Ocean Optics Summer Class

Calibration and Validation for
Ocean Color Remote Sensing

Shallow-water Remote Sensing

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Delivered at the Darling Marine Center
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SEQUOIA

HYDROLIGHT

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

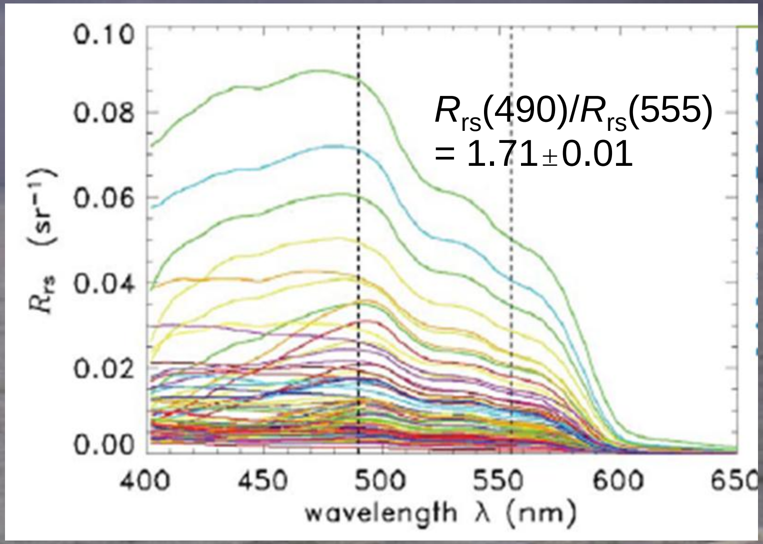
- Ecosystem managers need to map and monitor bottom type and water quality for management of coral reefs, sea grass beds, kelp forests, fisheries, and recreation
  - episodic (hurricane effects, harmful algal blooms, pollution events)
  - long-term (global climate change, anthropogenic changes from coastal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

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

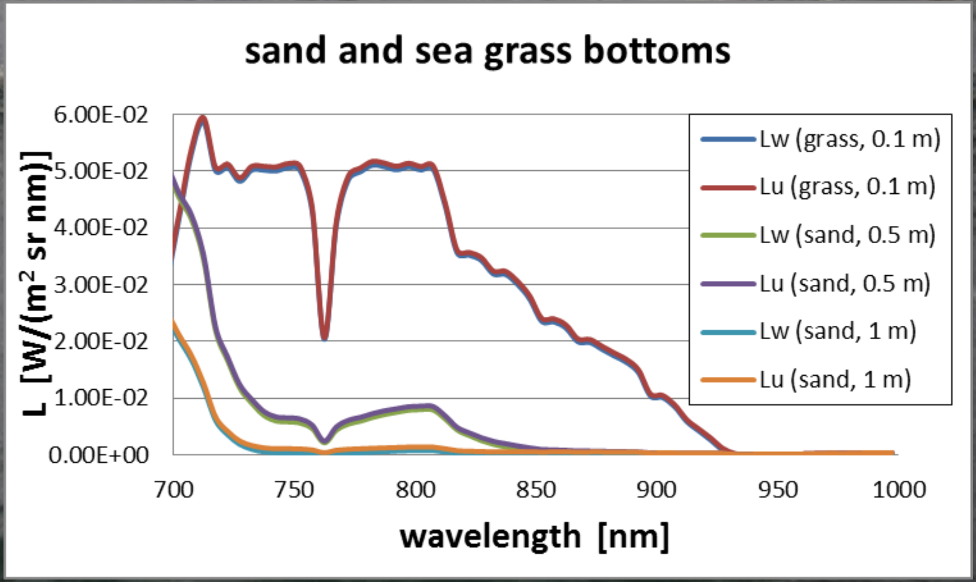
Problems

We have already seen that…

- Statistical algorithms often fail in optically shallow waters (bottom-reflectance effects)



- Black-pixel and similar open-ocean atmospheric correction algorithms also fail for shallow water (bottom reflectance; absorbing aerosols from nearby land)



Atmospheric Correction

We need 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)

Two techniques:

- Empirical Line Fit (ELF)
- Radiative transfer

Empirical Line Fit (ELF)

Estimate L_w at the sea surface at a particular location (x_o,y_o) within the image.

The difference in the estimated $L_w(x_o,y_o,\lambda)$ and the measured at-sensor radiance looking at that point, $L_u(x_o,y_o,\lambda)$, is the contribution by surface reflectance and all atmospheric path radiances:

$L_{diff}(x_o,y_o,\lambda) = L_u(x_o,y_o,\lambda) - L_w(x_o,y_o,\lambda)$

Assume that the atmosphere, solar illumination, and surface wave conditions are the same for every pixel of the entire image.

Subtract the same L_{diff} from L_u(sensor) viewing each pixel (x,y) to obtain L_w(surface) at each pixel in the image:

$L_w(x,y,\lambda) = L_u(x,y,\lambda) - L_{diff}(x_o,y_o,\lambda)$ This is the ELF technique

Empirical Line Fit (ELF)

Determining L_w has the problem of above-surface (what is ρ in the Carder method?) or below-surface (what is K_{Lu}?) estimation.

The major drawback of this atmospheric correction technique is that it requires someone in the field, usually in a small boat, to make the needed sea-surface measurements at the time of the overflight.

An ELF based on a single point measurement of R_{rs} 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.

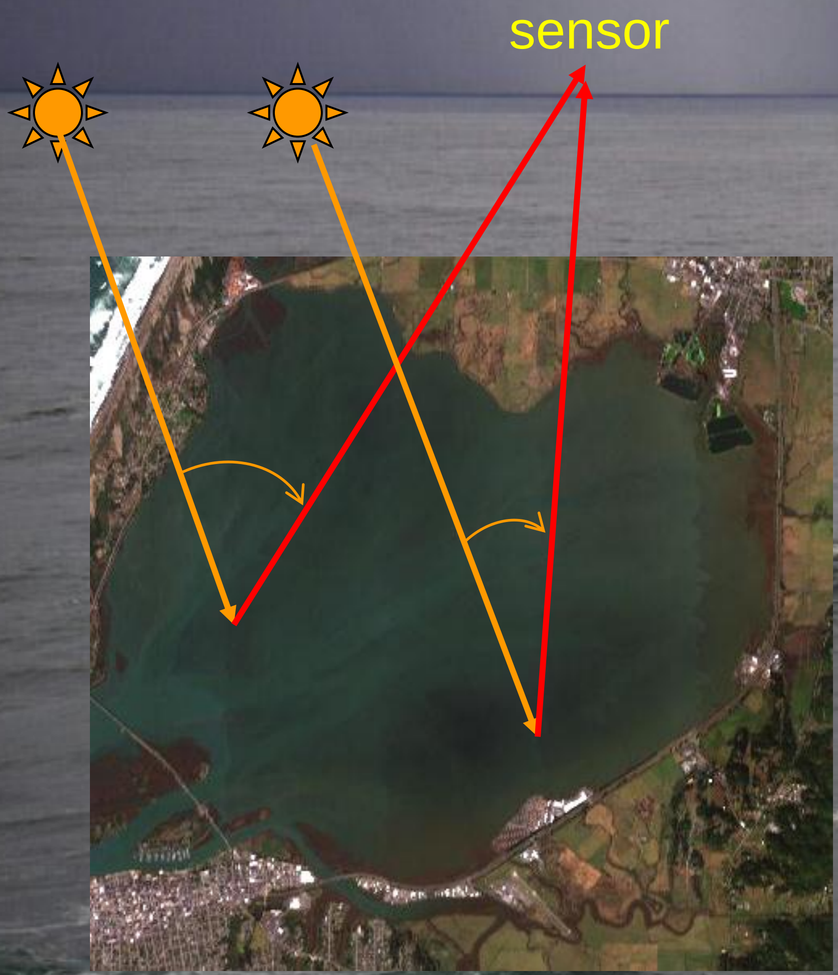
Radiative Transfer Techniques

If we know (or can estimate) the inherent optical 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 and is used by several research groups (see the TAFKAA references in the papers directory).

TAFKAA has been used to create large look-up tables for various wind speeds, sun angles, viewing directions, and atmospheric properties (aerosols, surface pressure, humidity, etc). These calculations required ~6×10^7 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 atmospheric prediction models.

Spectrum Matching and Look-Up-Table R_{rs} Inversion

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

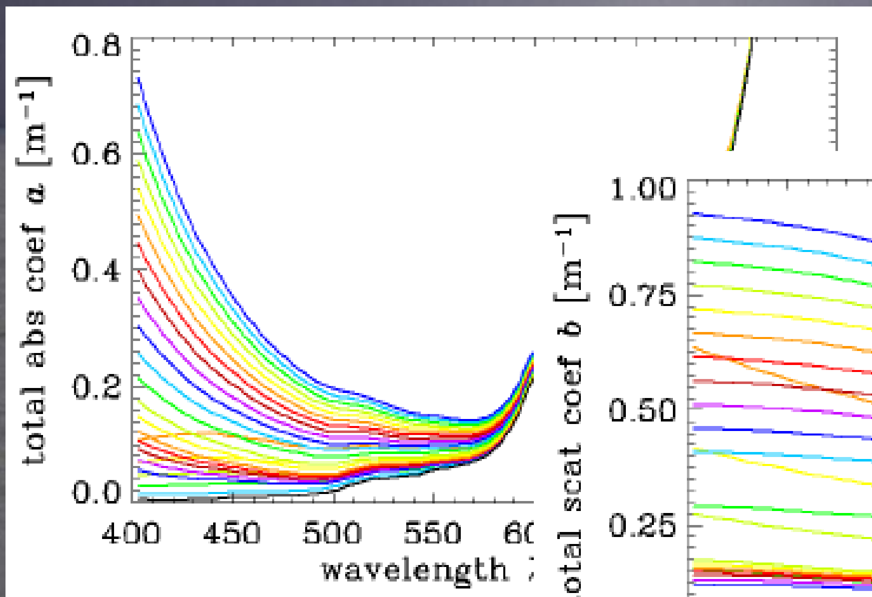
Radiative-transfer-based algorithms for hyperspectral sensors (~100 wavelengths, ~5 nm bandwidth) have shown great promise for coastal and shallow waters

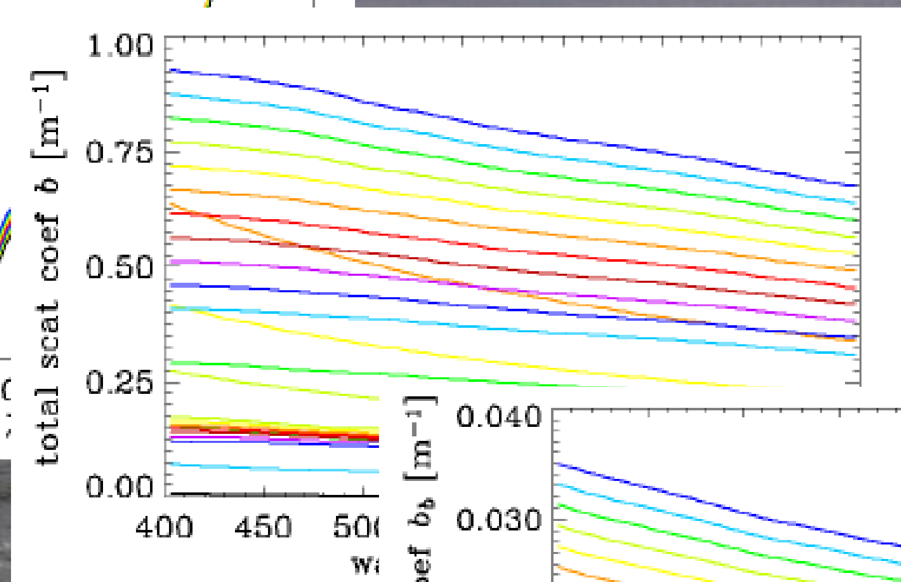
The first step is to create a database of R_{rs} spectra that correspond to all possible combinations of water absorption and scattering properties, bottom depths, and bottom reflectances that might be found in the area being studied.

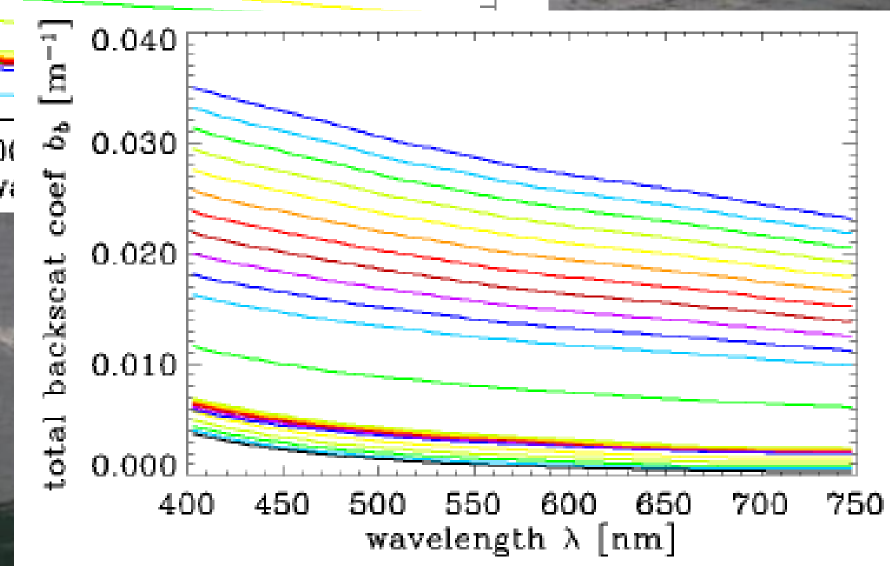
I do this with a special version of EcoLight (nadir-viewing R_{rs} only)

$$R_{rs}(\text{in air}, \theta, \varphi, \lambda) \equiv \frac{L_w(\text{in air}, \theta, \varphi, \lambda)}{E_d(\text{in air}, \lambda)} \qquad [\mathrm{sr}^{-1}]$$

R_{rs} Database Creation



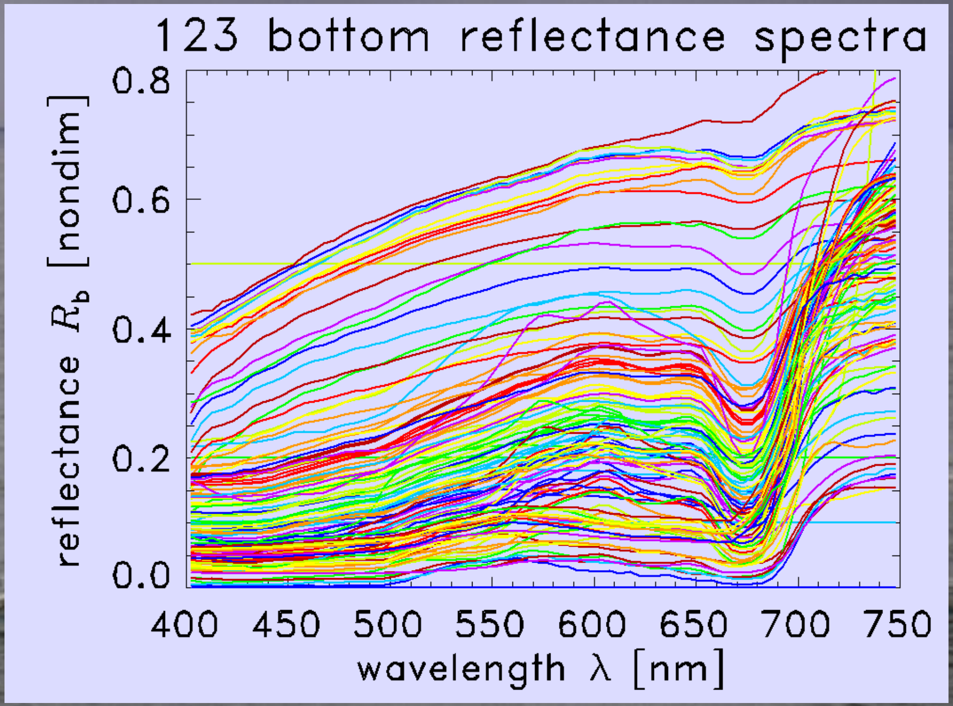




Many different absorption spectra, many different scattering spectra, and many different backscatter spectra. These spectra can be based on observations or models.

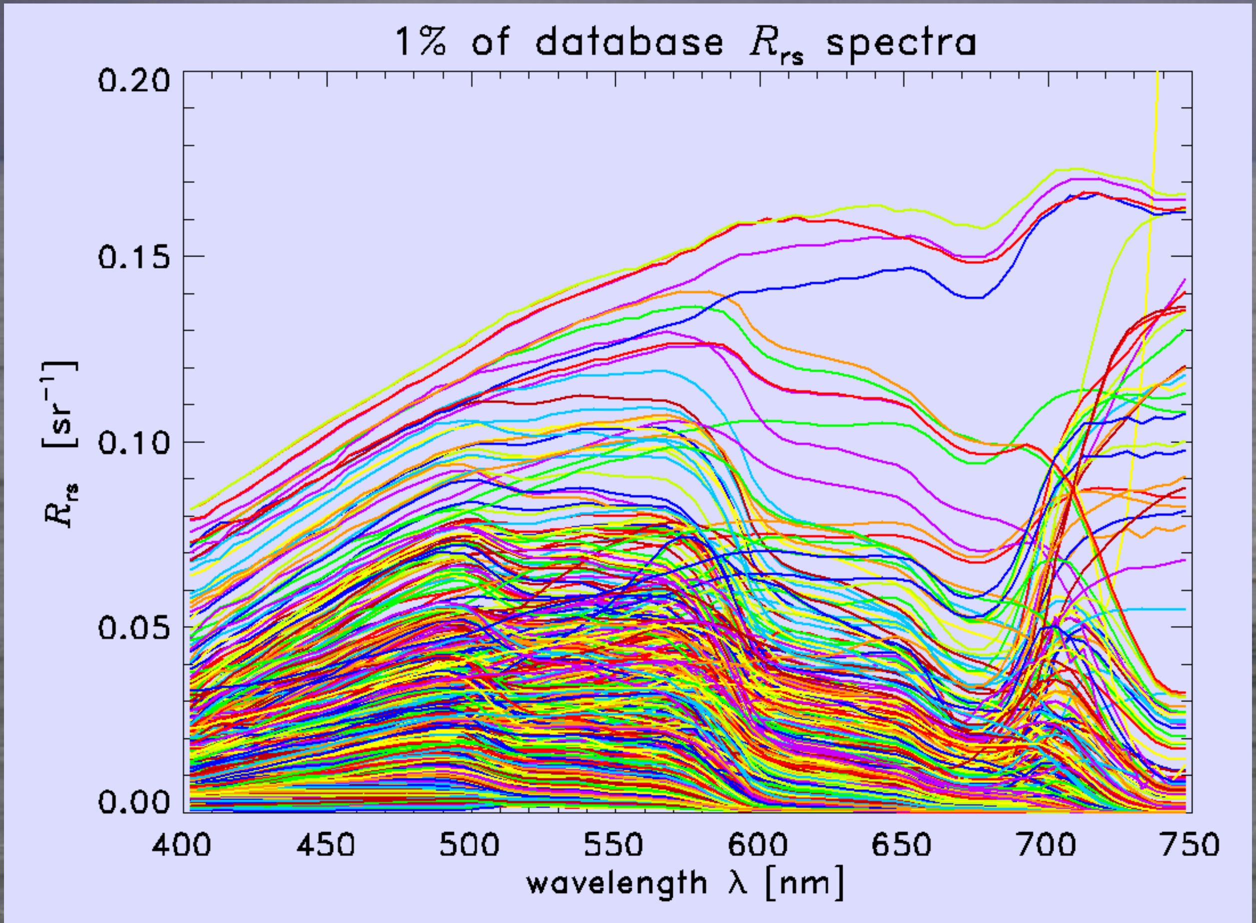
R_{rs} Database Creation

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)

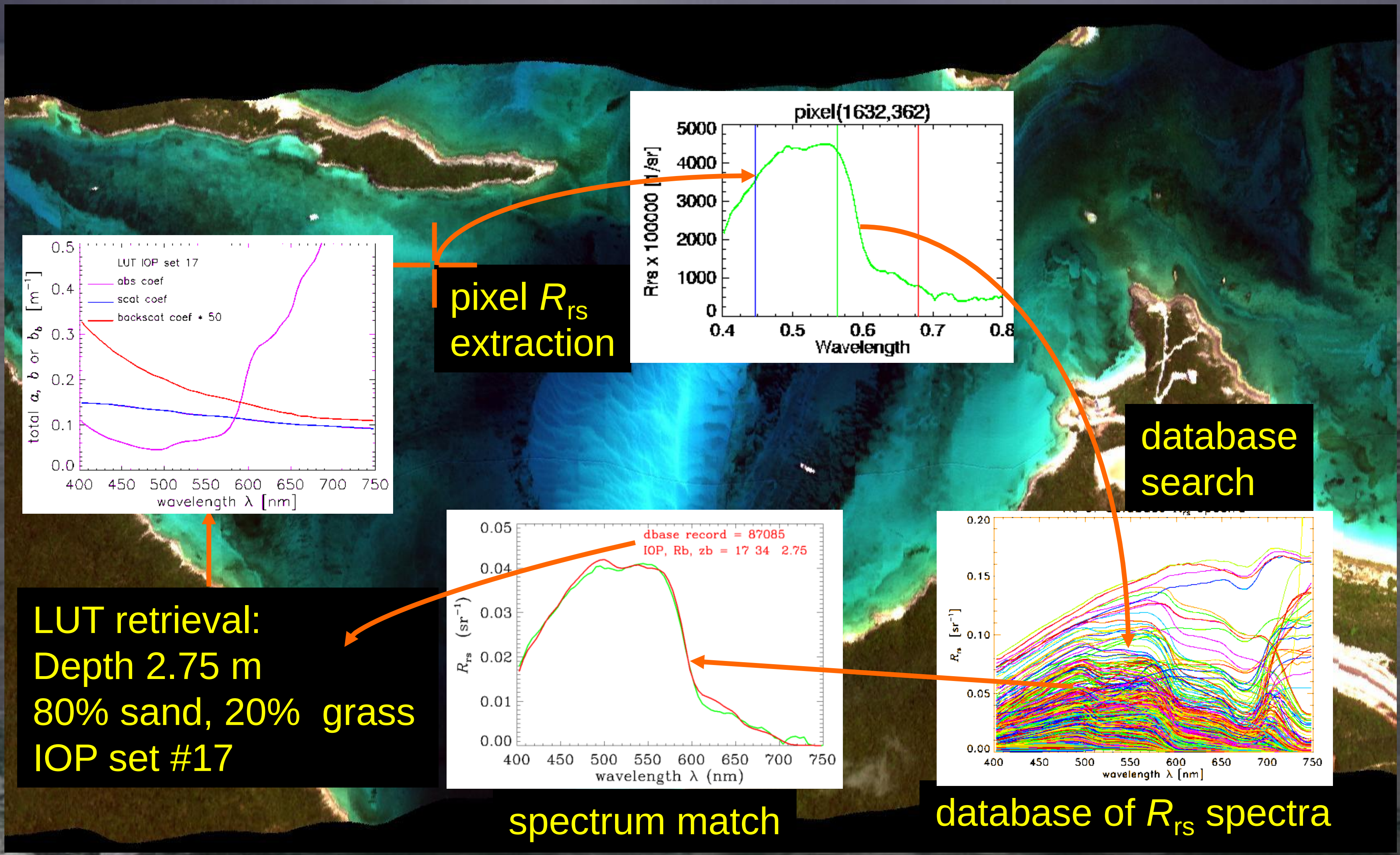
R_{rs} Database Creation



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)



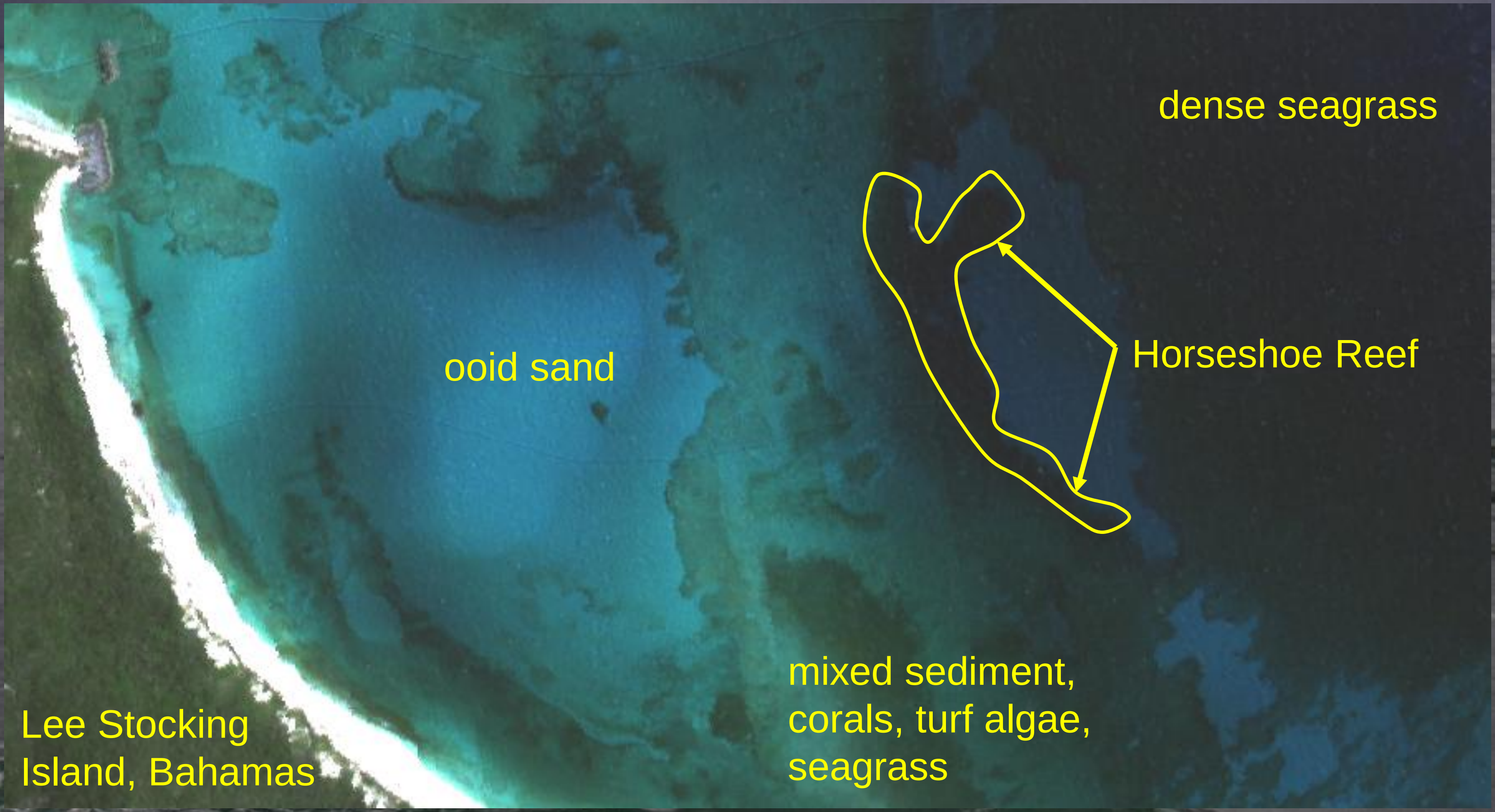
CRISTAL

The following results were generated using CRISTAL

CRISTAL ~~METH~~ (Comprehensive Reflectance Inversion based on Spectrum matching and TAble Lookup, ~~Multi-Environmental Techniques based on HydroLight~~) is a software package developed by me to handle the creation of R_{rs} databases, retrieval of environmental properties (water IOPs, bottom depth, and bottom reflectance or type) from hyperspectral imagery, and display of retrieved results.

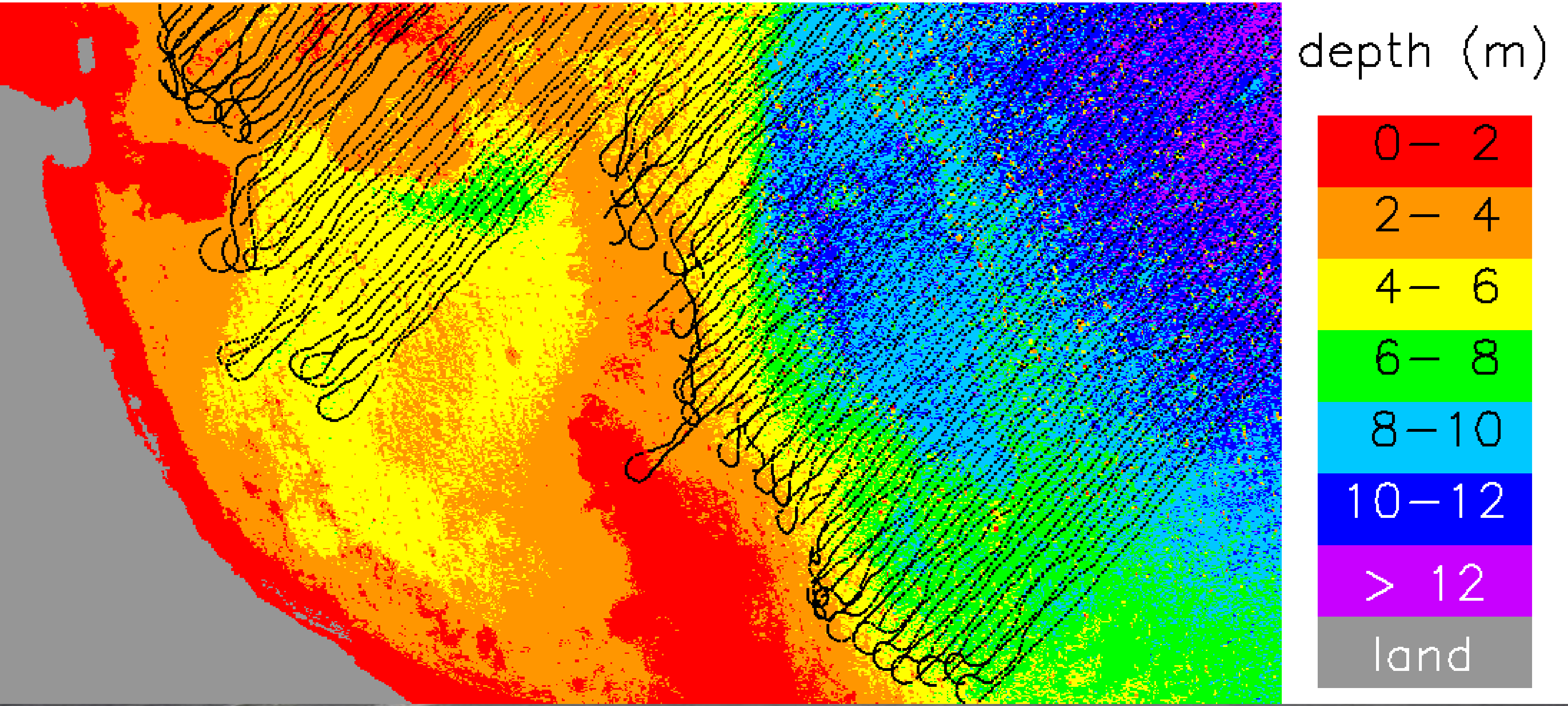
CRISTAL is currently in beta testing by the U.S. Navy. The code and processing details are still proprietary, but publications will be submitted asap and the code will eventually be made public.

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



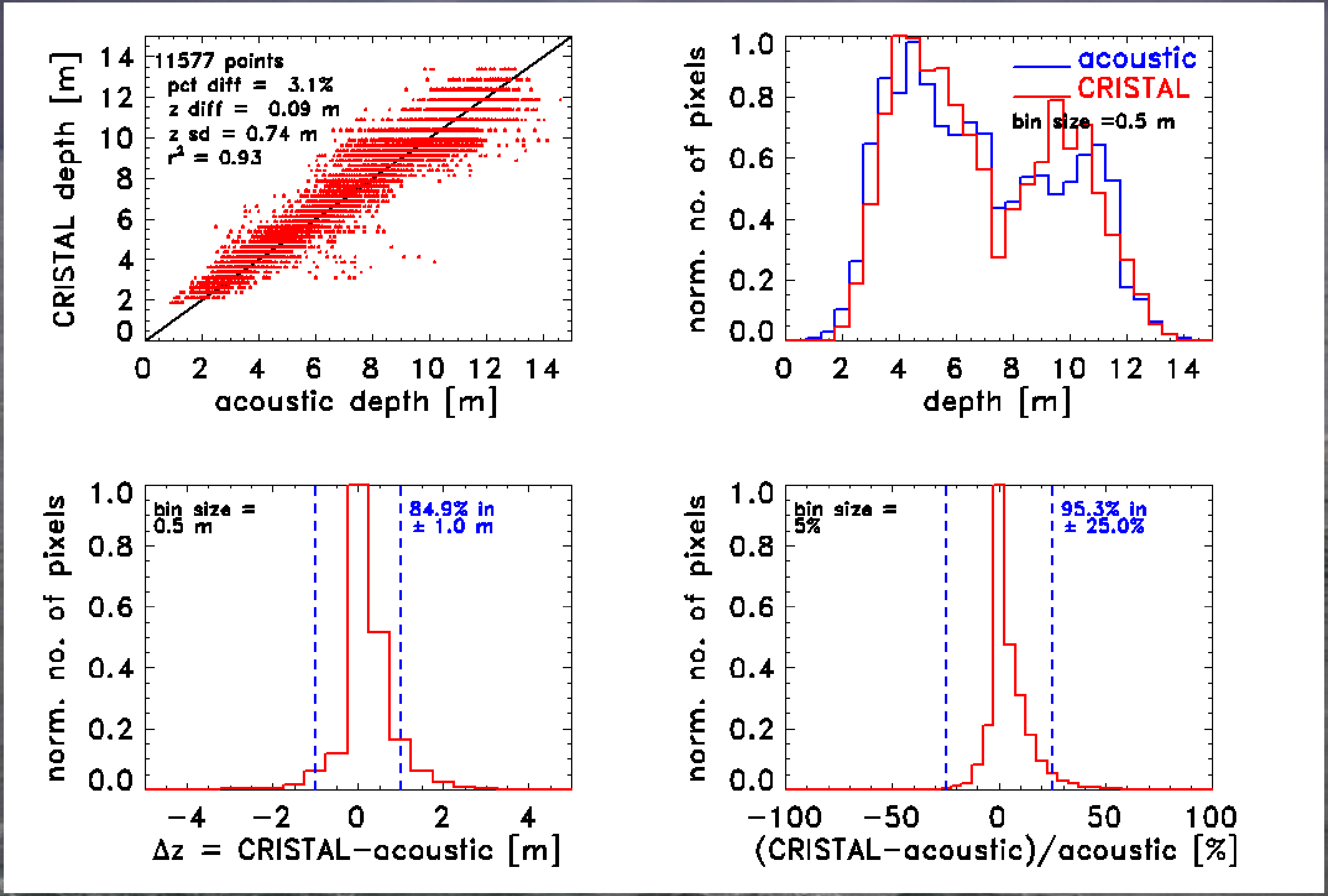
NRL-DC PHILLS image from ONR CoBOP program, May 2000
501x899 pixels at ~1.3 m resolution

Bathymetry Retrieval



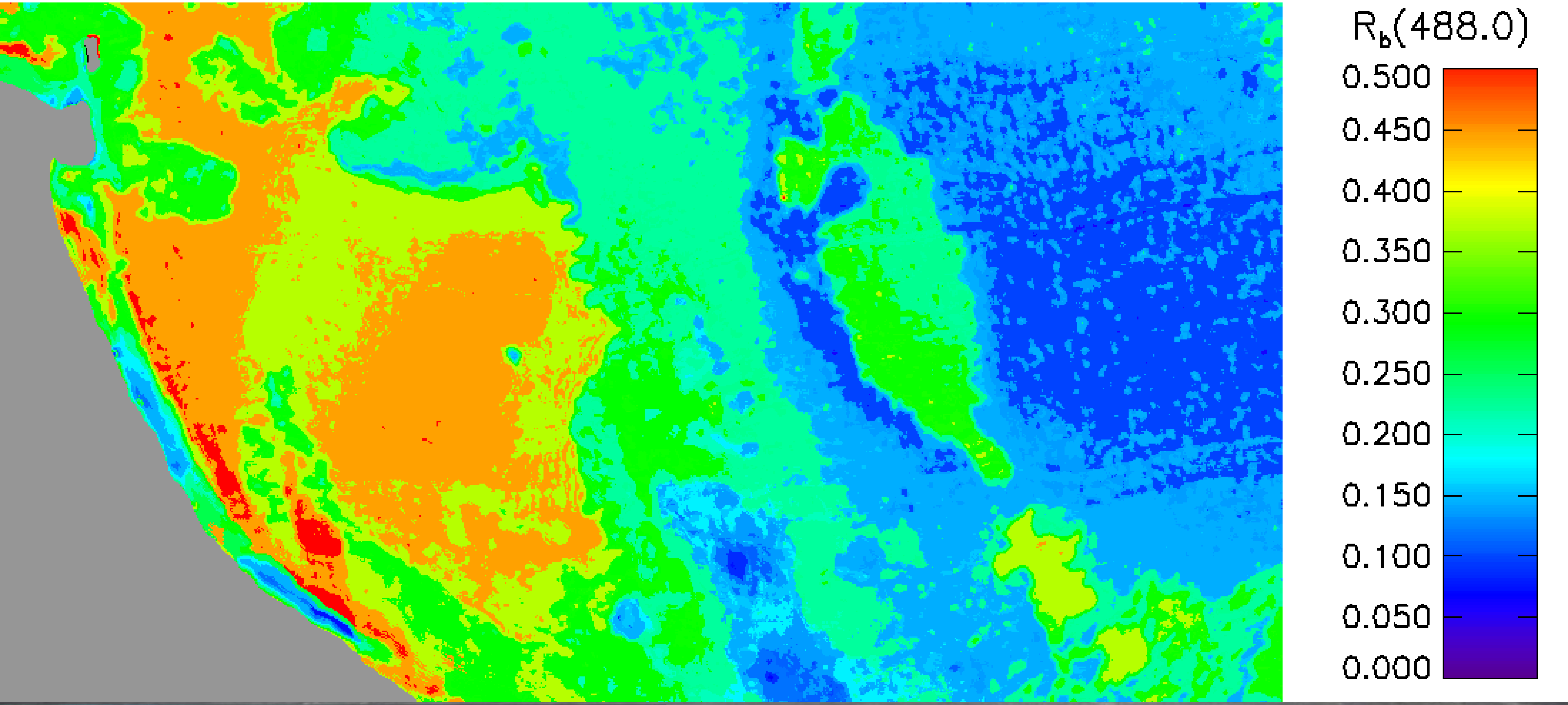
Black: NRL acoustic survey for ONR CoBOP program
Color: CRISTAL depth retrieval

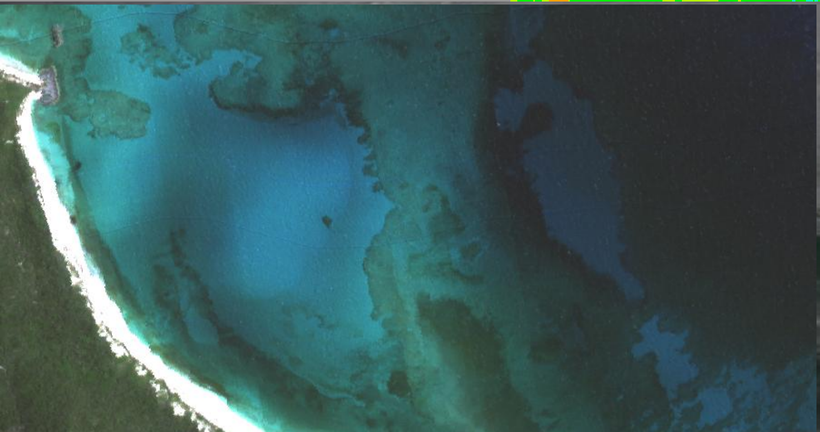
Depth Retrieval vs. Acoustic Bathymetry



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

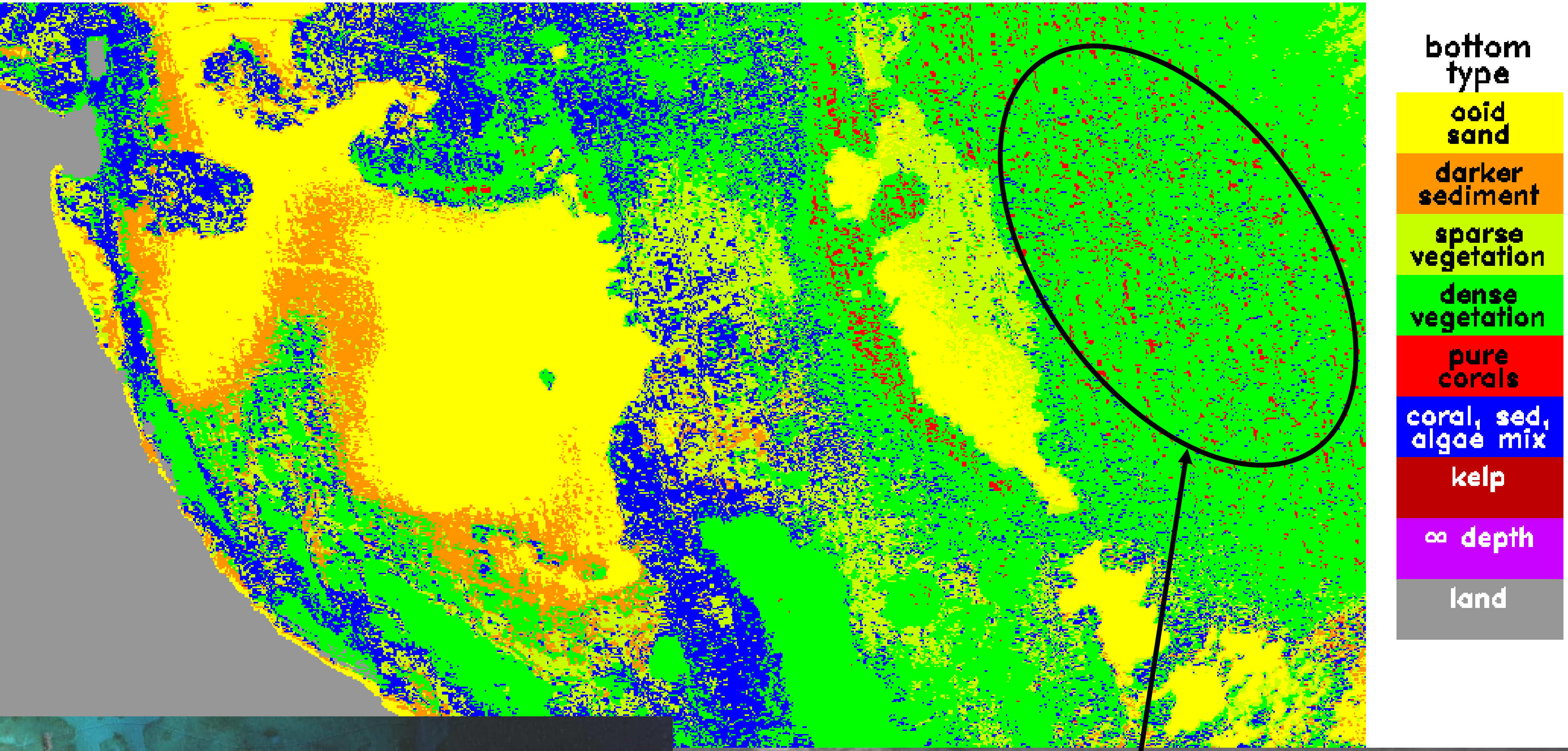
Bottom Reflectance

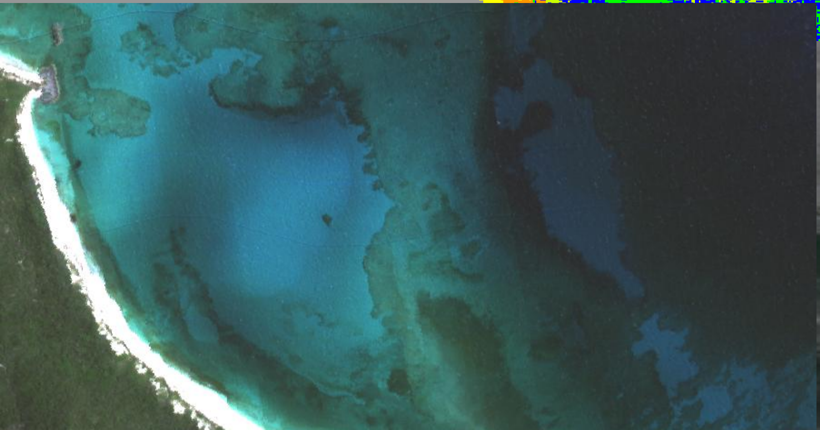




R_b(488) is what you would need for performance evaluation of a 488 nm bathymetric lidar

Bottom Classification



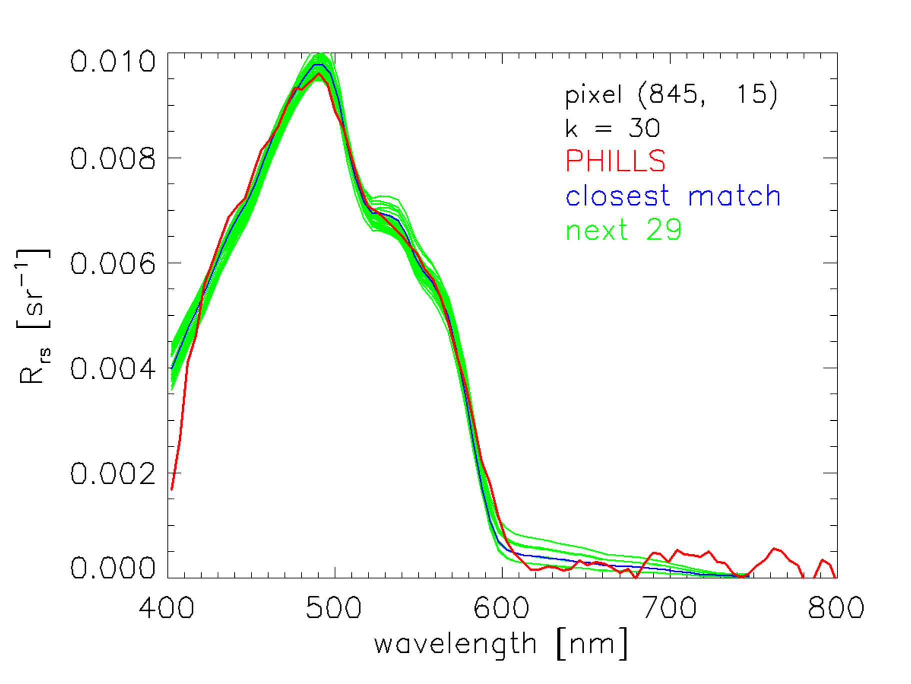


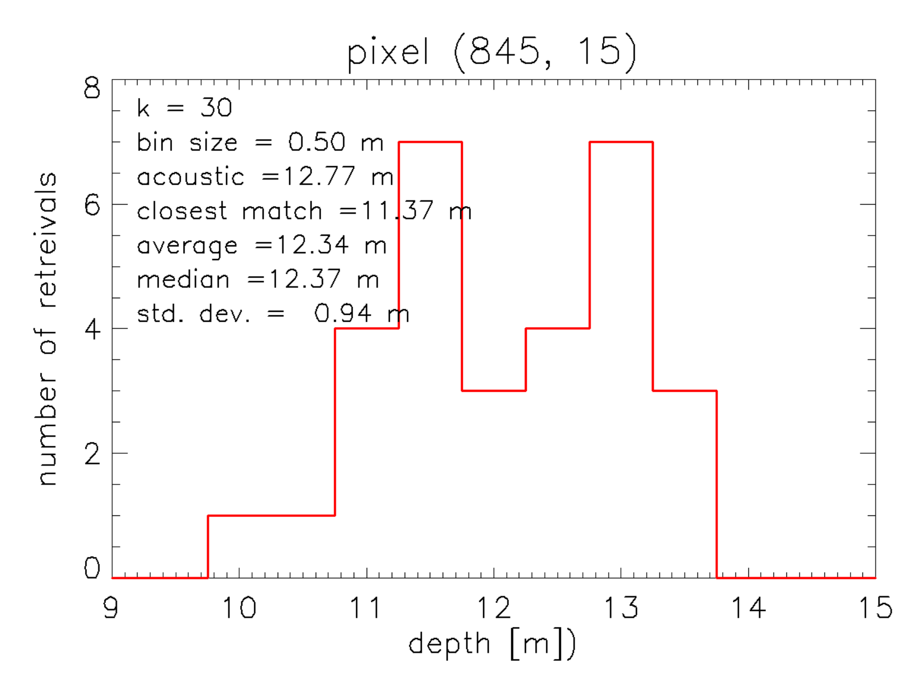
speckle due to whitecaps, which were not removed from the image spectra

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)

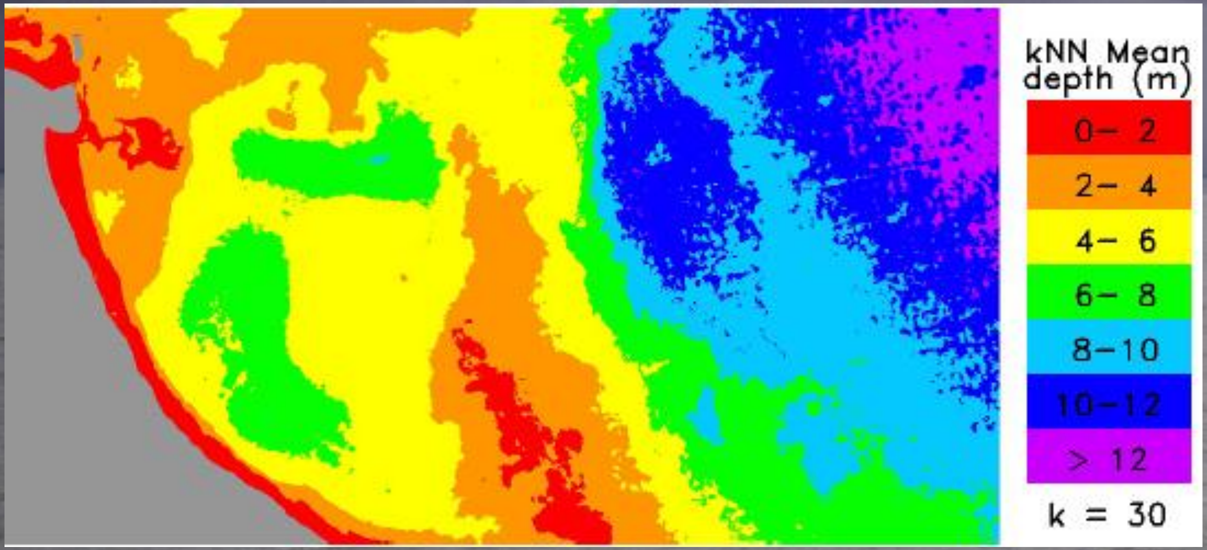




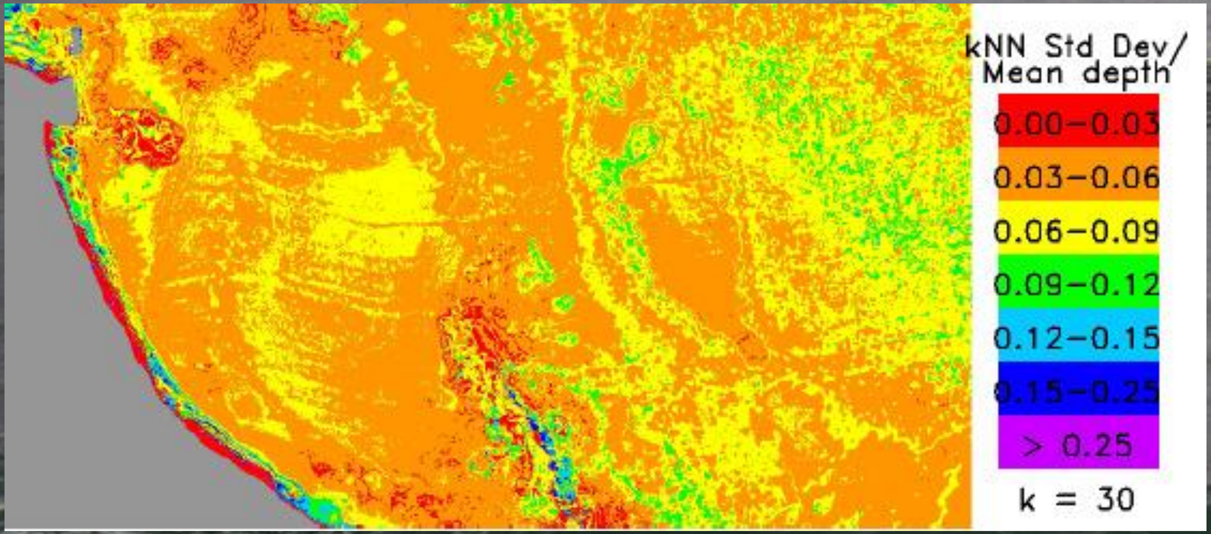
the 30 closest matches give a histogram of retrieved depths

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

kNN Error Analysis

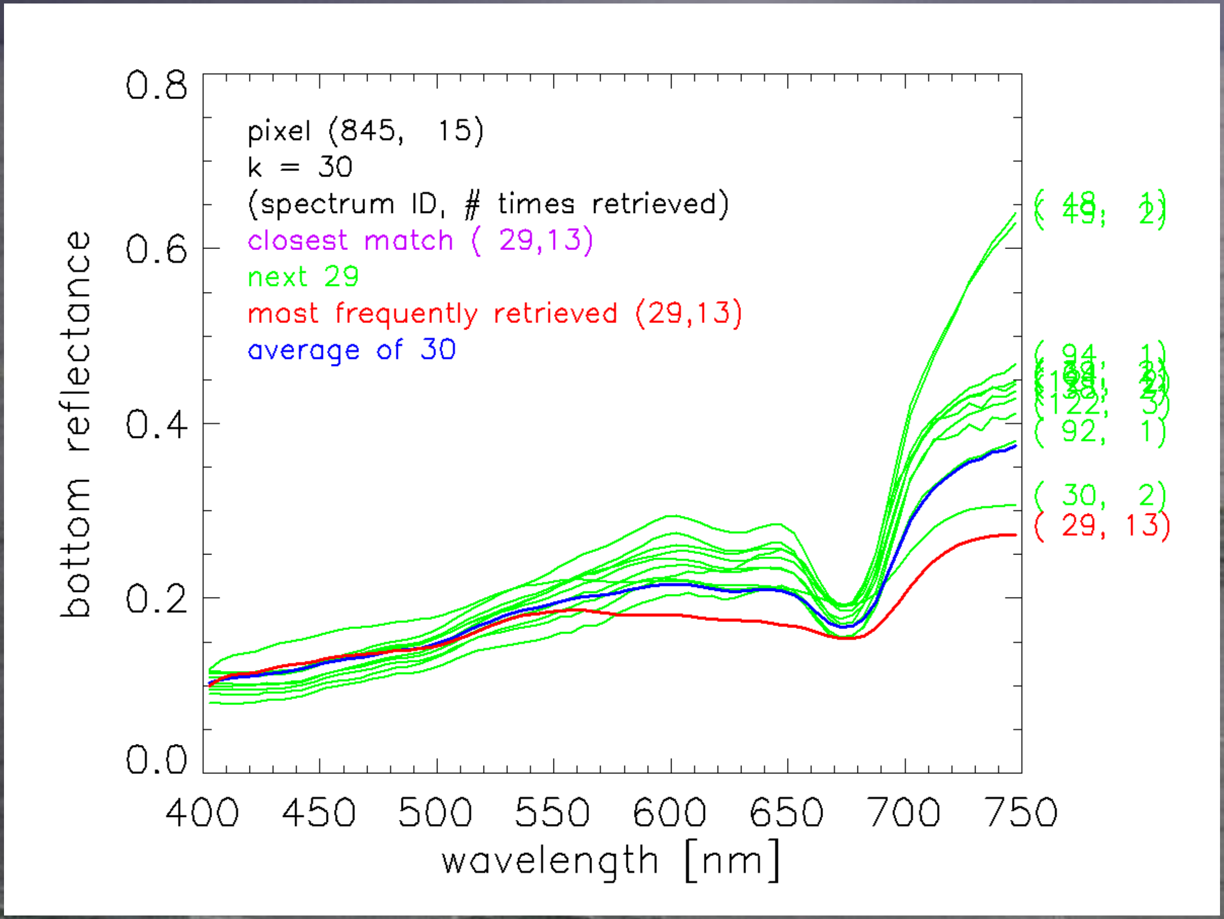


Retrieved depths from the mean of the closest *k* = 30 spectra



Std dev/mean depth for the closest *k* = 30 spectra

kNN Error Analysis



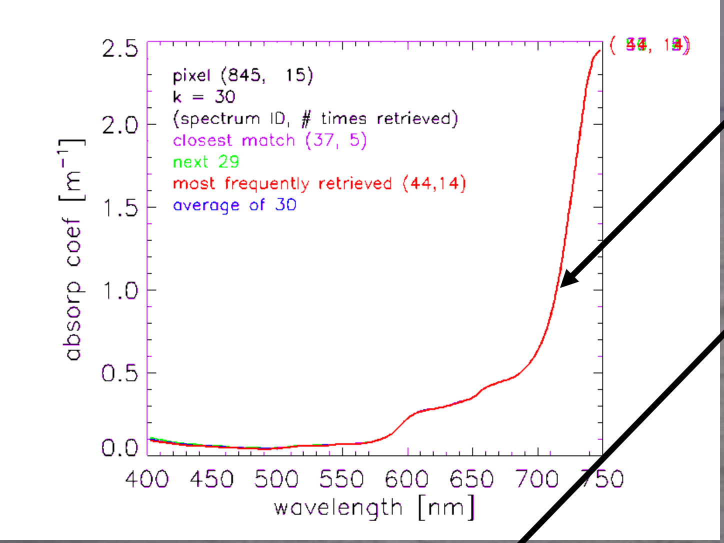
The closest and most frequently retrieved bottom reflectance spectrum was 30% sand and 70% seagrass.

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

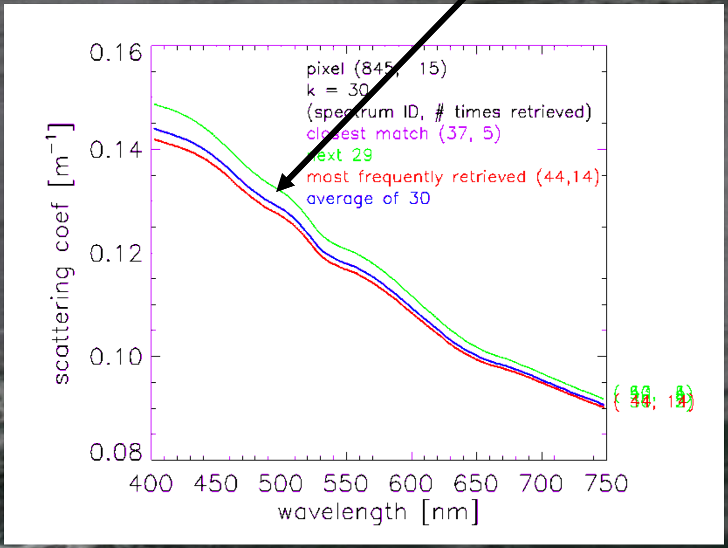
kNN Error Analysis

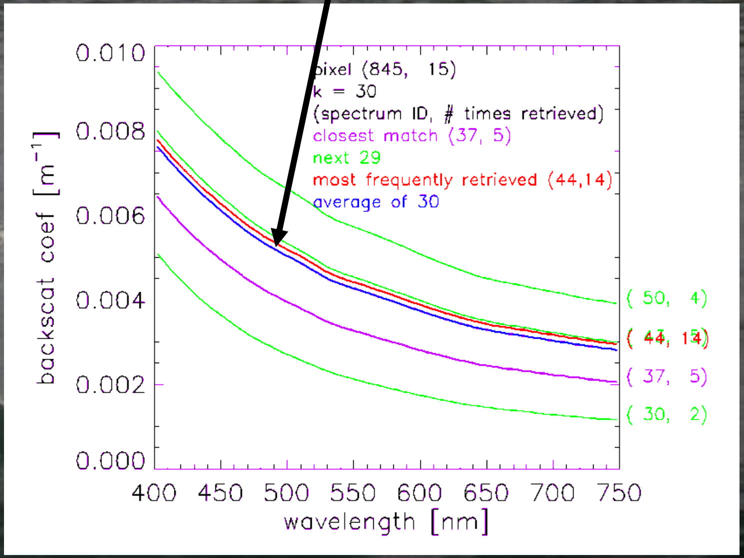
The retrieval is very certain about the absorption coefficient



The retrieval is fairly certain about the scattering coefficient

The retrieval is UNcertain about the backscatter coefficient



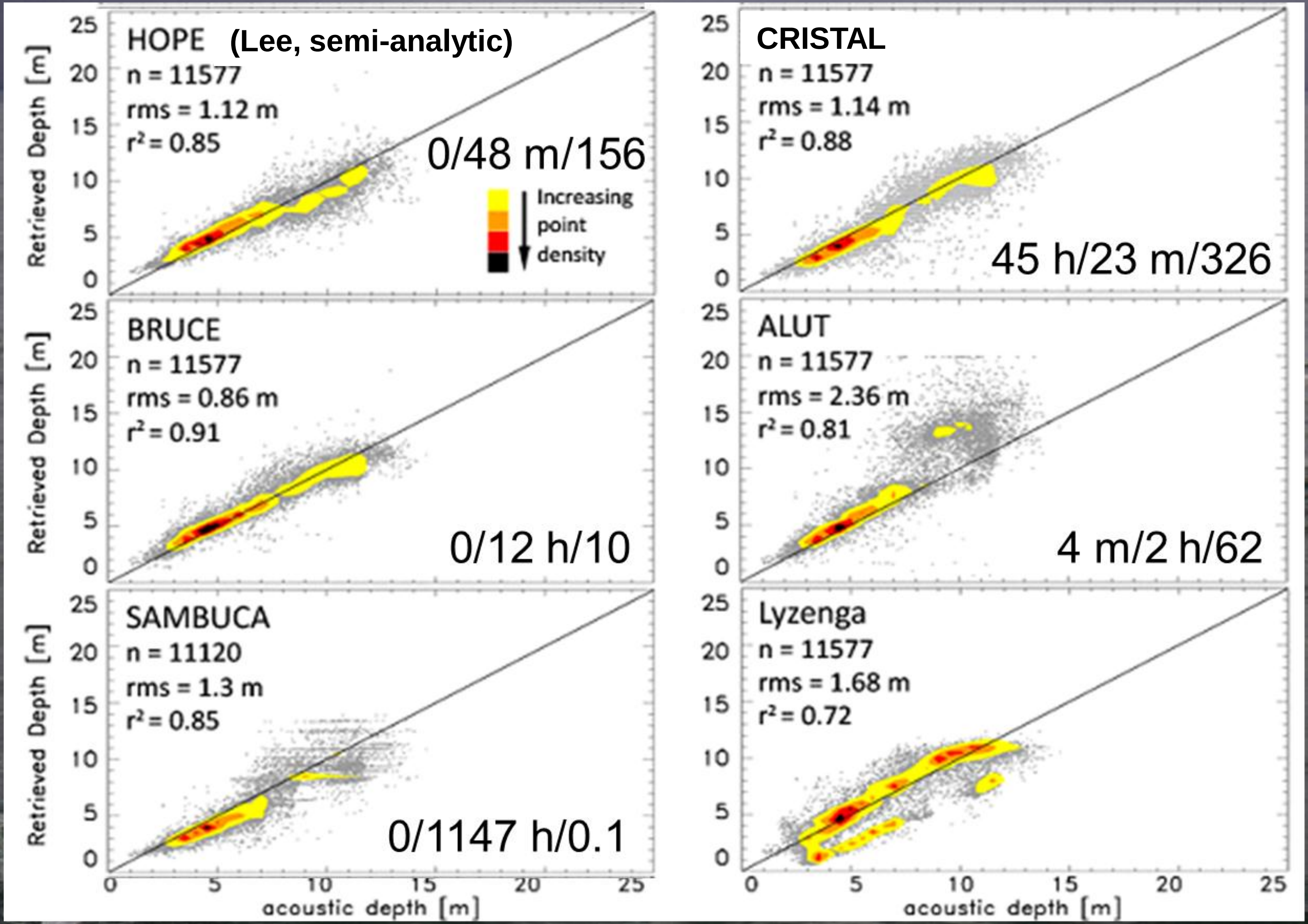


Does This Make Sense?

- 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})

Comparison with other Algorithms

preprocessing time / image processing time / pixels per sec



From Dekker et al, *Limnol Ocean. Methods*, in press, 2011

Kelp Mapping

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

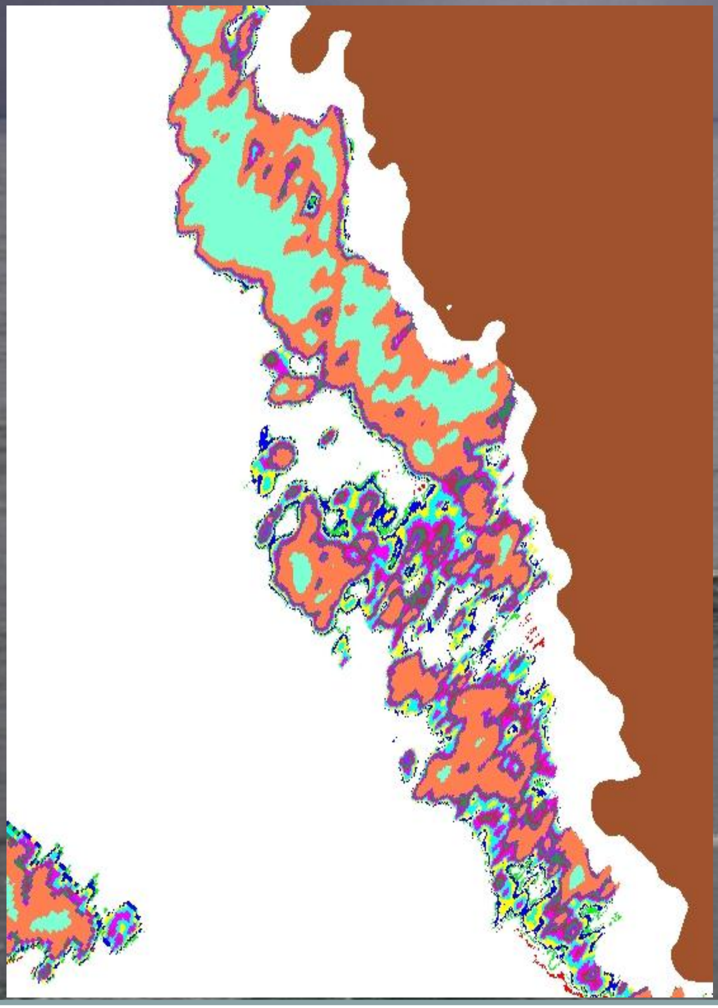
Bull kelp (*Nereocystis luetkeana*) is very important for food, medicines, sheltering of fish, and recreational diving. Harvesting is strictly managed in the US.

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

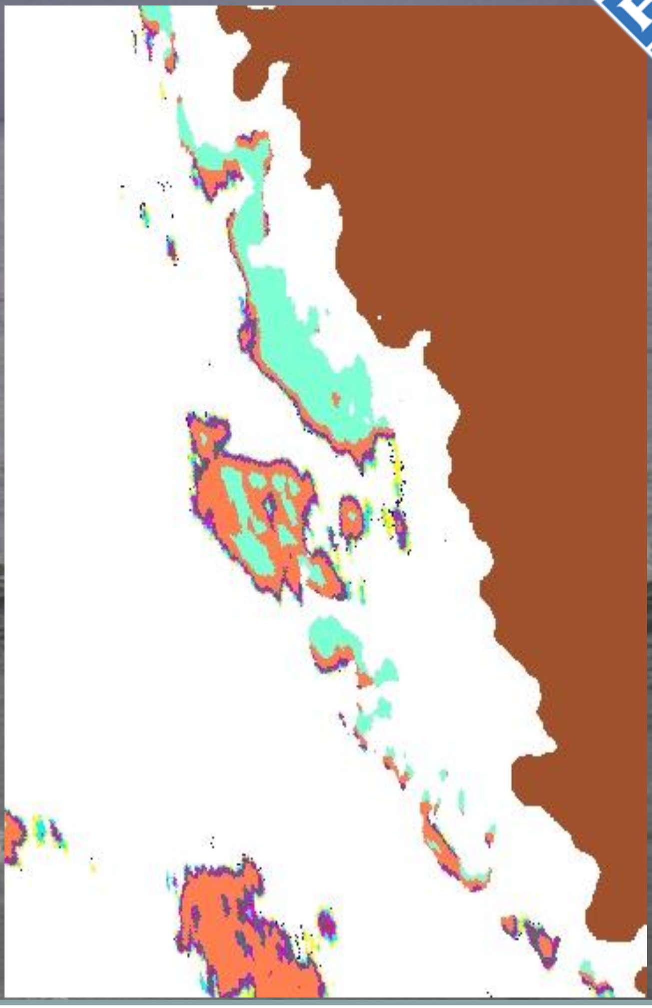
Mapping of Kelp Coverage
California Coast

CICORE

2002



2004



DEM Land | 0 % | 10 % | 20 % | 30 % | 40 % | 50 %

60 % | 70 % | 80 % | 90 % | 100 % | *100 %

Florida Environmental Research Institute

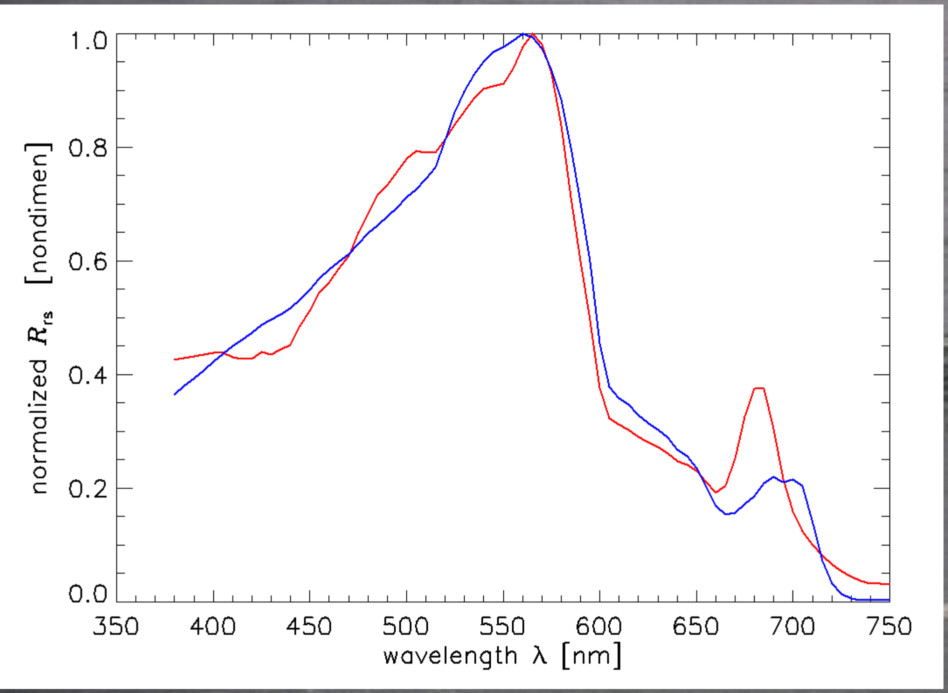
Humboldt Bay California
Eel Grass Mapping

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

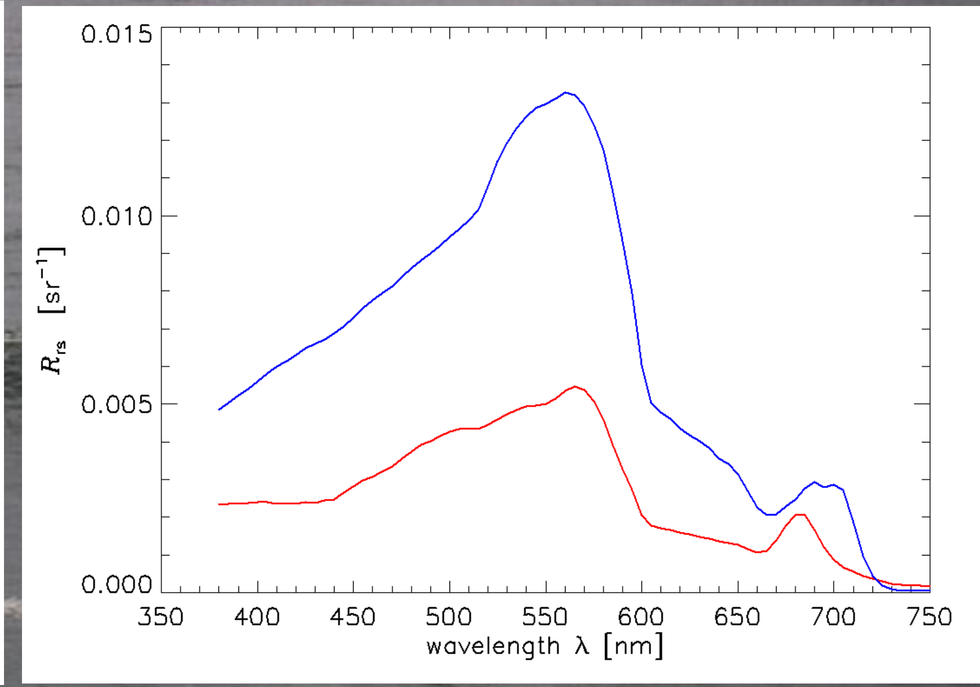
HSI determined eel grass distributions, previously unknown.

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

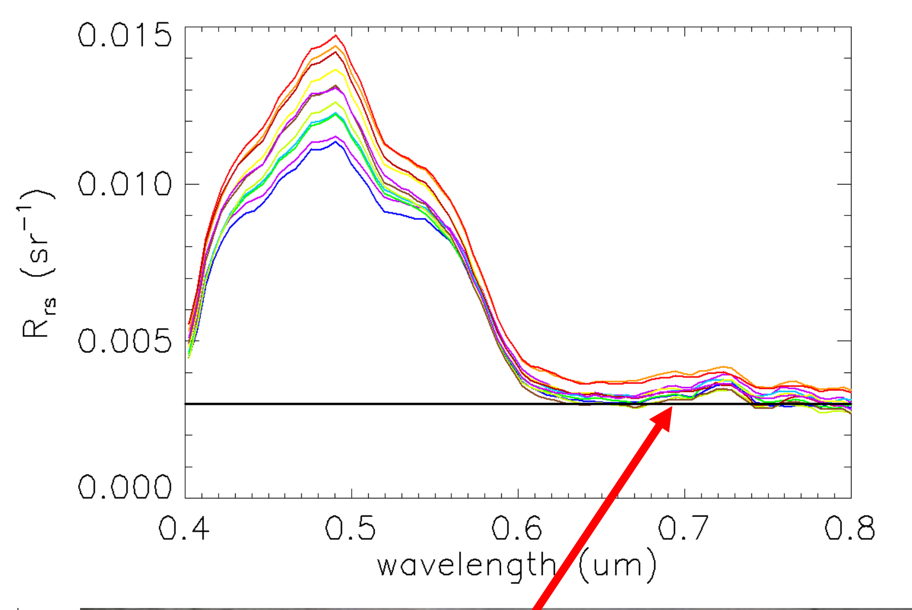


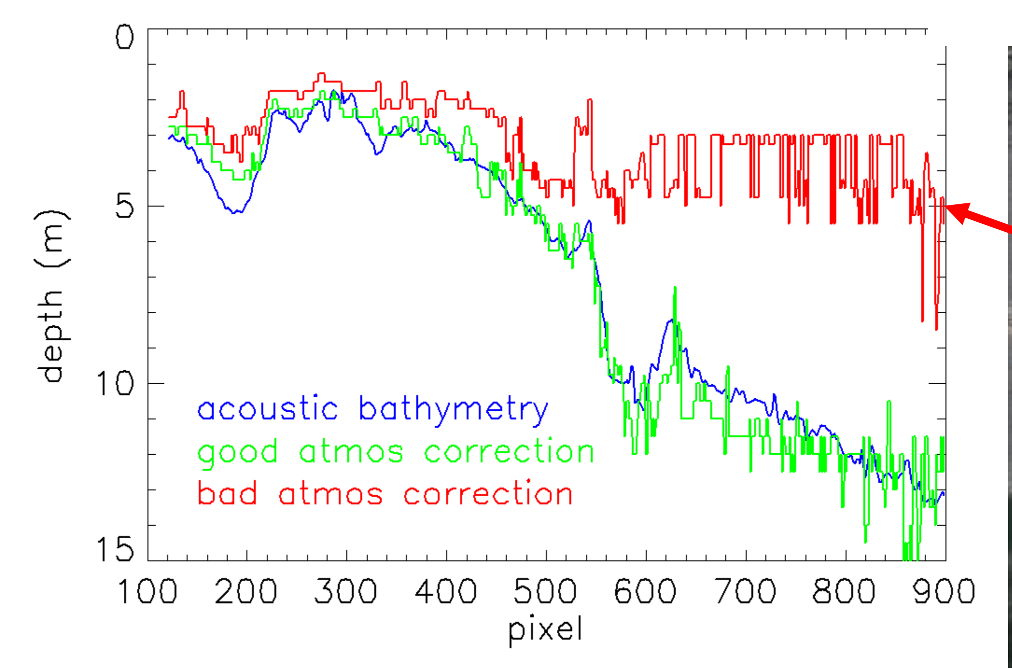
calibrated R_{rs} spectra

Red: infinitely deep water, Chl = 10 mg m^{-3}
Blue: 2 m deep clear water, sea grass bottom

Remaining Problems: Atmospheric Correction

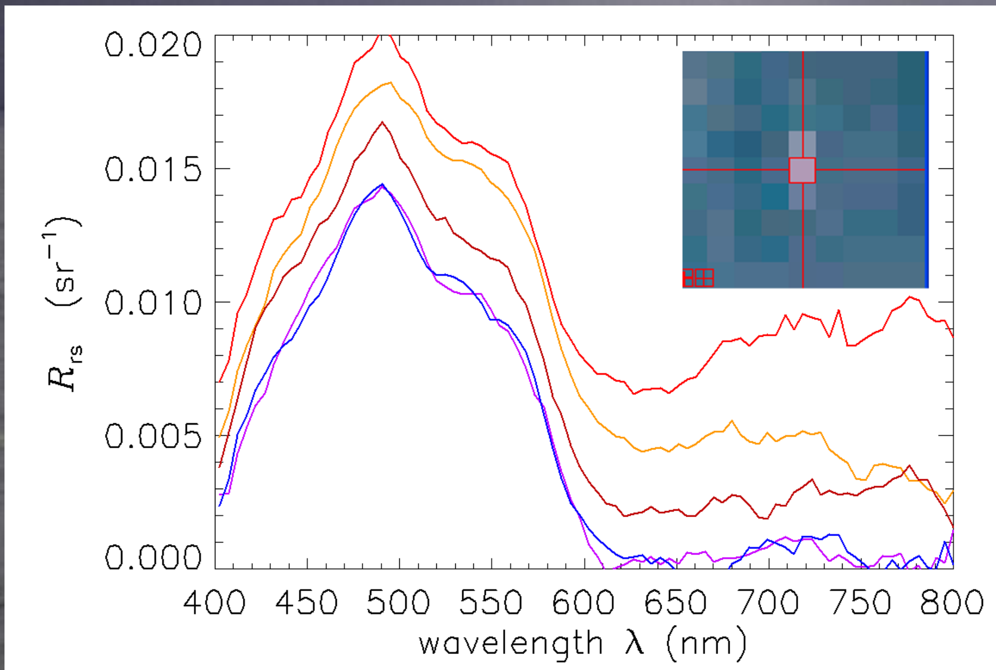
As always, good retrievals depend on having a good atmospheric correction

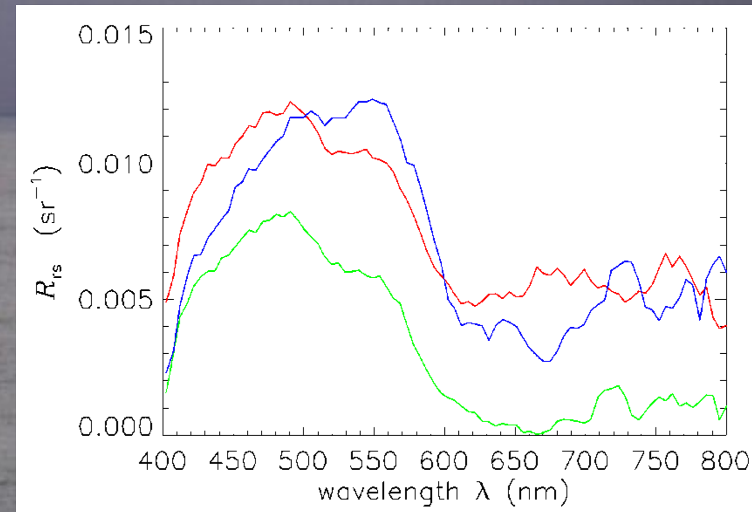




atmospheric undercorrection by 0.003 1/sr gives bottom depths too shallow

Remaining Problems: Glint Removal



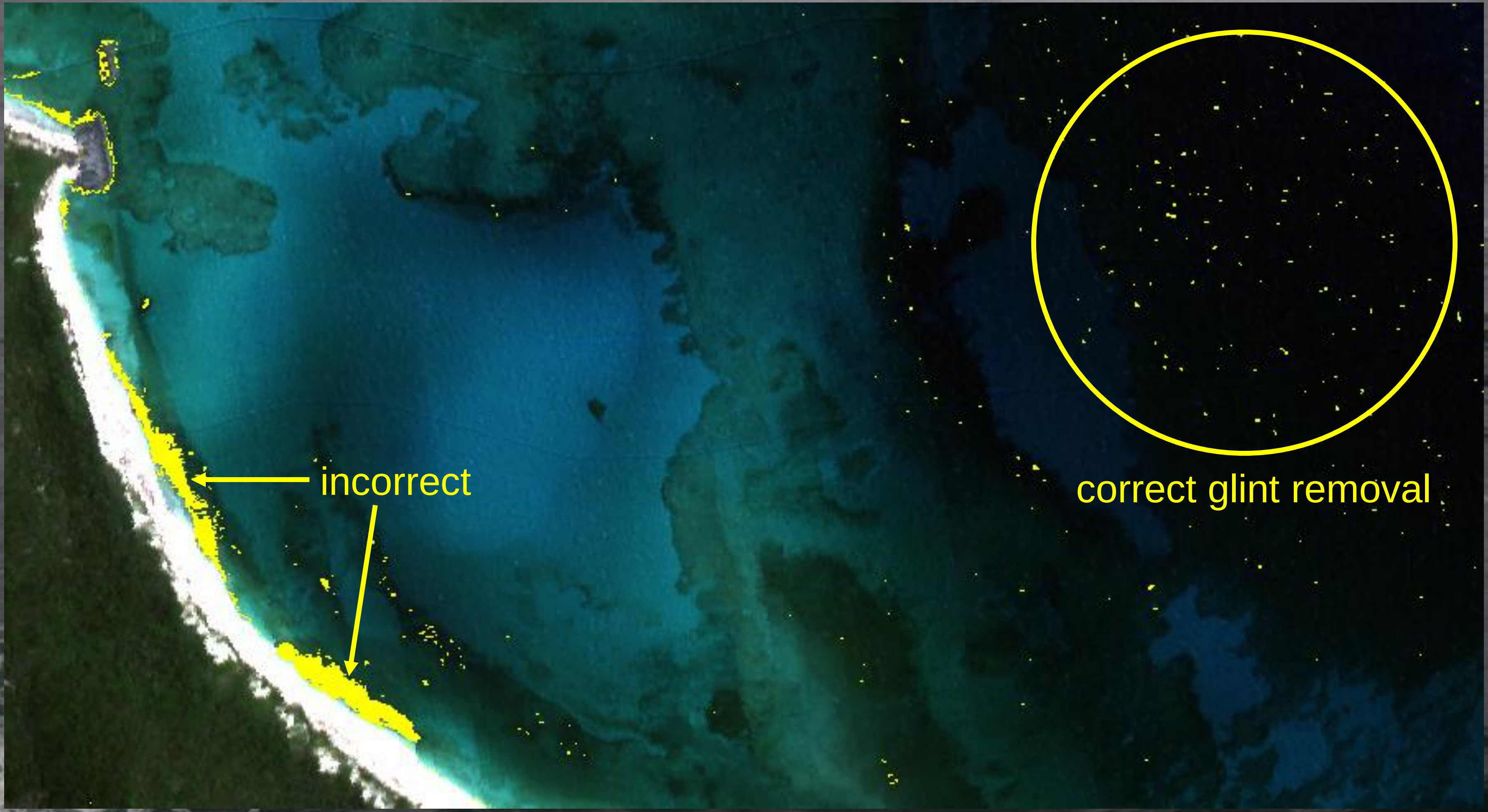


spectra for glint-contaminated deeper water (red), uncontaminated deeper water (green), and uncontaminated shallow-water (blue)

I haven't figured out any way to automate glint and cloud removal (for shallow water) using *just* spectral information for a given pixel ☹

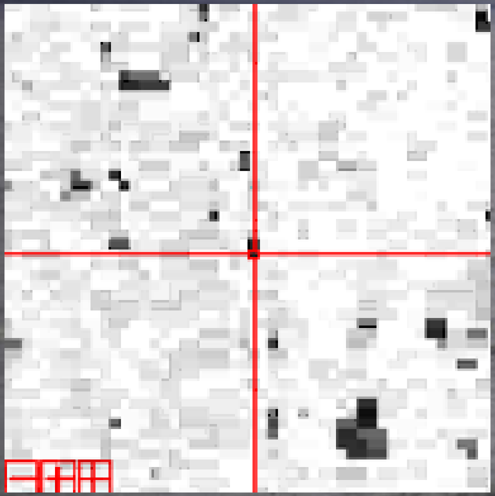
Remaining Problems: Glint Removal

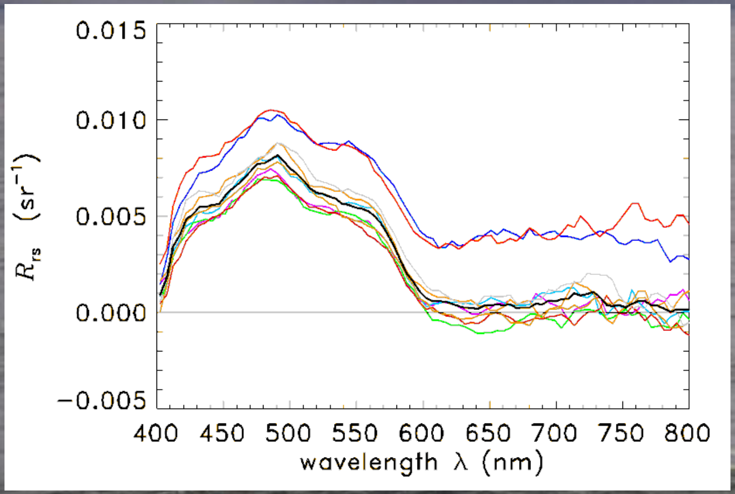
Standard algorithms for whitecap and glint removal also remove very shallow water (same for thin clouds)

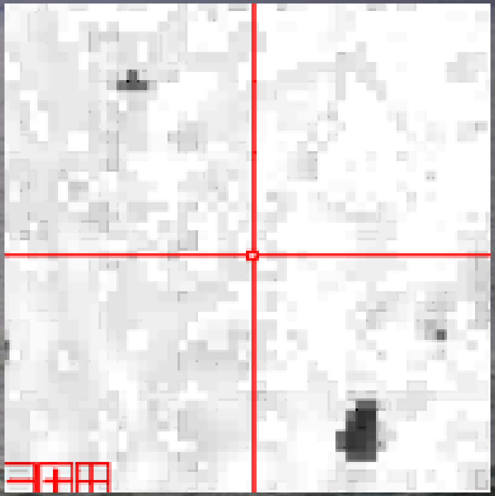


Remaining Problems: Glint Removal

Glint can be removed fairly well using spatial information, but at a cost…







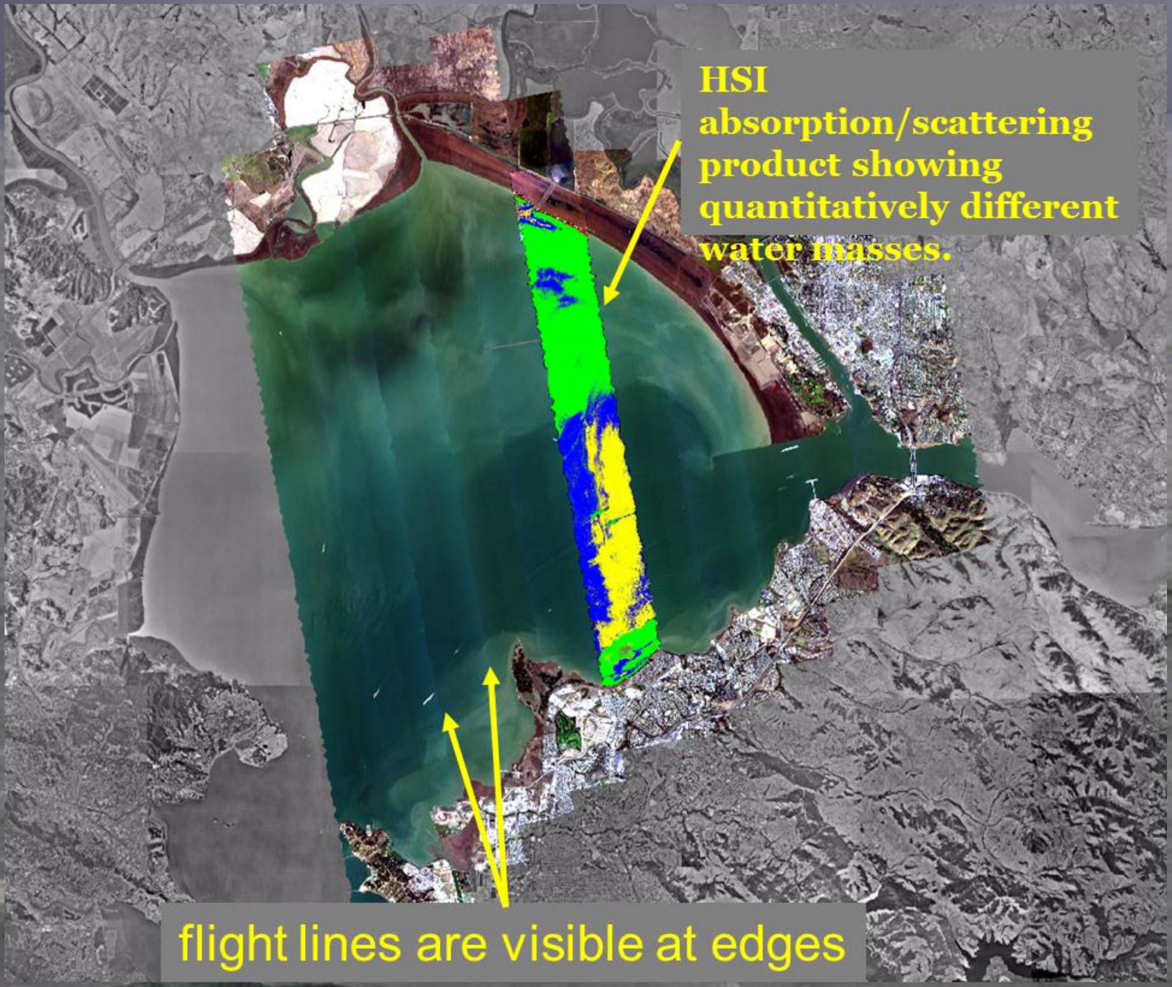
Retrieved depths: white is 10-11 m; black is 2-3 m because of glint

9 spectra for a 3x3 block centered on the red crosshairs

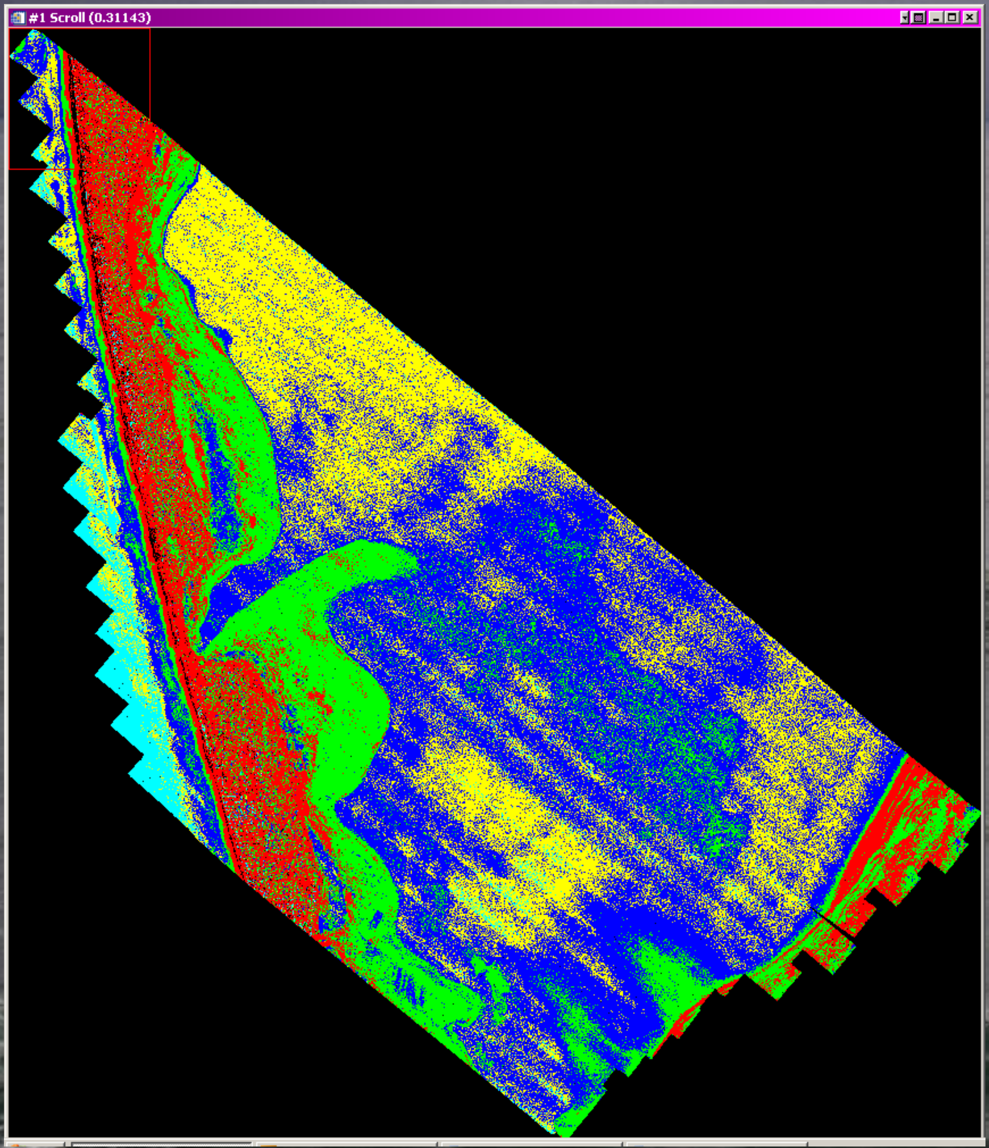
Omit the largest *m* spectra in an *nxn* block and average (black) the remaining spectra before retrieval

Spatial smoothing can remove all but large blocks of glint, but at the cost of degrading the spatial resolution

Remaining Problems: Atmospheric Correction



Remaining Problems: Atmospheric Correction



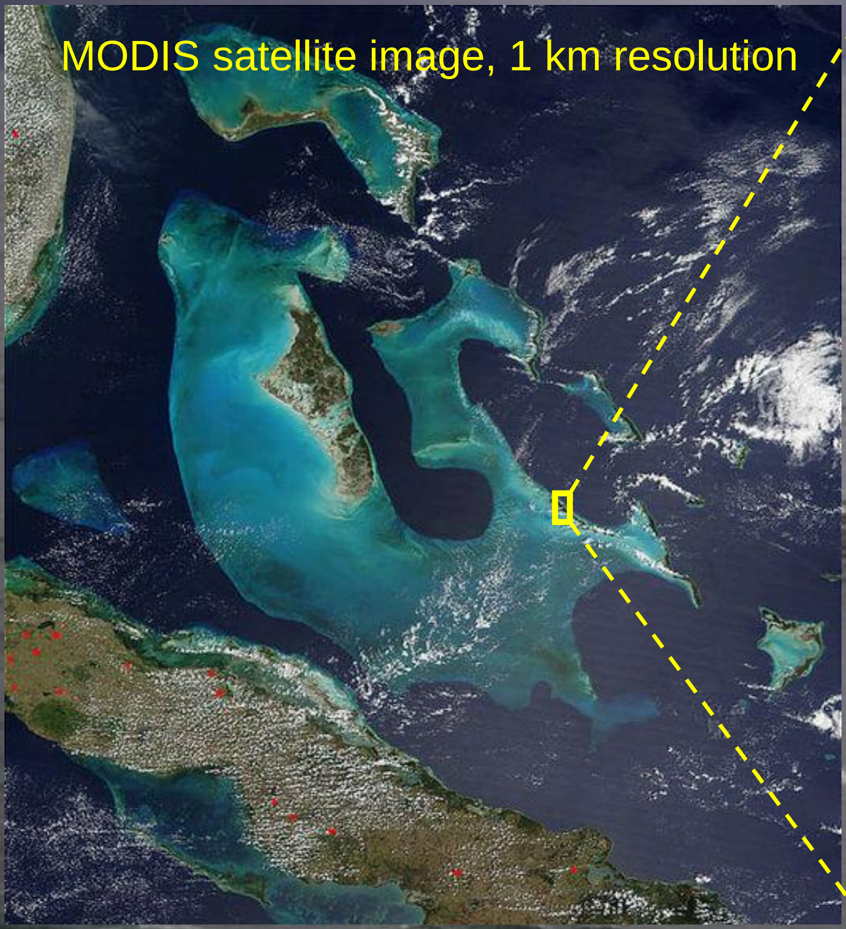
Effects of imperfect atmospheric correction on retrieved (by spectrum matching) bathymetry. The overall pattern is correct but note the “striping” in retrieved depths.

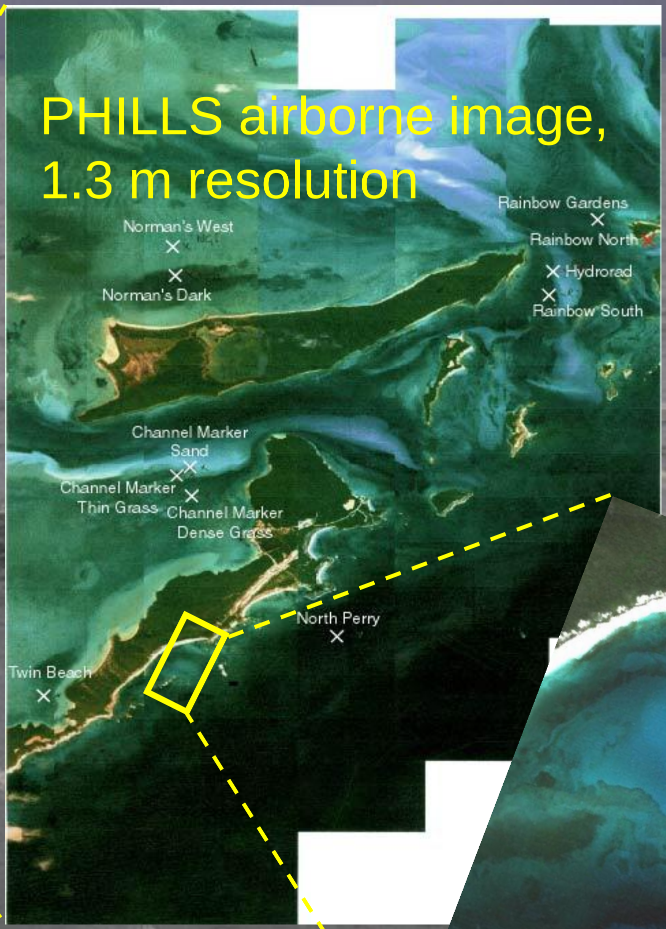
1 m contours (RGBYC =1-5 m)

courtesy of P. Bissett, FERI

Remaining Problems: Data Managment

Suppose we want to map all of the world's coral reefs at 10 m resolution



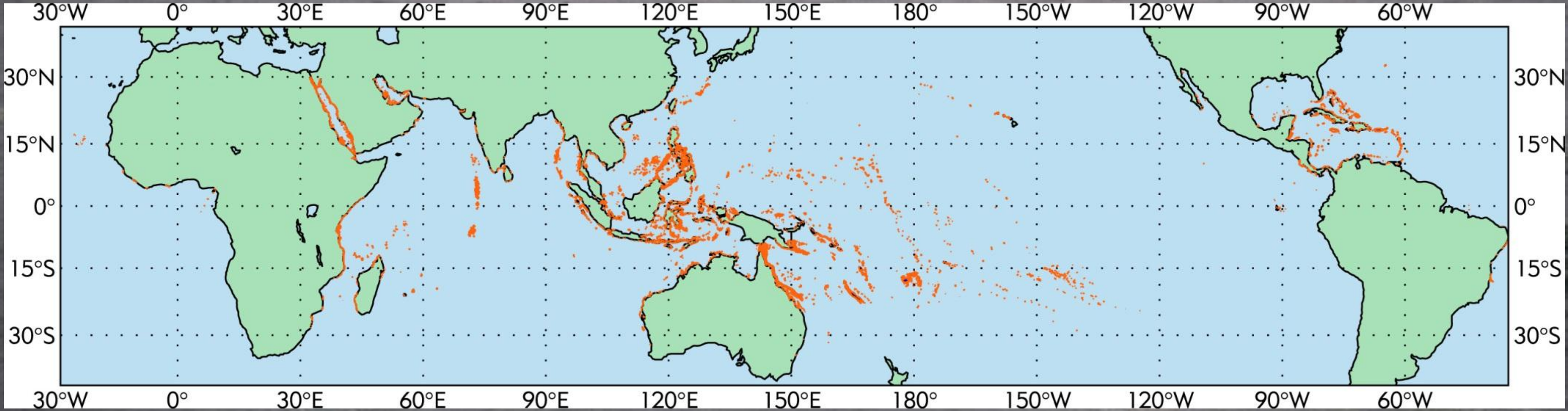


$$\frac{\text{area of the Bahamas banks}}{\text{area of my image}} \approx 200{,}000$$

Remaining Problems: Data Managment

$$\frac{\text{area of the Bahamas banks}}{\text{area of my image}} \approx 200{,}000$$

$$\frac{\text{area of all coral reefs}}{\text{area of my image}} \approx 1{,}000{,}000$$



Remaining Problems: Data Managment

For the Bahamas image I had 25 sets of water properties, 123 bottom types, and 83 depths (25 cm depth resolution), so ≈ 250,000 Rrs spectra.

To cover the range of all water bodies, I might need 1000 (or more??) combinations of absorption, scatter, and backscatter spectra to represent the possible combinations and concentrations of phytoplankon, mineral particles, and dissolved substances. To cover likely ranges of bottom types and mixtures, maybe need 500 bottom reflectance spectra. Probably OK with existing depth resolution, so order of 100 bottom depths. Thus I would have 1000 x 500 x 100 = 50,000,000 R_{rs} spectra

$$\frac{\text{global database size}}{\text{Bahamas database size}} \approx 200$$

Remaining Problems: Data Managment

To map all coral reef areas at 10 m resolution (the minimun to be useful):

Imaged area increase: factor of 1,000,000

Spatial resolution (decrease from 1 m to 10 m): factor of 0.01

Wavelength resolution (still hyperspectral): factor of 1

Database size (search time increase per pixel): factor 200

Total computational increase: 2,000,000

Bahamas image processing time: ~ 1 hour (2 GHz PC)

Global processing time: ~ 200 years

Lava Falls, Grand Canyon

Lava Falls, Grand Canyon

Lava Falls, Grand Canyon

Lava Falls, Grand Canyon

Lava Falls, Grand Canyon