to reef degradation worldwide. Current estimates: 25–30% already severely degraded, 15% more critically threatened in 10–20 years, another 20% threatened over 20–40 years (from E. Hochberg)

Coral Reef Assessment

Problem

Photoquadrat Transect: detailed, laborious, small footprint

“Manta-Tow”: quick, semi-quantitative, larger footprint



Very sparse surveys vastly undersample reef area across local and regional scales

(from E. Hochberg)

CORAL: COral Reef Airborne Laboratory

CORAL

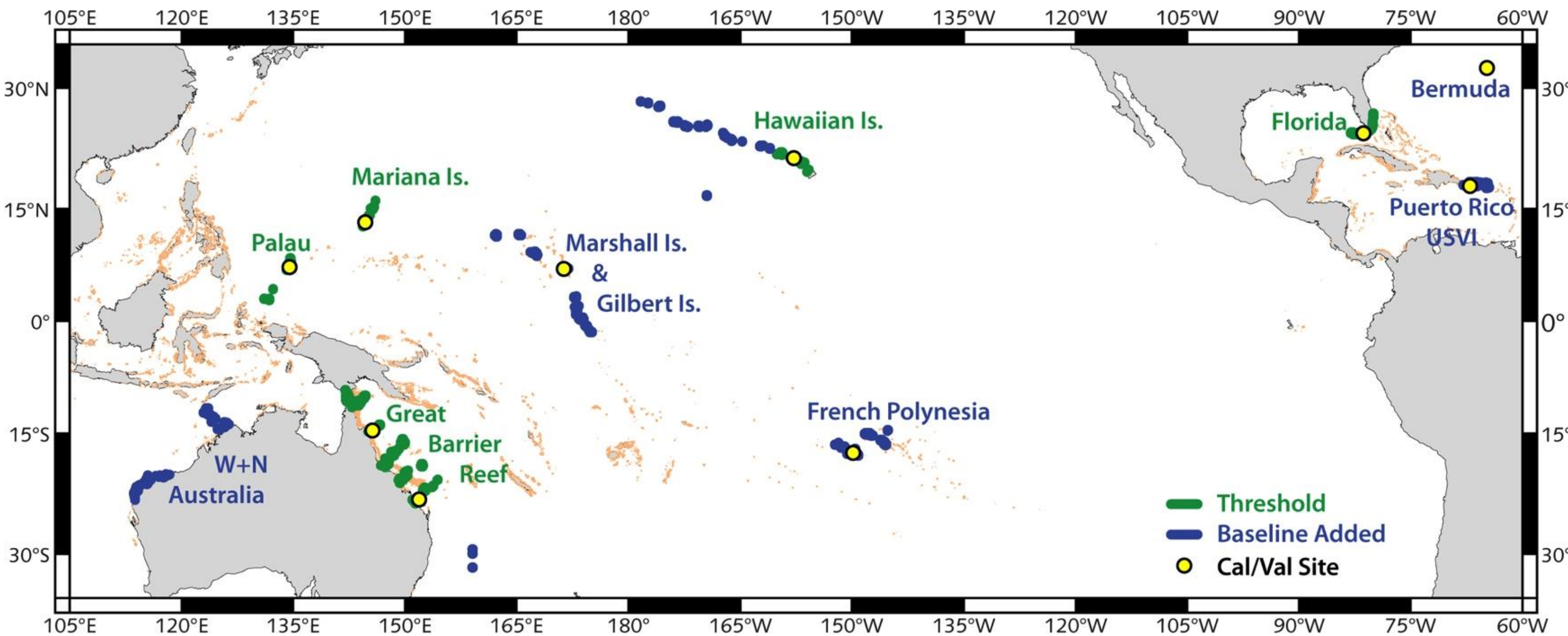
Overarching Science Question

What is the relationship between coral reef condition and biogeophysical forcing parameters?

CORAL Science Objectives

O1. Make high-density observations of reef condition for 3.3% of world's reef area (green in map below) — 3 orders of magnitude more than current, in situ observations.

O2. Establish empirical models that relate reef condition to biogeophysical forcing parameters.



(from E. Hochberg)

Engineering Constraints

We want meter-scale pixels and hyperspectral imagery

MODIS sensor orbit: 44,460 km in 99 min → 7500 m/s

CASI frame rate = 33 frames/sec

7500 m/s X 0.03 sec/frame → 225 m/frame

1 m/frame → 0.0001 sec exposure time

Counting Photons

You can't get meter-scale hyperspectral imagery from a polar-orbiting satellite because there just aren't enough photons reaching the TOA. See www.oceanopticsbook.info/view/remote_sensing/level_2/counting_photons for order-of-magnitude estimates.

- View a larger surface area, which both increases the number of photons leaving the surface and allows for longer integration times.
- View the surface area for a longer time, e.g., from a geostationary satellite that can stare at the same point for very long times (but a geostationary satellite has an altitude of 36,000 km, which makes the solid angle much smaller).
- Increase the bandwidth.
- Increase the aperture of the receiving optics.
- Use multiple detector elements to observe the same ground pixel nearly simultaneously, either on the same or successive scans, and then combine the photons collected from the different sensors
- Get closer to the surface, e.g. by using an airborne sensor flying at a few kilometers above the sea surface. This greatly increases the solid angle of the sensor and allows for longer integration times for a slowly flying aircraft.

The praticable solution: Fly low and slow with an airborne hyperspectral sensor

Science Issues

Atmospheric correction

- Black pixel assumption isn't valid because of bottom reflectance
- Often have absorbing aerosols in coastal waters

Retrieval algorithms

- Statistical algorithms often fail in shallow coastal waters because of complex mixtures of phytoplankton, minerals, and dissolved substances
- Bottom-reflectance causes non-uniqueness in band-ratio algorithms

Three Techniques for Atmospheric Correction

- "Black-pixel" technique: developed for open-ocean (often Case 1 water), multi-spectral, satellite ocean color remote sensing (SeaWiFS, MODIS, etc.) Werdell discussed. Works well for deep Case 1 water, but fails for optically shallow and highly scattering Case 2 waters.

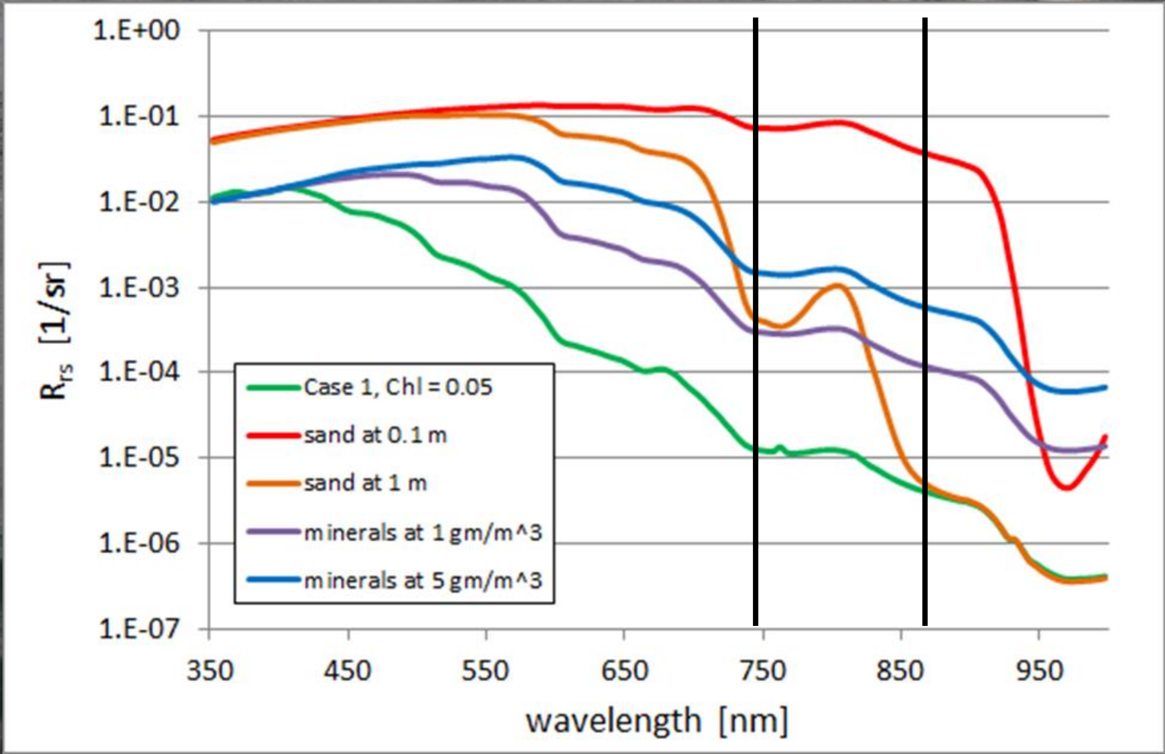
- Empirical Line Fit (ELF): A correlational technique that relates measured sea-level R_{rs} spectra to at-sensor radiances. In principle can correct for any atmospheric conditions, but requires field measurements of R_{rs} at time of image acquisition

- Radiative Transfer Techniques: Explicitly compute and remove the atmospheric path radiance for given atmospheric conditions and viewing geometry. In principle can correct for any atmospheric conditions, but requires knowledge of atmospheric conditions at time of image acquisition

Black-pixel Technique and Extrapolation

This technique DOES NOT WORK for remote-sensing of shallow waters, because bottom reflectance often makes $L_w(\lambda_1)$ and $L_w(\lambda_2)$ non-zero. It fails for Case 2 waters with high mineral concentrations, because scattering by mineral particles can also make $L_w(\lambda_1)$ and $L_w(\lambda_2)$ non-zero. It also fails if the aerosols are highly absorbing (dust, soot) as is often the case in coastal waters.

It has inherent problems because small errors in the near IR can give big errors (even negative L_w) near 400 nm.



Requirements for Shallow or Case 2 Water

We need to have an atmospheric correction technique that

- does not require zero water-leaving radiance at particular wavelengths (no “black pixel” assumption)

- works for any water body (Case 1 or 2, deep or shallow)

- works for any atmosphere (including absorbing aerosols, which are common in coastal areas)

- does not require ancillary field measurements that cannot be obtained on a routine basis or in denied-access areas

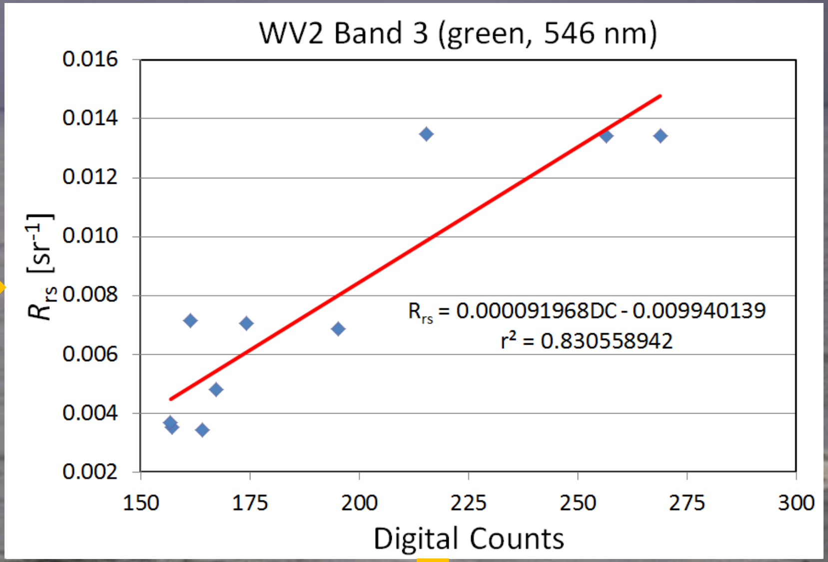
Faster, cheaper, better: pick any 2. Here it’s pick any 3.

Empirical Line Fit

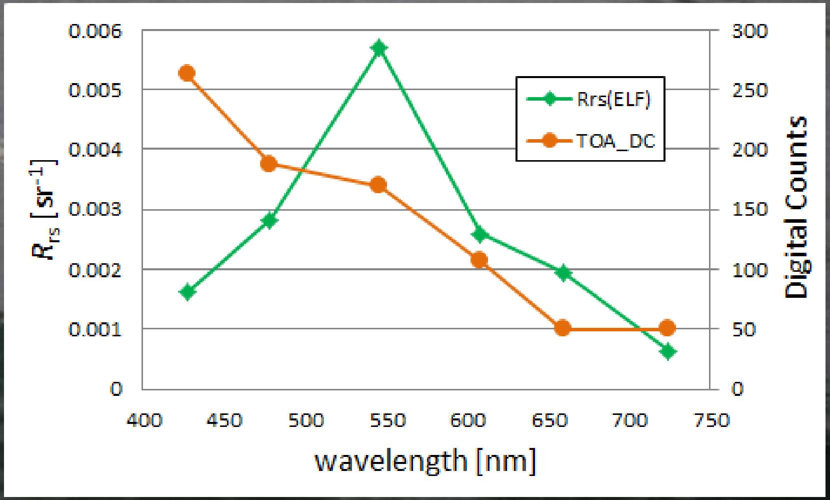
- Measure R_{rs} at several points *within the image area at the time of image acquisition*
- Correlate the measured R_{rs} with the at-sensor signal at each wavelength to get a function—the empirical line fit—that converts at-sensor values to sea-level R_{rs}
- Apply this ELF to all pixels in the image
- In principle, the ELF technique can correct for any atmospheric conditions (which do not need to be known)

Empirical Line Fit

Example using WorldView-2 satellite multispectral imagery of St. Joseph's Bay, FL



There is a different ELF for each wavelength



Empirical Line Fit

The major drawback of the ELF technique is that it requires someone in the field, usually in a small boat, to make the needed sea-surface R_{rs} measurements at the time of the overflight.

An ELF based on measurements in one part of the image will give a bad correction for an image if the atmospheric conditions vary over the image (clouds, variable aerosol concentration), or the sea surface reflectance varies (wind speed varies)

The ELF can also become inaccurate for large off-nadir viewing angles because of different atmospheric path lengths and scattering angles.

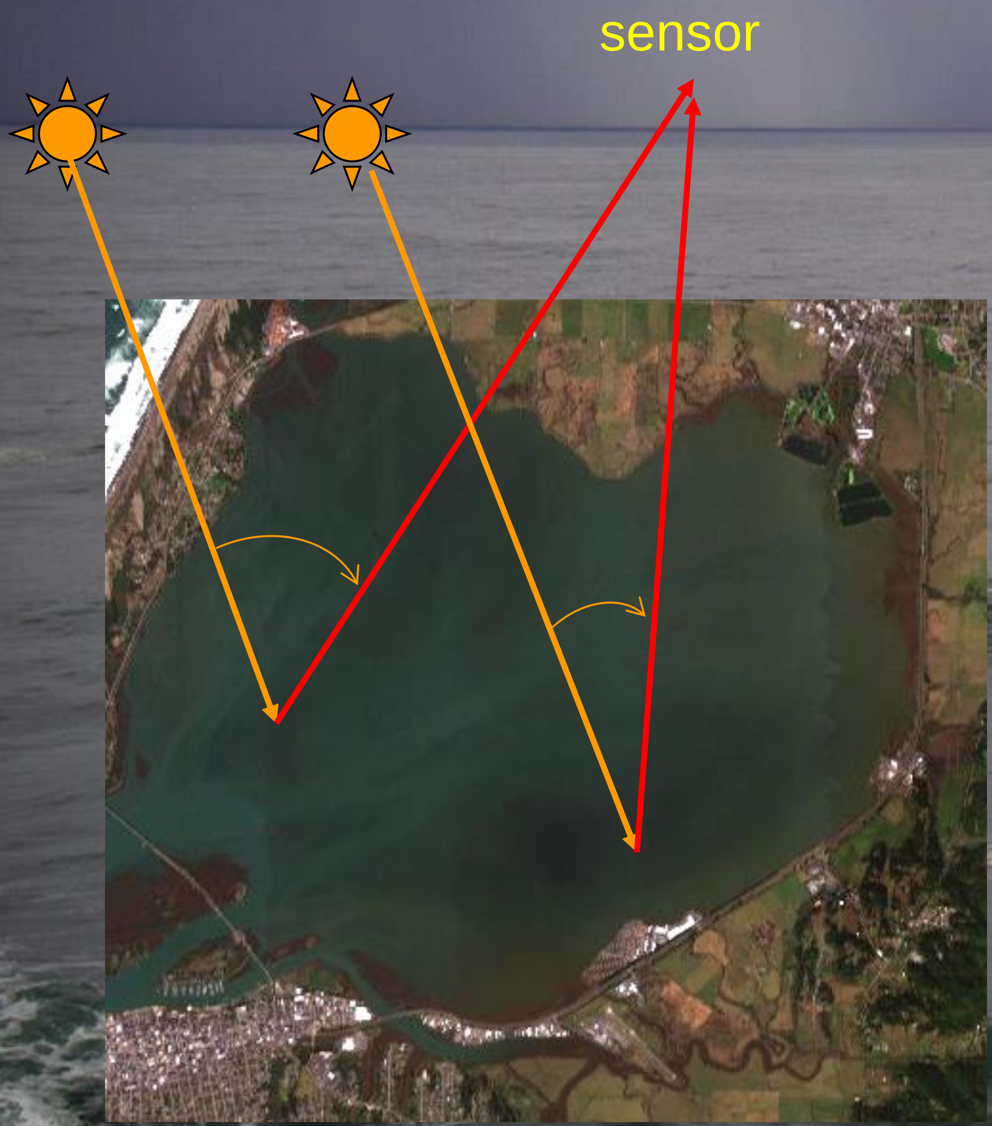
Radiative Transfer Techniques

If we know the absorbing and scattering properties of the atmosphere, then we can use an atmospheric radiative transfer (RT) model to compute the atmospheric path radiance and surface reflectance contribution to the measured total, and subtract it out to obtain the water-leaving radiance.

Example: the TAFKAA RT model was developed by the US Navy for this purpose (Gao et al, 2000; Montes et al, 2001; TAFKAA = The Algorithm Formerly Known As ATREM; ATmospheric REMoval).

TAFKAA has been used to create large look-up tables for various wind speeds, sun angles, viewing directions, and atmospheric properties (aerosol type and concentration, surface pressure, humidity, etc). These calculations (including polarization) required ~6 x 10^7 RT simulations with TAFKAA, taking several months of time on a 256 processor SGI supercomputer.

Radiative Transfer Techniques

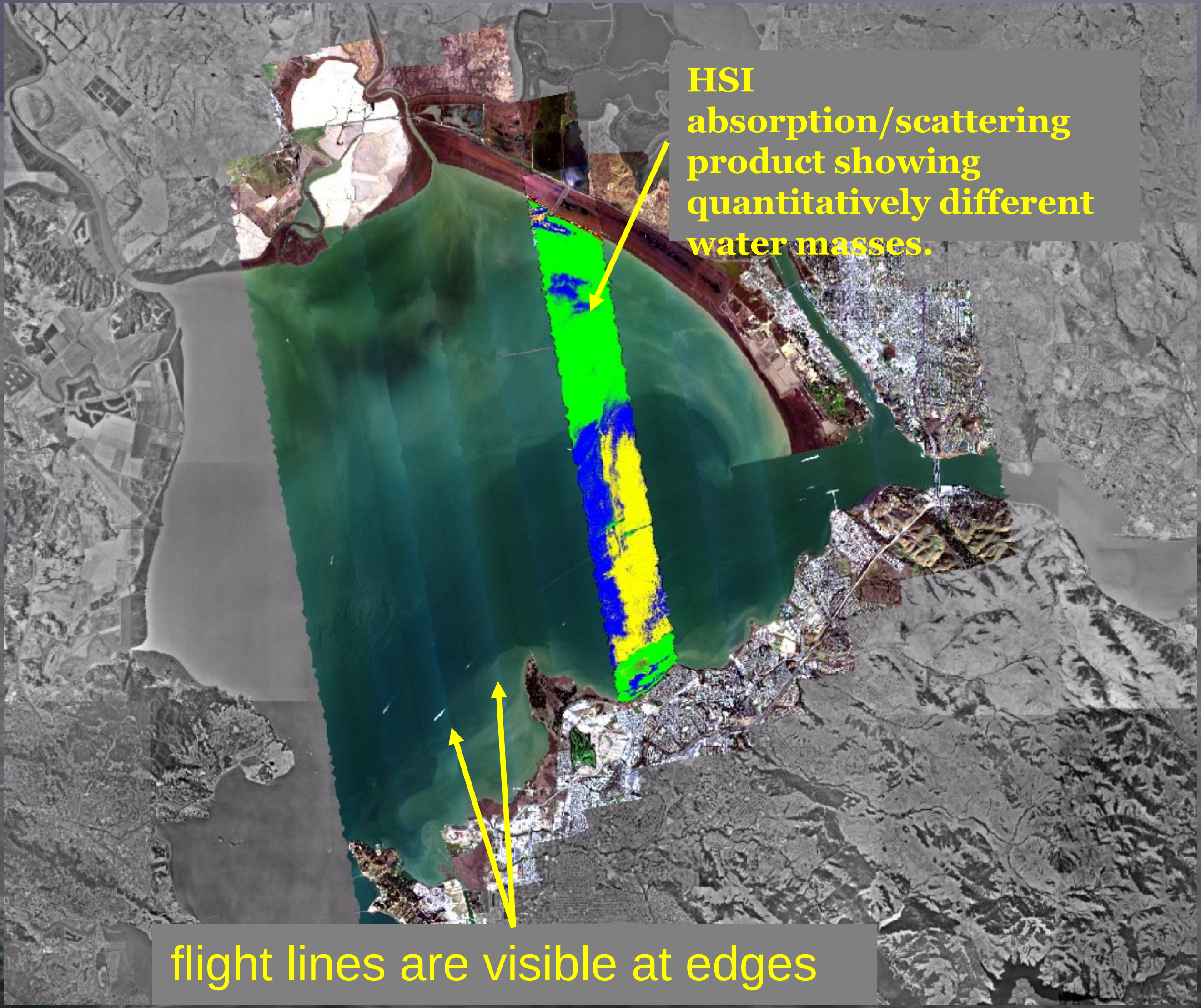


When correcting an image, each pixel in the scene has a different viewing geometry, and thus gets a different correction.

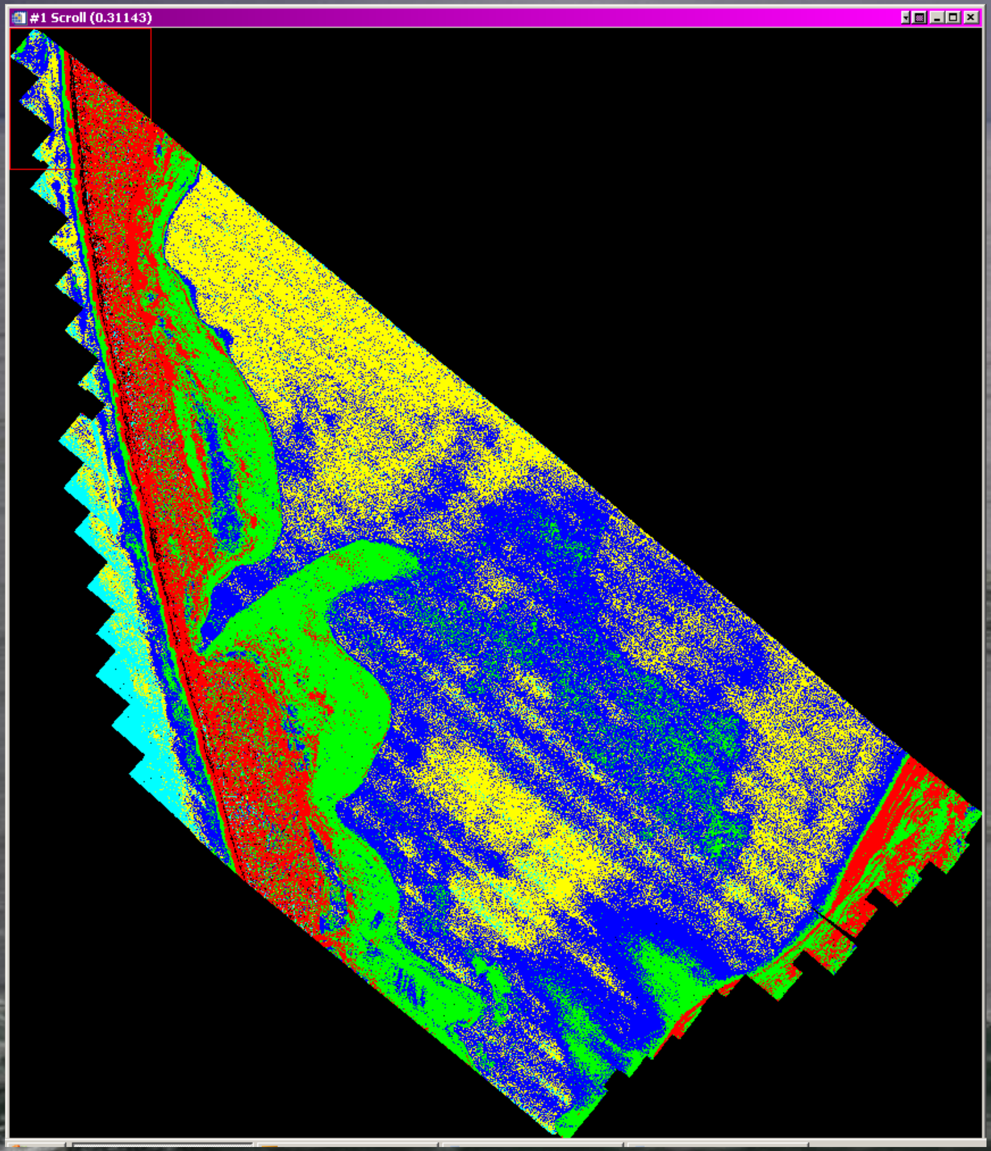
The main disadvantage of any RT method is that it requires measurement or estimation of the atmospheric properties.

This also requires having someone in the the field making meteorological measurements, or the use of imperfect atmospheric prediction models.

Imperfect Atmospheric Correction Visible in RGB



Imperfect Atmospheric Correction Effects on Bathymetry



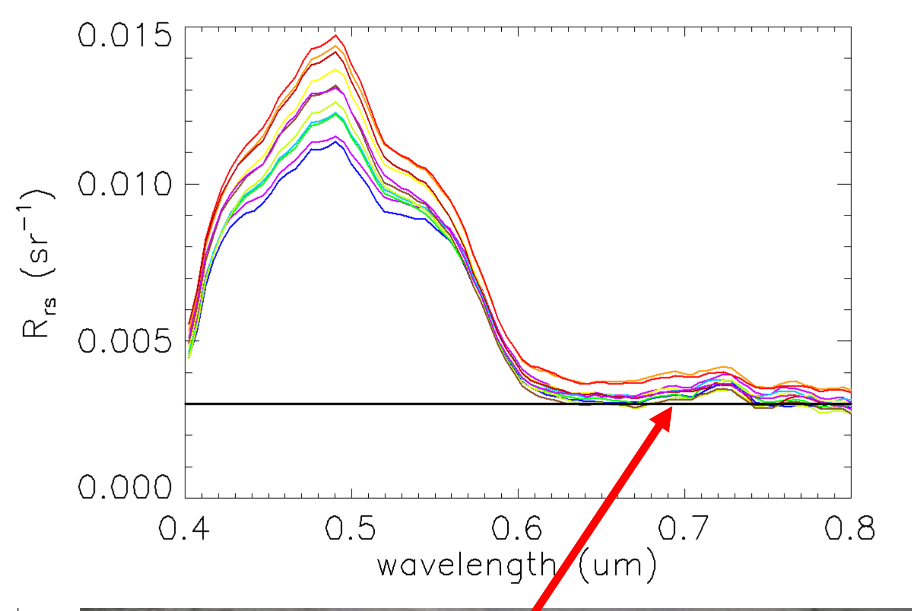
Effects of imperfect atmospheric correction on retrieved (by spectrum matching) bathymetry. The overall pattern is correct but note the "striping" in retrieved depths.

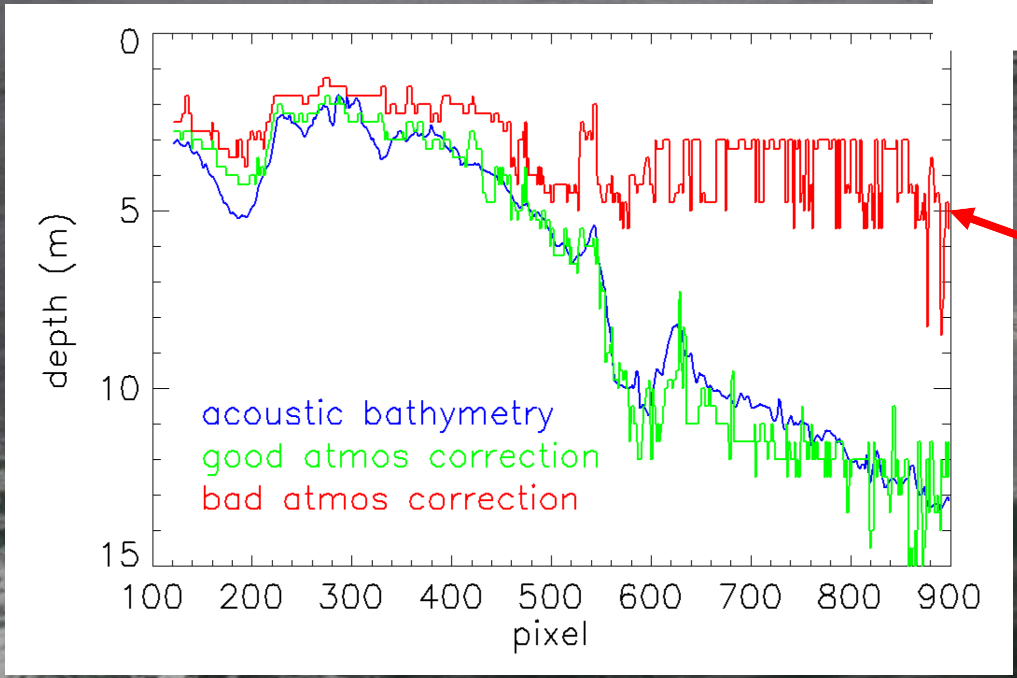
1 m contours (RGBYC =1-5 m)

courtesy of P. Bissett, FERI

Bad Atmospheric Correction = Bad Retrieval

Good retrievals depend on having a good atmospheric correction





atmospheric undercorrection by 0.003 1/sr gives bottom depths too shallow

A Hybrid ELF-TAFKAA correction

Hill et al. (2014; *Estuaries and Coasts*, DOI 10.1007/s12237-013-9764-3):

- Sea-level R_{rs} measurements were made at points in the imaged area at the time of the image acquisiton (as done for ELF)
- For each R_{rs}, they searched the TAFKAA database of 75×10^6 spectra to find the one that best matched the measured R_{rs}
- The atmospheric parameters used to create the TAFKAA best-match spectrum for each measured R_{rs} were then used to deduce a single “best-guess” set of atmospheric parameters for the image area
- The deduced set of atmospheric parameters was then used (along with the sensor viewing geometry) to obtain a TAFKAA-corrected R_{rs} for each image pixel

- This worked well for their airborne hyperspectral image

Retrieval Algorithms

- Statistical band-ratio algorithms don’t work well for retrieval of bathymetry and bottom classification, so...
- Use spectrum matching to well calibrated and atmospherically corrected $R_{rs}(\lambda)$

Two flavors of spectrum matching:

- Match image $R_{rs}(\lambda)$ to a semianalytical model
- Match image $R_{rs}(\lambda)$ to a precomputed database

The Semi-analytical Model of Lee et al. for Deriving IOPs and Bottom Depth from R_{rs}

Lee et al., Applied Optics, 1998 (model development)
Lee et al., Applied Optics, 1999 (model testing)

Used single-scattering theory and various assumptions to derive an approximate formula for $r_{rs} = L_u/E_d$ (in water) in shallow waters with a reflecting bottom.

$u = \mathrm{b_b}/(\mathrm{a} + \mathrm{b_b})$

$r_{rs}^{dp} = gu$ in deep water

$g = g_0 + g_1 u^{g2}$

Then add a correction factor to the deep-water r_{rs}^{dp} to account for bottom reflectance contribution:

$$r_{rs} = r_{rs}^{dp} \, \{1 - A_0 \exp[-(K_d + K_u^C) H]\} + A_1 \rho \exp[-(K_d + K_u^B) H]$$

rewrite $K_d = D_d(a + b_b)$, etc. to get

Our proposed SA formula for deep and shallow water r_{rs} is then

$$r_{rs} = (g_0 + g_1 u^{g_2}) u \left(1 - A_0 \exp\left\{-\left[\frac{1}{\cos(\theta_w)} + D_0(1 + D_1 u)^{0.5}\right] \alpha H\right\}\right) + A_1 \rho \exp\left\{-\left[\frac{1}{\cos(\theta_w)} + D_0'(1 + D_1' u)^{0.5}\right] \alpha H\right\}. \quad (11)$$

The values of $g_{0,1,2}$, $A_{0,1}$, $D_{0,1}$, and $D_{0,1}'$ are derived from Hydrolight-generated r_{rs} values.

$\alpha = a + b_b$, ρ is the bottom reflectance, θ_w is the in-water sun zenith angle, and H is the bottom depth

The IOPs a and b_b are modeled by simple formulas:

$$a(\lambda) = a_w(\lambda) + a_\phi(\lambda) + a_{CDOM}(\lambda)$$

$$a_\phi(\lambda) = \{a_0(\lambda) + a_1(\lambda) \ln [\, a_\phi(440) \,] \}\, a_\phi(440)$$

$a_0(\lambda)$ and $a_1(\lambda)$ are known generic phytoplankton spectral shapes

$$a_{CDOM}(\lambda) = a_{CDOM}(440) \exp [-0.015\, (\lambda - 440)]$$

$$b_b(\lambda) = b_{bw}(\lambda) + b_{bp}(400)\, (400/\lambda)^Y$$

$b_{bp}(400) = 0.018\, b_p(400)$ (assumes a Petzold phase function)

$$b_p(\lambda) = B\, Chl^{0.62}\, (550/\lambda)$$

Y is a function of $R_{rs}(440)/R_{rs}(490)$

$$R_{rs} = 0.518\, r_{rs} / (1 - 1.562\, r_{rs})$$

and so on (see the paper for details)

The final model thus relates R_{rs} to the

absorption, via $a_{CDOM}(440)$ and $a_{\phi}(440) = 0.06 Chl^{0.65}$
backscatter, via B
bottom reflectance ρ
bottom depth H

which are the unknowns to be retrieved from a measured hyperspectral $R_{rs}(\lambda)$

the sun zenith angle is known

Then used HydroLight for a wide range of input IOPs, bottom depths, sun angles, etc. to generate r_{rs} values, which were then fit with the model to determine the parameter values

Table 1. Environmental Input used in the Hydrolight Simulations

Variable	Inputs
Solar zenith angle	0°, 30°, 60°
Particle phase function	Petzold average particle
Chlorophyl a [chl-a] (mg m^{-3})	0.4, 1.0, 2.0, 5.0
$a_g(440)$ (m^{-1})	0.05, 0.1, 0.3
B	0.3, 1.0, 5.0
ρ	0, 0.1, 0.3, 1.0
H (m)	0.5, 1, 3, 8, 16, 32, infinite
λ (nm)	400–700, every 20 nm

used HydroLight to generate pseudo data for determining parameter values because no real data were available

$$
\begin{aligned}
r_{rs} \approx\ & (0.070 + 0.155u^{0.752})u\left(1 - 1.03\exp\left\{-\left[\frac{1}{\cos(\theta_w)} + 1.2(1 + 2.0u)^{0.5}\right]\alpha H\right\}\right) \\
& + 0.31\rho\exp\left\{-\left[\frac{1}{\cos(\theta_w)} + 1.1 \times (1 + 4.9u)^{0.5}\right]\alpha H\right\}. \qquad (21)
\end{aligned}
$$

Nonlinear minimization gives the final model with parameter values shown

The final model is then fit to a measured hyperspectral $R_{rs}(\lambda)$ spectrum using a predictor-corrector algorithm to retrieve IOPs and depth

initial guesses for $a_{CDOM}(440)$, $a_{\phi}(440)$, B, ρ, H

use SA model to predict $R_{rs}(\lambda)$

compare predicted and measured $R_{rs}(\lambda)$ to get error

accept values of $a_{CDOM}(440)$, $a_{\phi}(440)$, B, ρ, H when $R_{rs}(\lambda)$ error stops decreasing

adjust current values of $a_{CDOM}(440)$, $a_{\phi}(440)$, B, ρ, H

Note that no in situ measurements are required, other than $R_{rs}(\lambda)$ itself

Retrieved vs Measured Phytoplankton Absorption

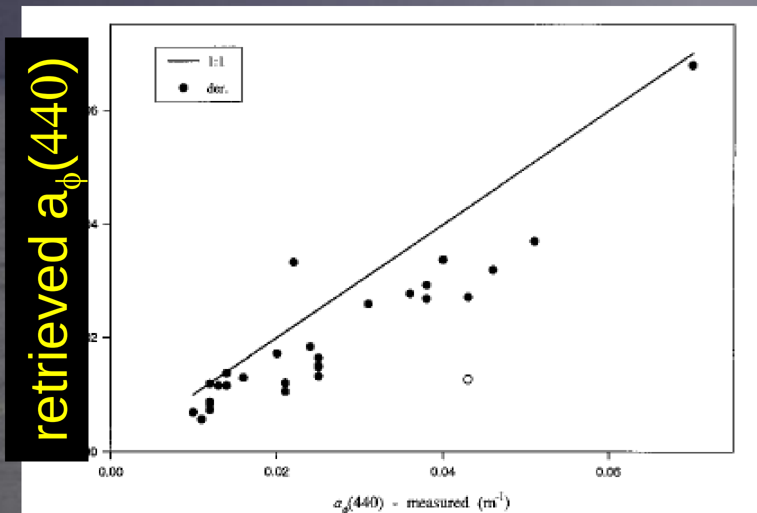


Fig. 13. Inve … ent at 440 nm compared … (The open circle one was …

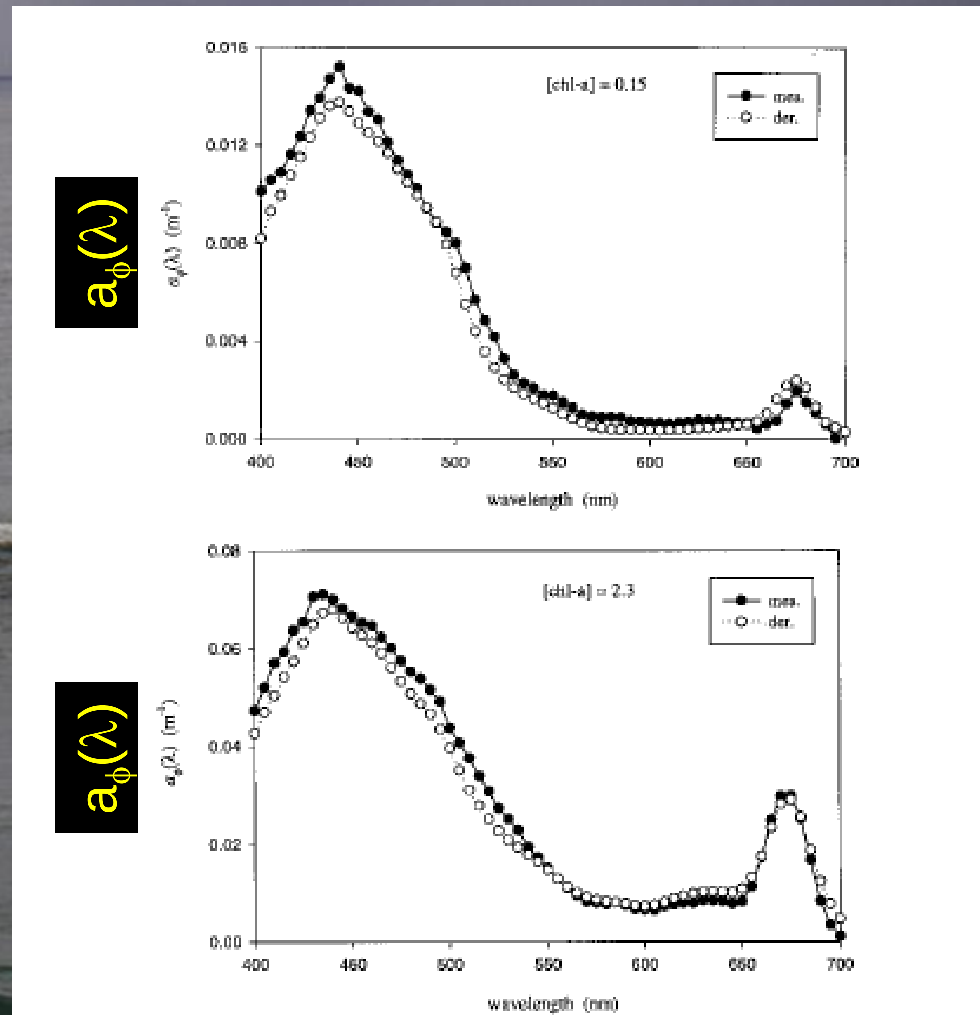


Fig. 14. Examples of inversion-derived versus pad-measured pigment absorption spectra.

Retrieved vs Measured CDOM Absorption and Depth

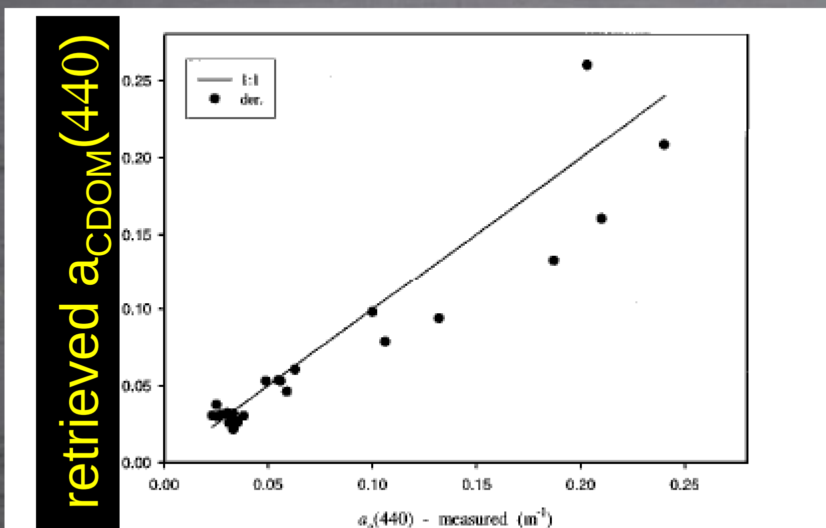


Fig. 15. Inve … at 440
nm compared

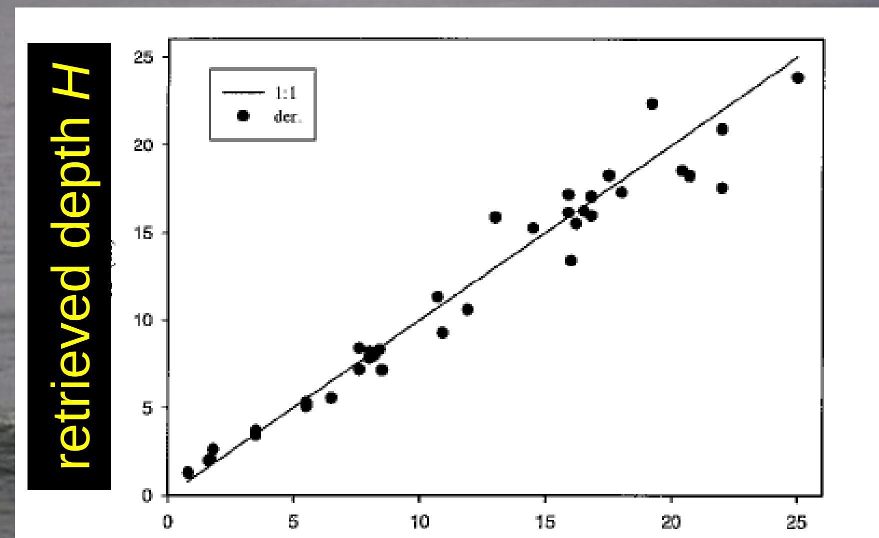


Fig. 12. Inve … h field data.

Spectrum Matching to a Database

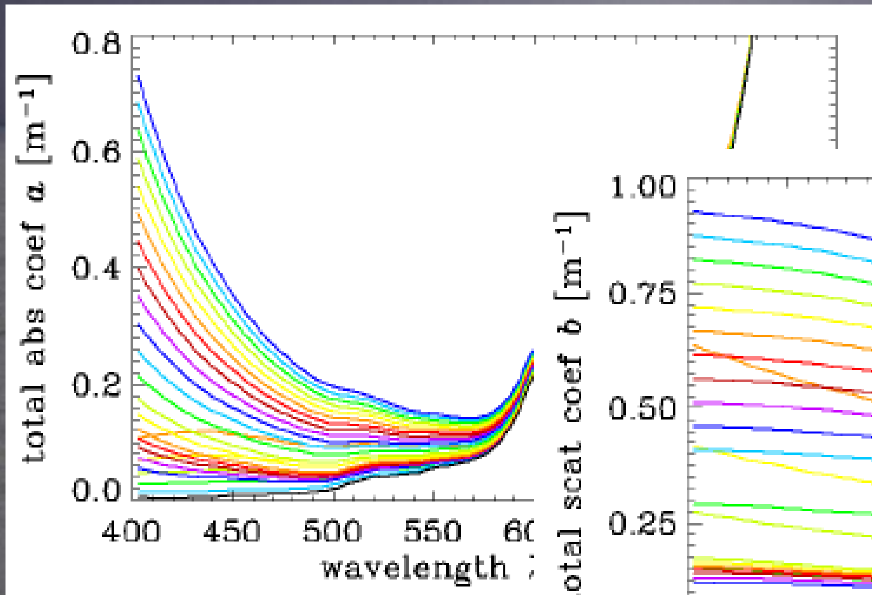
(Mobley et al., 2005. *Applied Optics*, 44(17), 3576-3592)

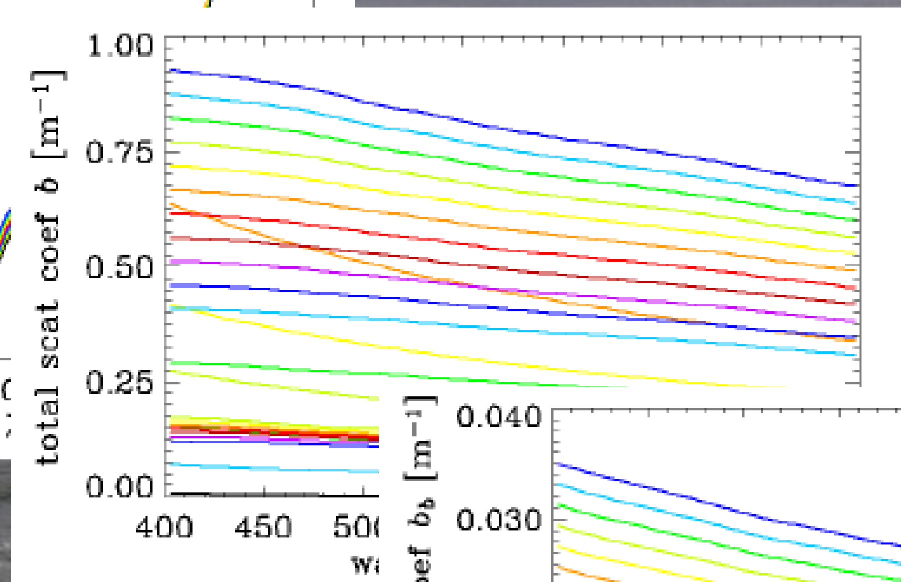
The first step is to create a database of R_{rs} spectra that correspond to all possible combinations of water absorption and scattering properties, bottom depths, and bottom reflectances that might be found in the area being studied.

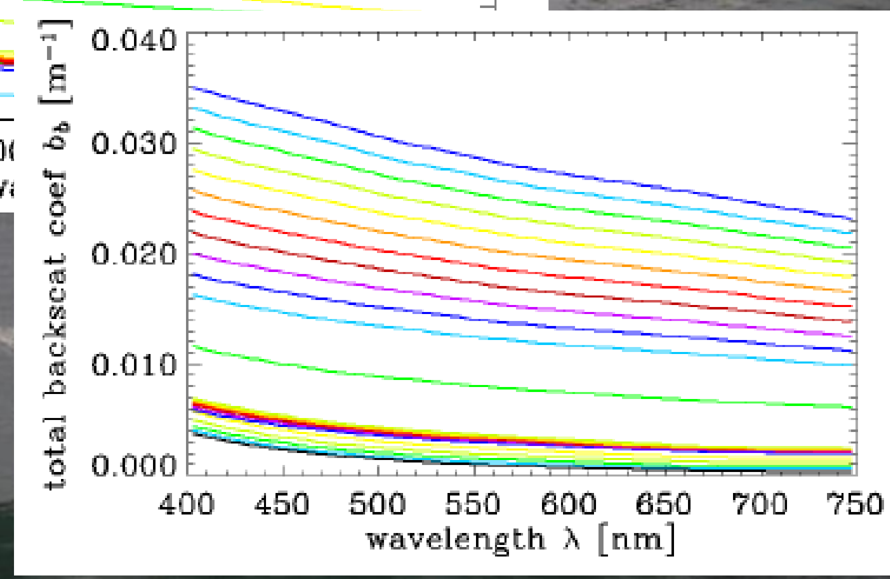
This is done with a special version of EcoLight (nadir-viewing R_{rs} only)

Then match image R_{rs} spectra to the database R_{rs} spectra.

R_{rs} Database Creation



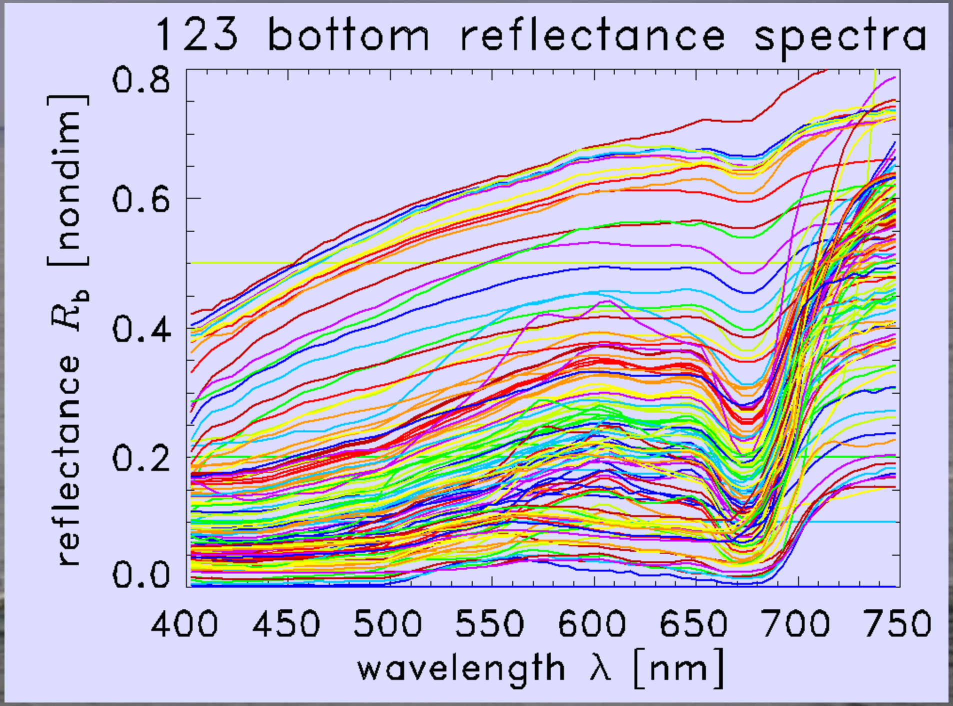




Many different absorption spectra, many different scattering spectra, and many different backscatter spectra. These spectra can be based on observations or models.

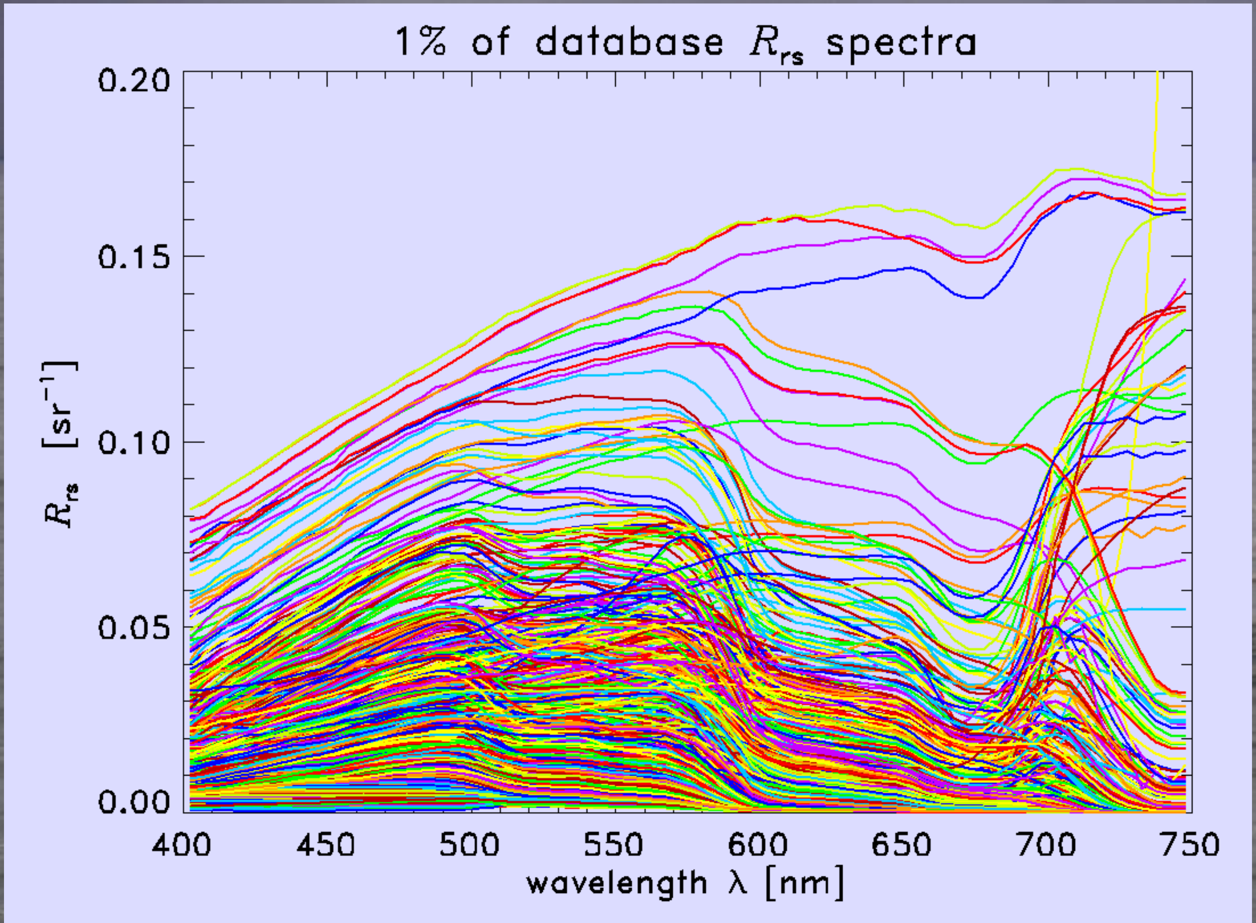
R_{rs} Database Creation

Many different bottom reflectance spectra (pure bottom types and mixtures of bottom types), with the bottom placed at many depths, e.g. z_b = 0.01, 0.25, 0.50, 0.75, 1.0, ...,14.75, 15.0, 15.5, ..., 19.5, 20, 25, 30, 50 m, and ∞



The database creation run shown here (for Bahamas waters) used 25 sets of water properties x 123 bottom reflectances x 83 depths, so 25 x 123 x 83 ≈ 250,000 EcoLight runs to generate 250,000 R_{rs} spectra from 400 to 750 nm by 5 nm (about a week of computer time on a 2 GHz PC)

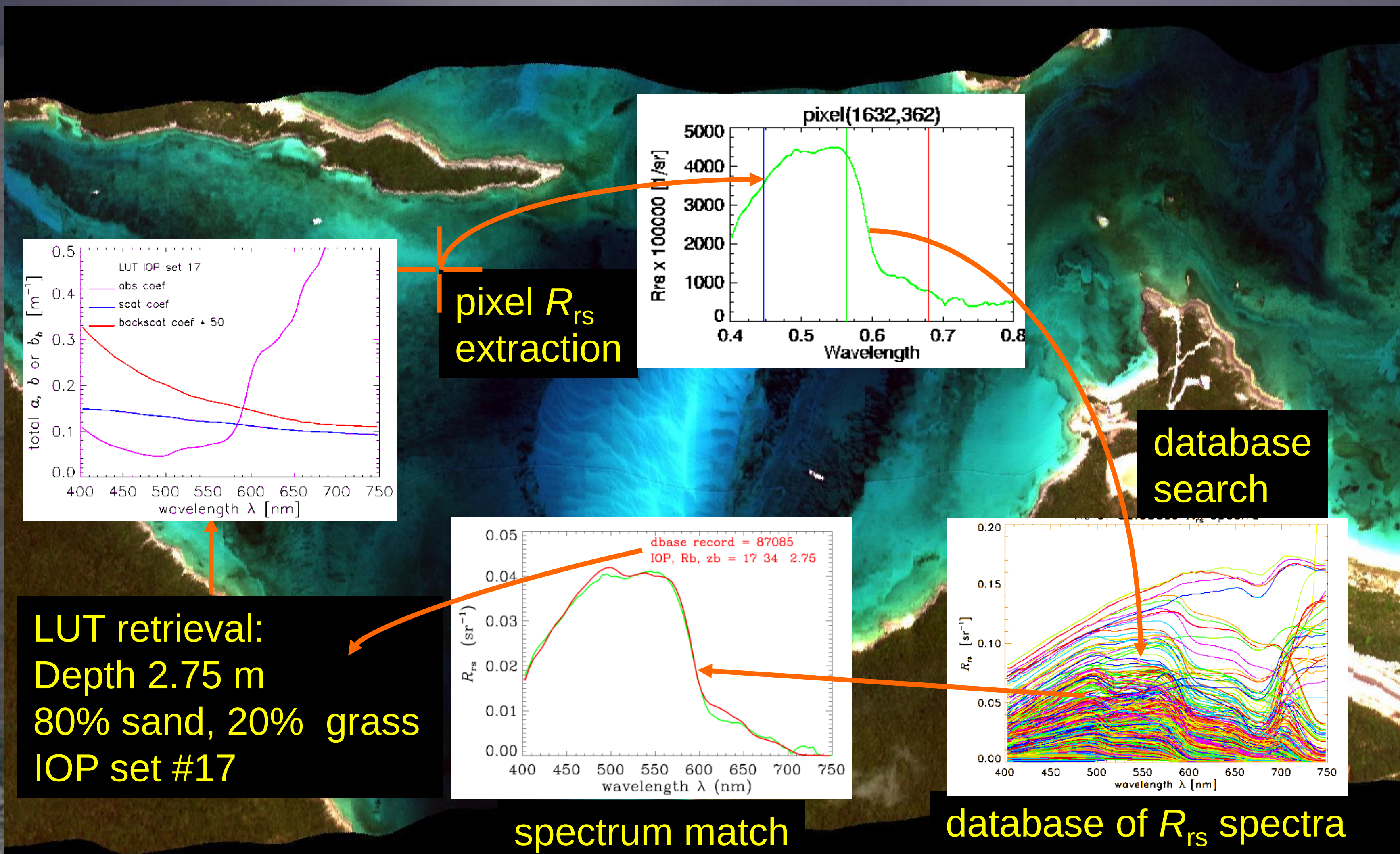
R_{rs} Database Creation



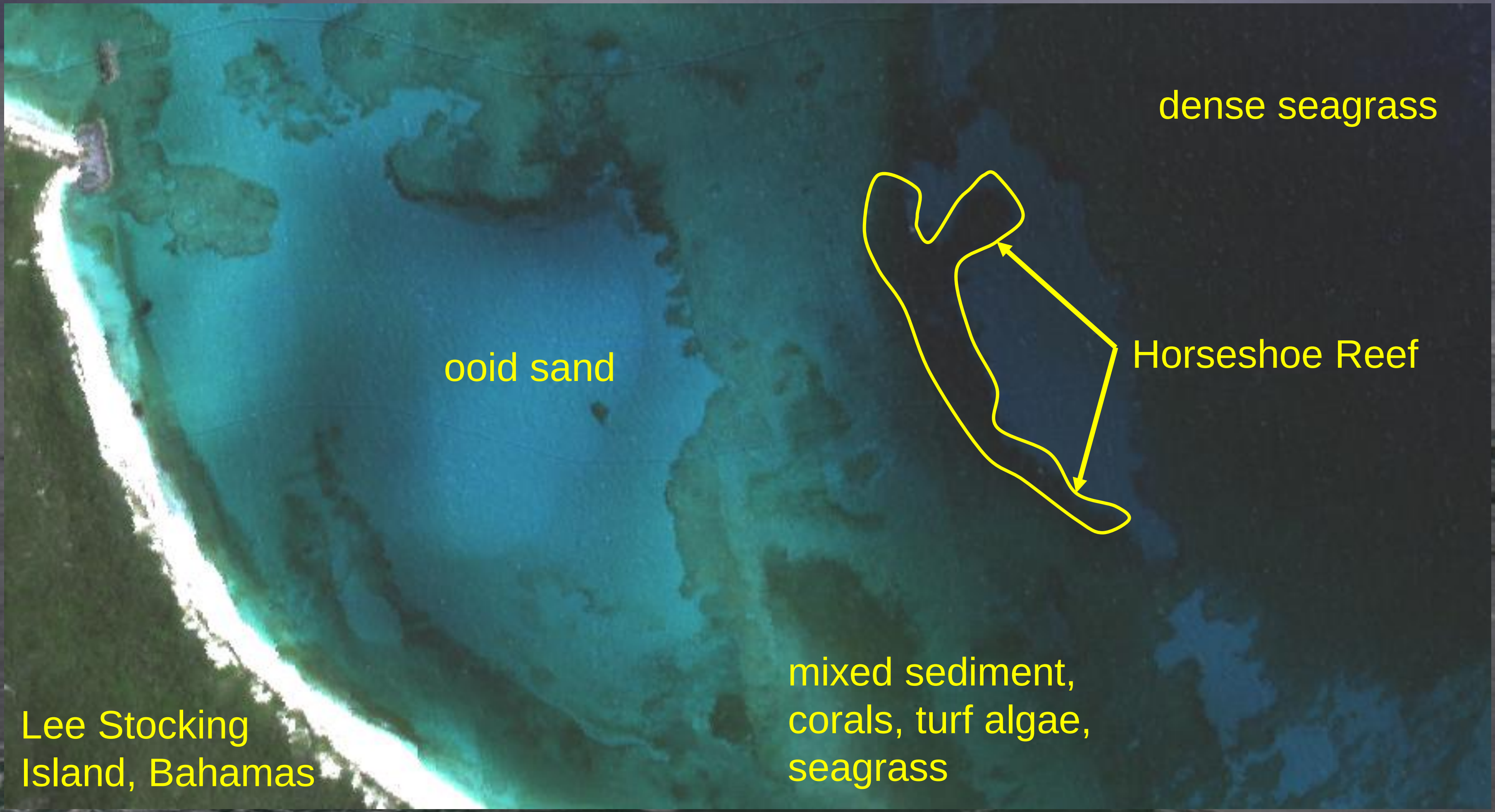
Each R_{rs} spectrum in the database corresponds to a known set of water properties (*a*, *b* and b_b spectra), a bottom reflectance spectrum (bottom type), and a water depth.

Image Processing

(after atmospheric correction)

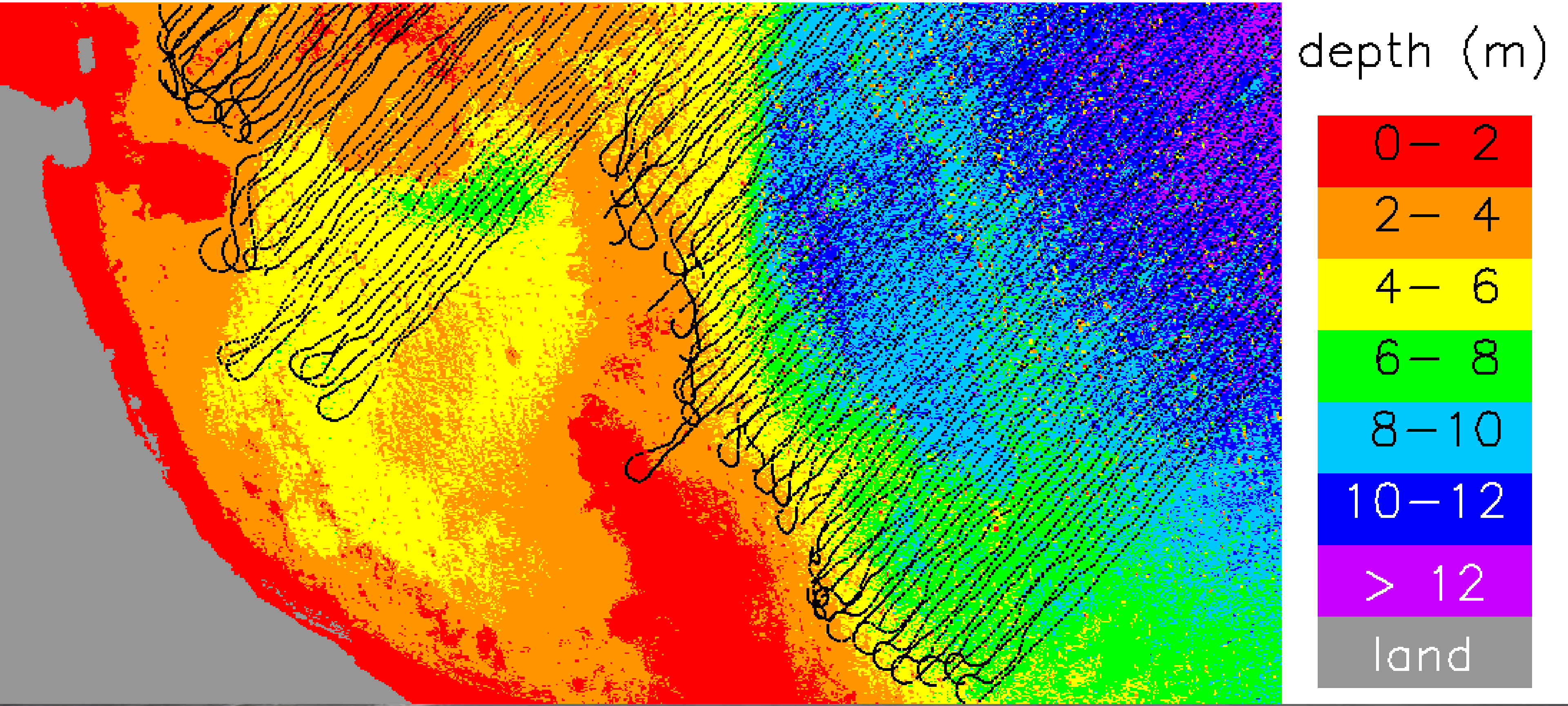


Example: Airborne Hyperspectral Image of Very Clear Water in the Bahamas



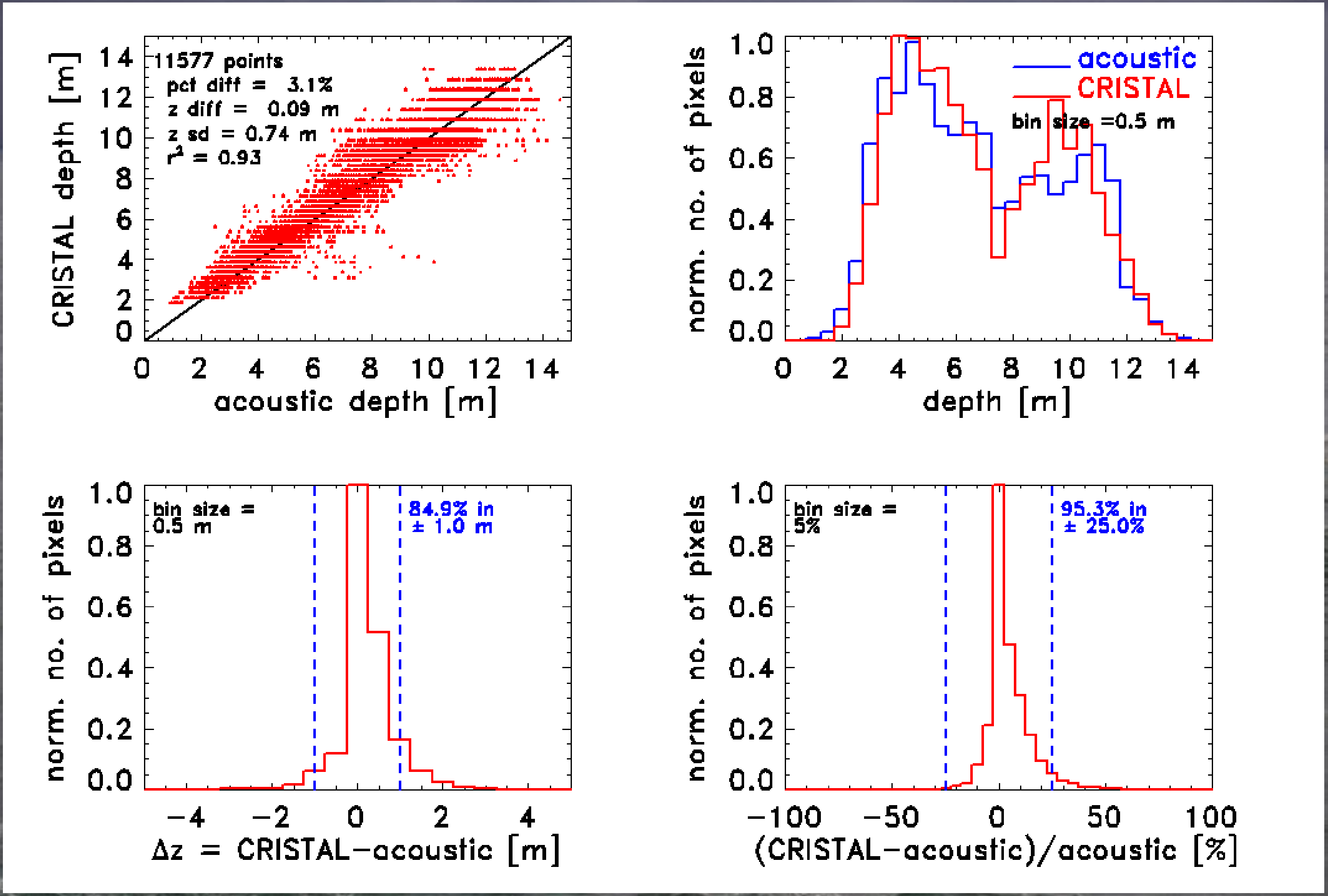
NRL-DC PHILLS image from ONR CoBOP program, May 2000
501x899 pixels at ~1.3 m resolution

Bathymetry Retrieval



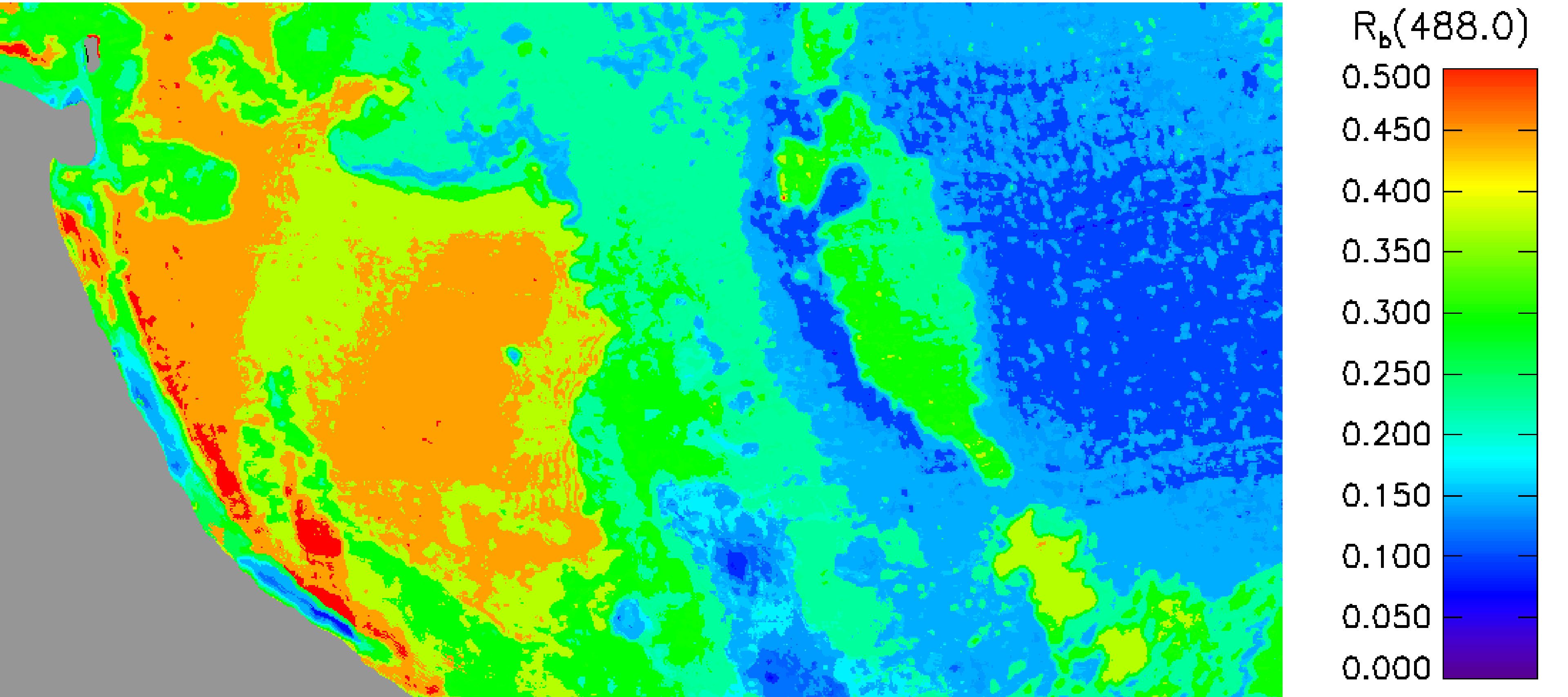
Black: NRL acoustic survey points for ONR CoBOP program
Color: depth retrieval

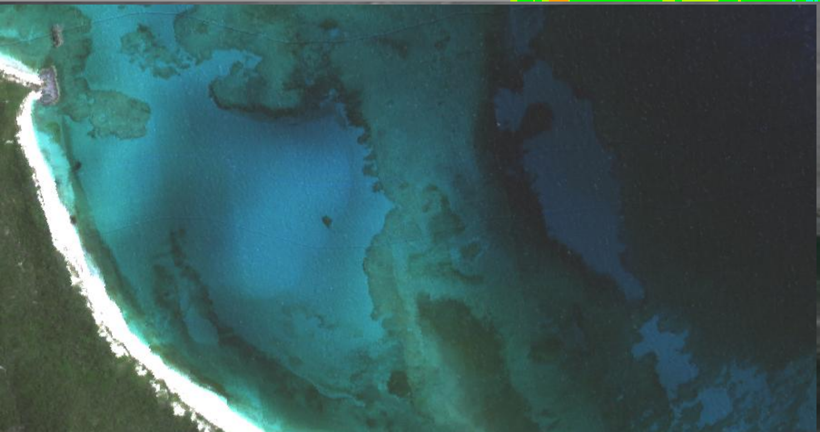
Depth Retrieval vs. Acoustic Bathymetry



These retrieval errors also include errors due to latitude-longitude calculations in mapping acoustic ping locations to image pixels (horizontal errors of several meters or more due to failure of built-in navigation instrument), and due to whitecaps

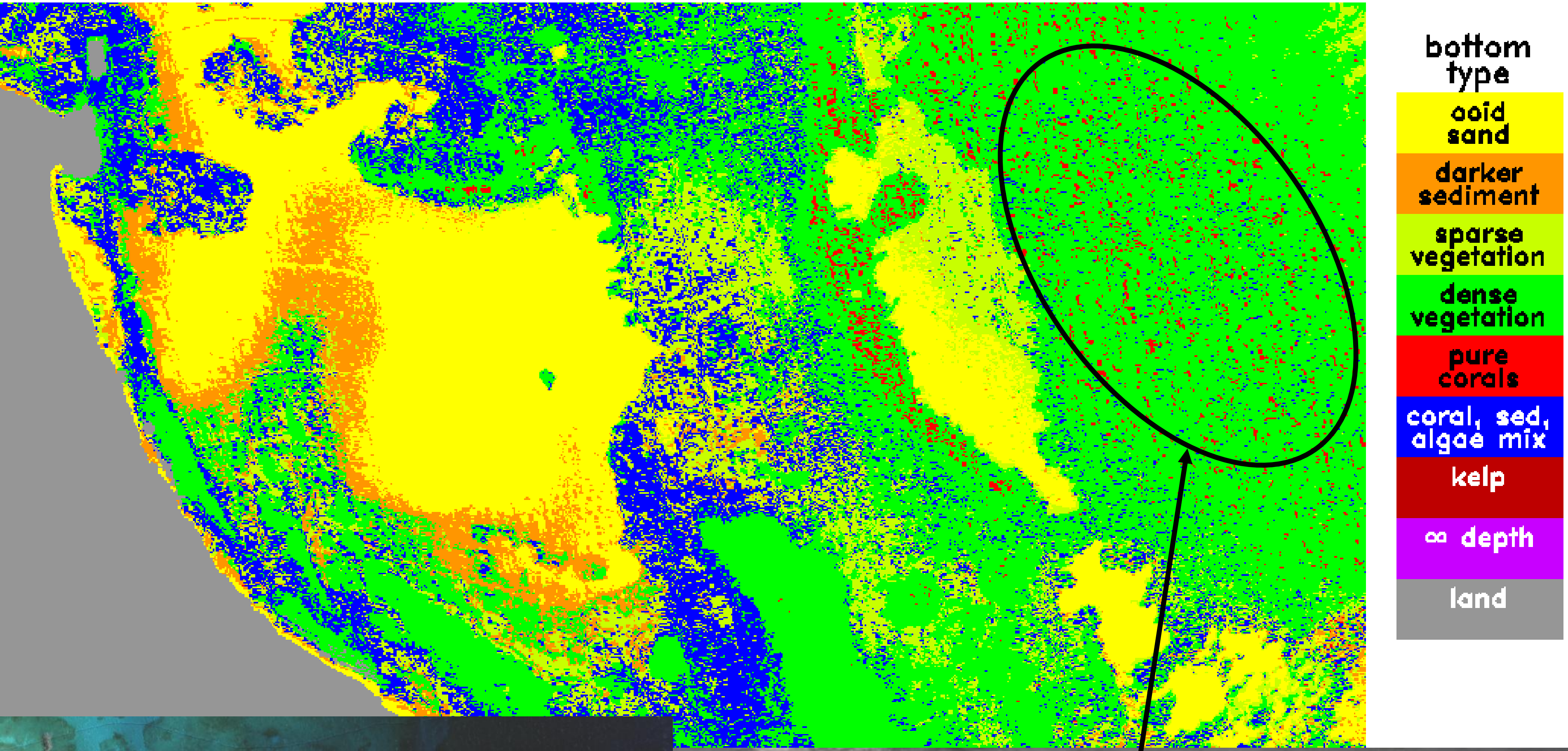
Bottom Reflectance

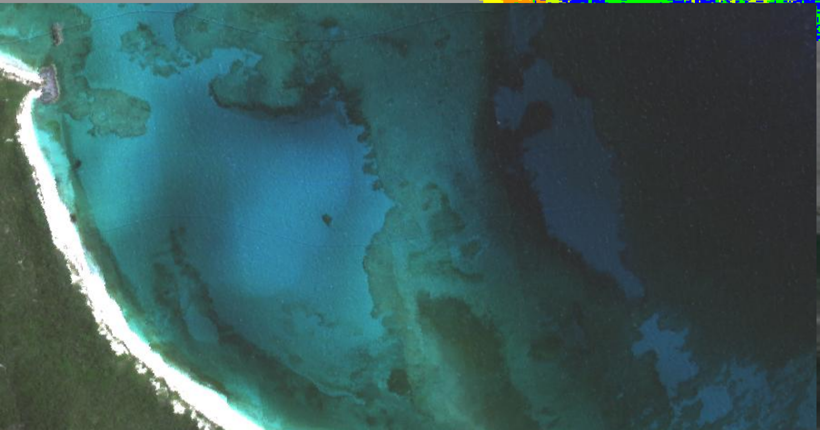




R_b(488) is what you would need for performance evaluation of a 488 nm bathymetric lidar

Bottom Classification



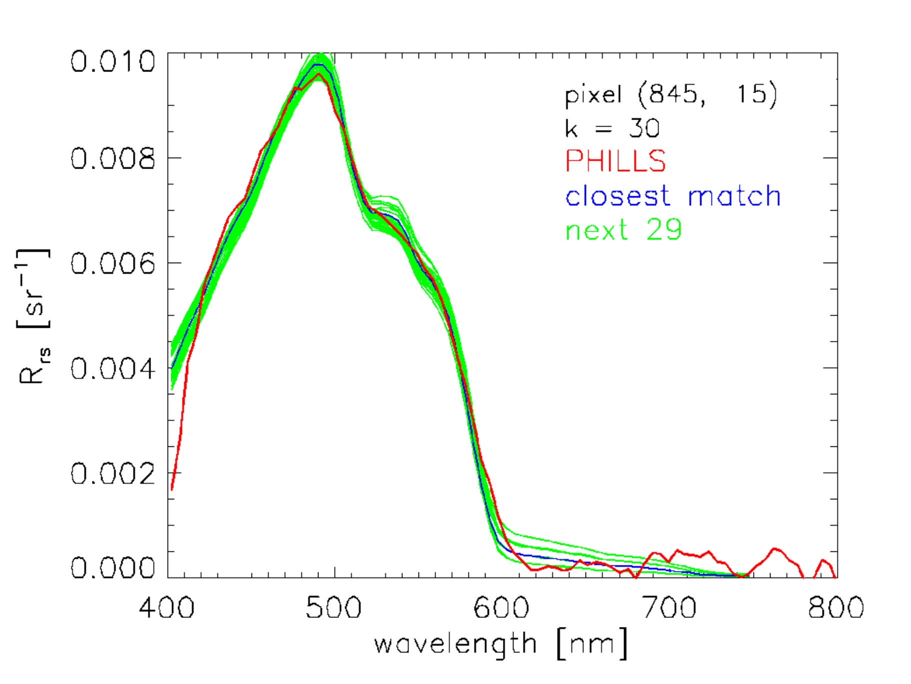


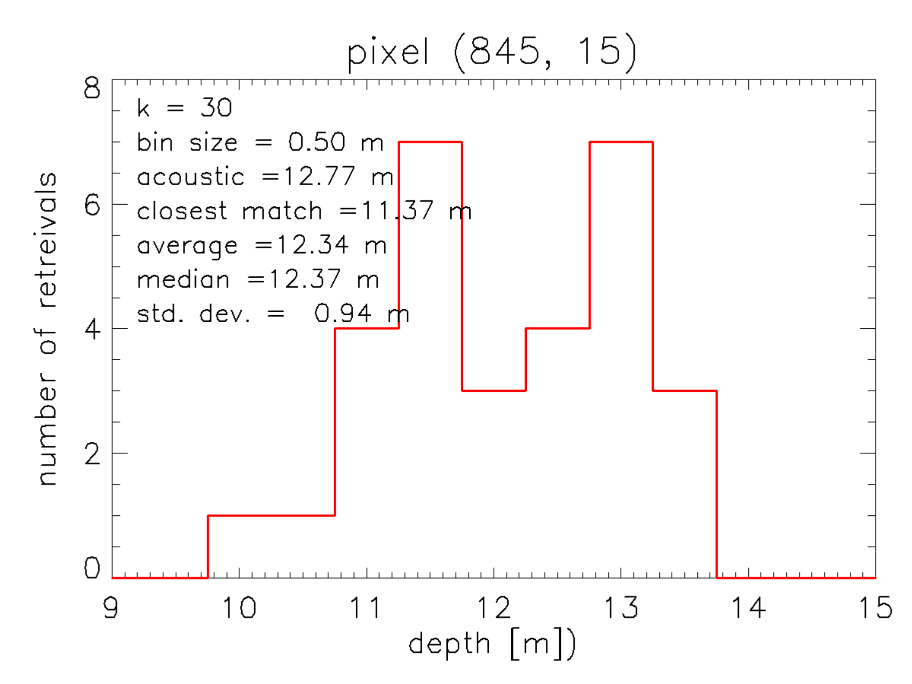
speckle due to whitecaps, which were not removed from the image spectra

kNN Error Analysis

Being able to place error bars or confidence estimates on retrievals is often as important as the retrieved value itself

Can do this statistically from the distribution of retrieved values for the *k* closest matching spectra (k Nearest Neighbors, or kNN)

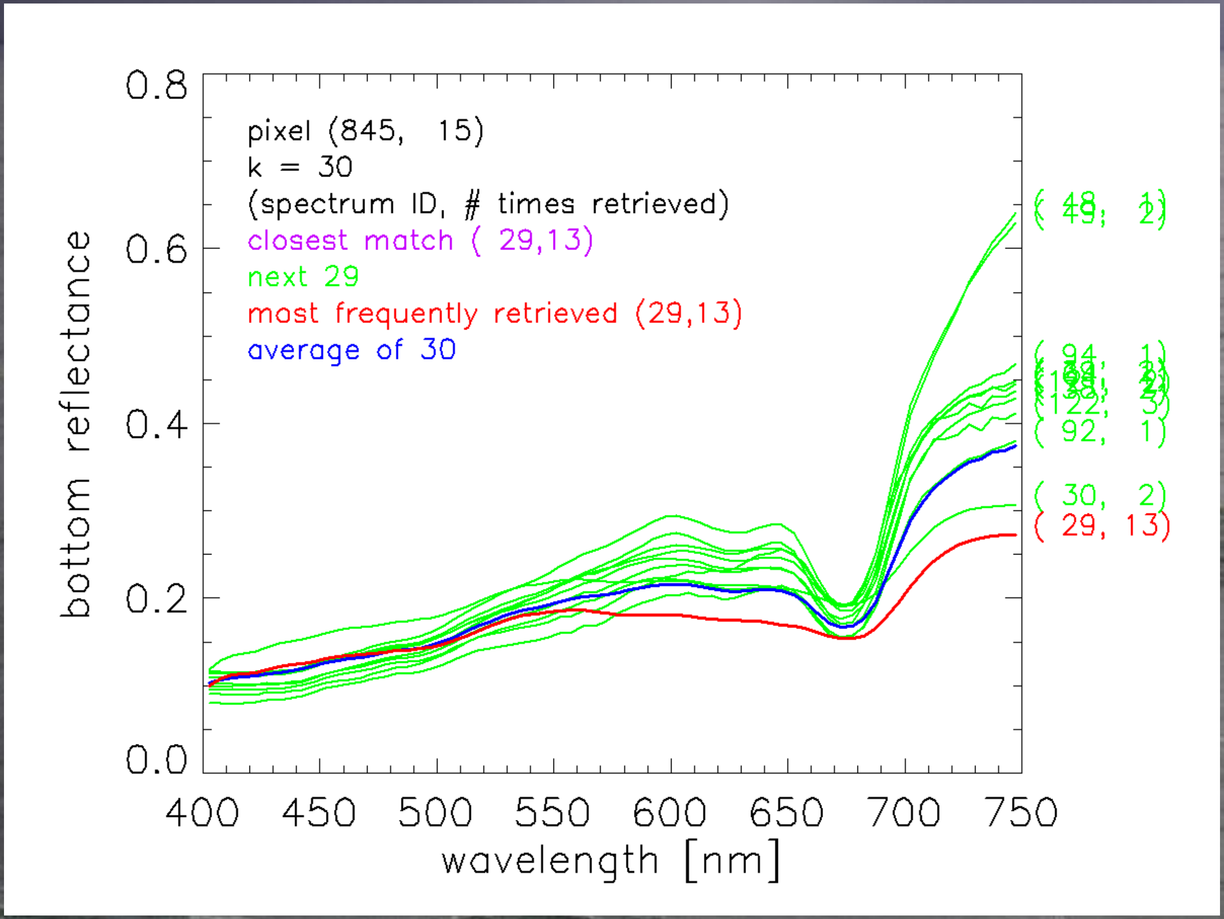




the 30 closest matches give a histogram of retrieved depths

the average or median gives a better estimate of the depth, plus an error estimate

kNN Error Analysis

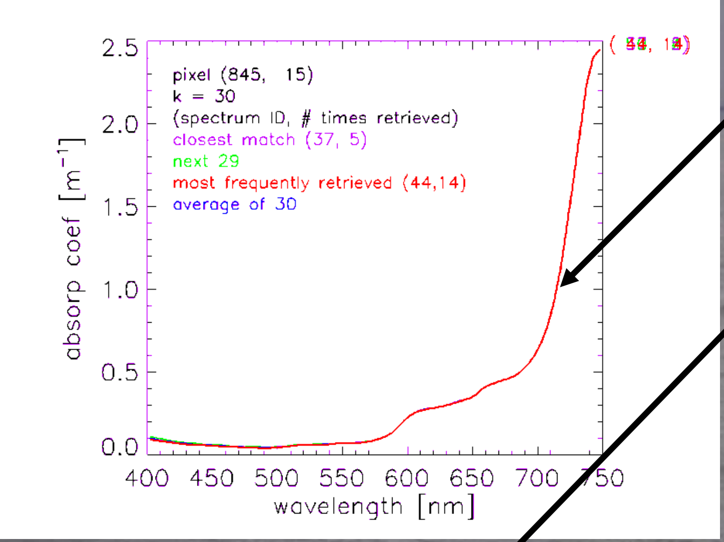


The closest and most frequently retrieved bottom reflectance spectrum was 30% sand and 70% seagrass.

The other bottoms are similar mixtures of sand and grass, sargassum, turf algae, and macrophytes.

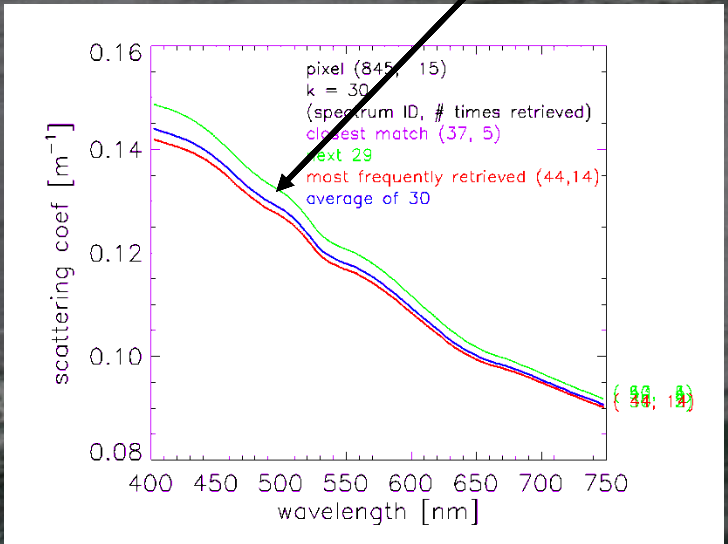
So we can be fairly certain that the bottom is dense vegetation, probably sea grass

kNN Error Analysis

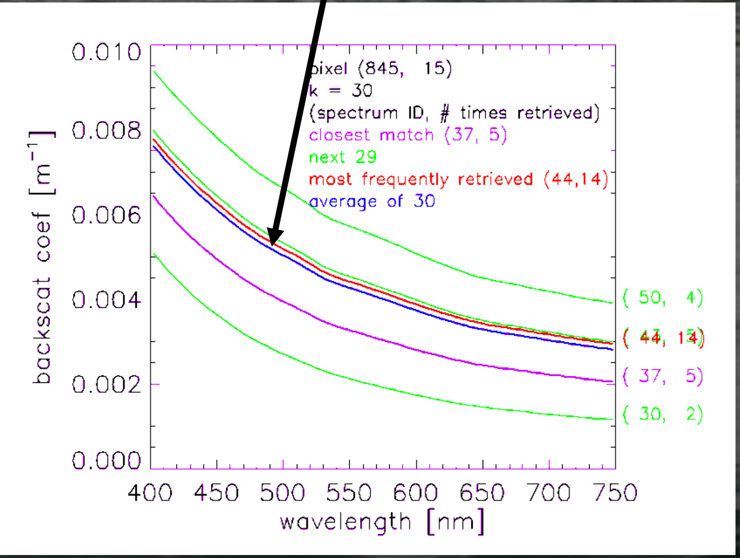


The retrieval is very certain about the absorption coefficient

The retrieval is fairly certain about the scattering coefficient



The retrieval is UNcertain about the backscatter coefficient



Does This Make Sense?

- In these very clear waters, the water absorption determines how much light gets to the bottom and back to the surface. Water-column scattering and backscatter contribute less to the water-leaving radiance in shallow water than does the bottom reflectance.

- The retrieval was therefore most certain about the absorption coefficient, and least certain about backscatter.

- The bottom reflectances all had similar reflectance spectra because it's the reflectance that is important. The retrieval wasn't able to distinguish between sea grass, turf algae, *sargassum*, and macrophytes, which all have similar reflectances.

- In very shallow (<5 m) clear water, the retrieved bottom reflectance becomes very certain and the water scattering and backscatter very uncertain (i.e., least important in determining R_{rs})

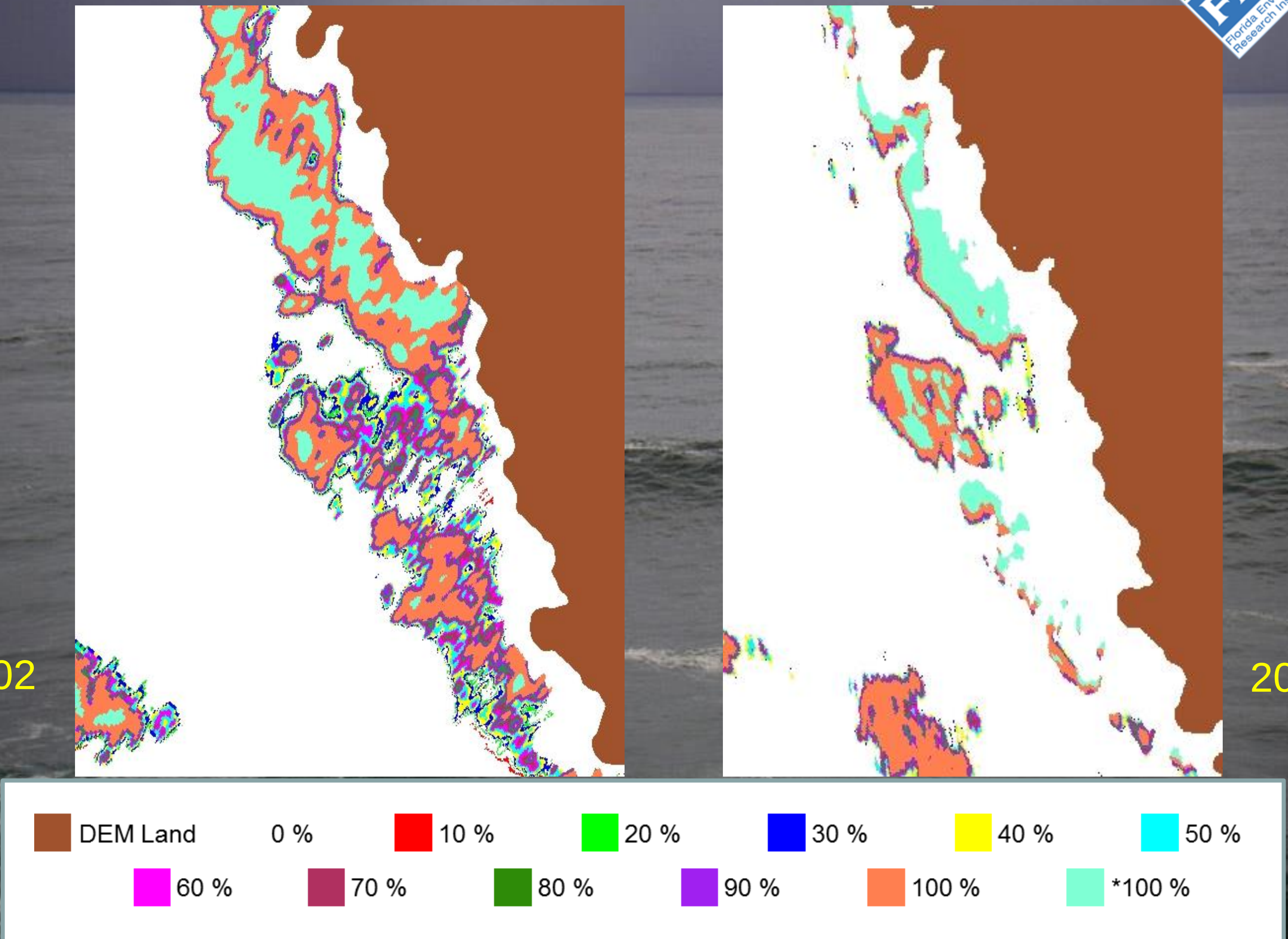
Kelp Mapping

http://www.beachwatchers.wsu.edu/ezidweb/seaweeds/Nereocystis.htm

Bull kelp (*Nereocystis luetkeana*) is very important for food, medicines, sheltering of fish, and recreational diving. Harvesting is strictly managed in the US.

http://www.bestpicturesof.com/misc/pictures%20of%20bull+kelp/?page=2#Google

Mapping of Kelp Coverage California Coast



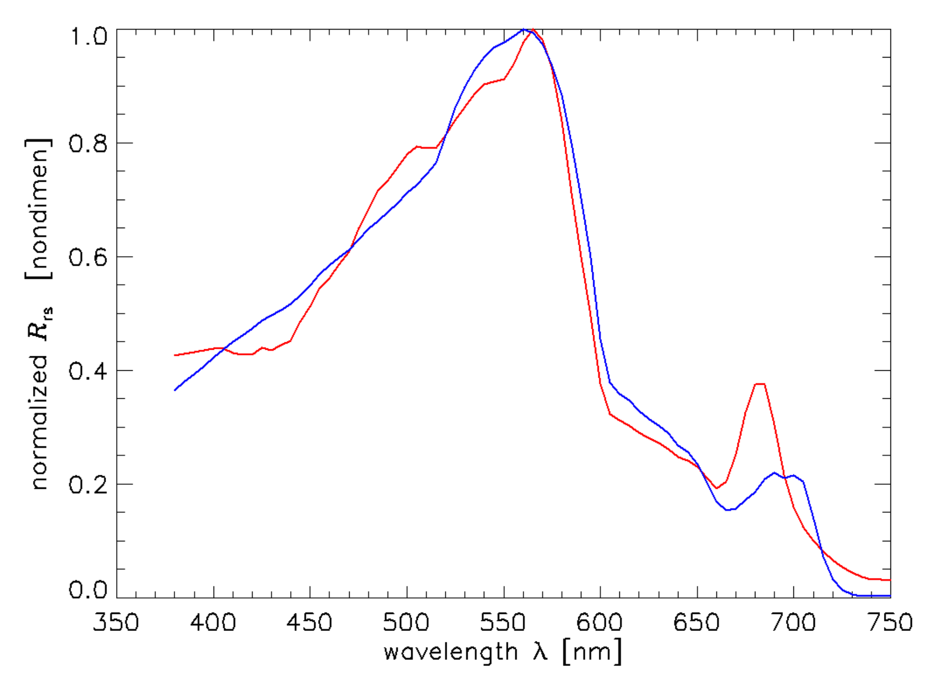
Humboldt Bay California
Eel Grass Mapping

Chaeli Judd, MS Thesis, Judd et al., 2006

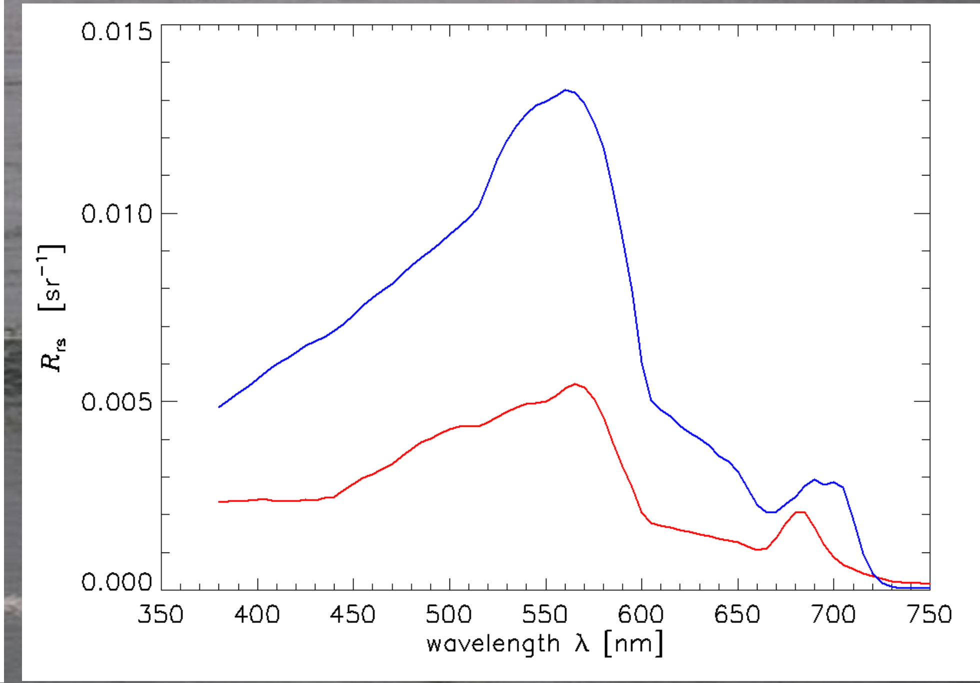
HSI determined eel grass distributions, previously unknown.

Uniqueness: Not a Problem (yet?)

Having well calibrated R_{rs} spectra removes the non-uniqueness that plagues band-ratio and other techniques that depend only on spectral shape. Both spectral shape and magnitude are critical.



normalized R_{rs} spectra



calibrated R_{rs} spectra

Red: infinitely deep water, Chl = 10 mg m^{-3}

Blue: 2 m deep clear water, sea grass bottom

नमस्ते

Kathmandu, Nepal, 2011