Shallow Water Remote Sensing

John Hedley, IOCCG Summer Class 2018

- Overview - different methods and applications
- “Physics-based” model inversion methods
- High spatial resolution imagery and Sentinel-2
- Bottom mapping
- Satellite derived bathymetry (SDB)

- Sun-glint correction of high spatial resolution images
- Model inversion methods and uncertainty propagation

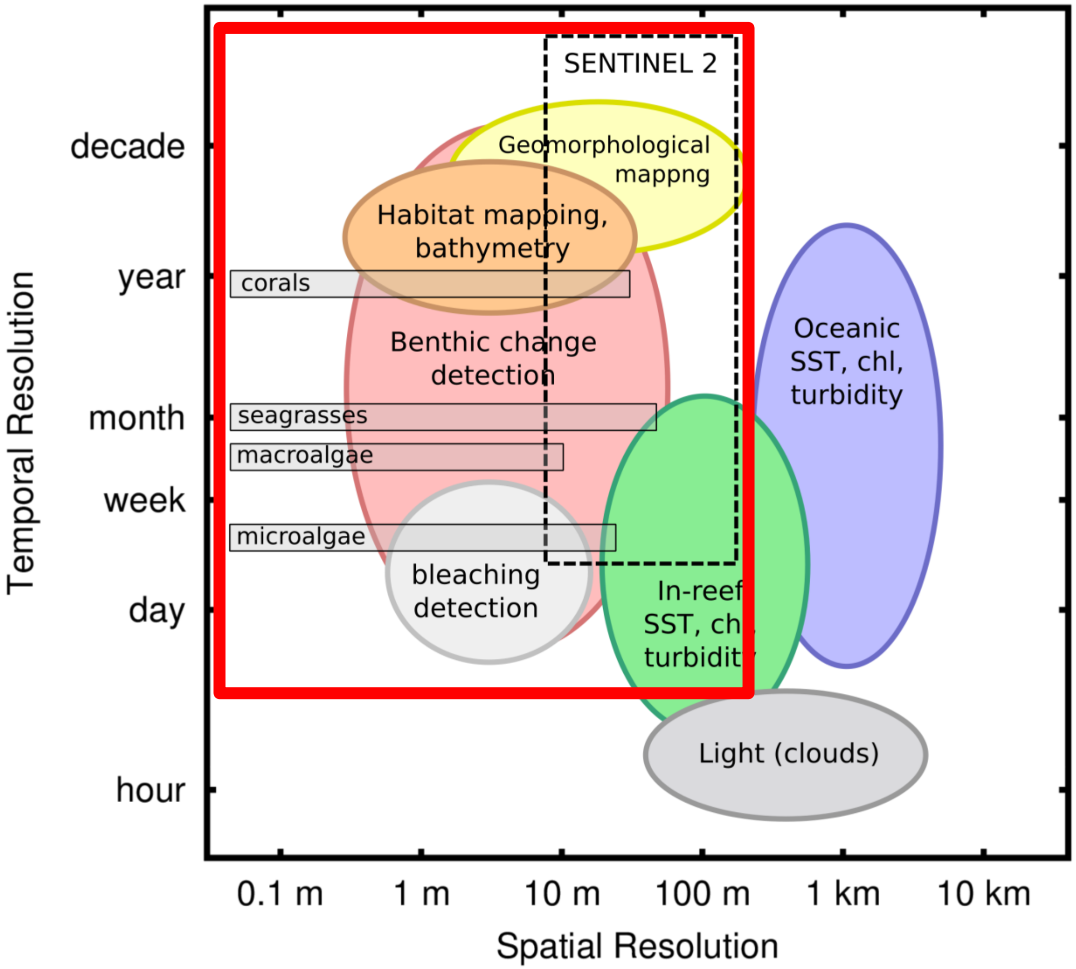
Objectives of shallow water remote sensing

- Bottom mapping
  - corals, seagrasses, macroalgae
- Water optical properties
- Bathymetry (depth)

Applications

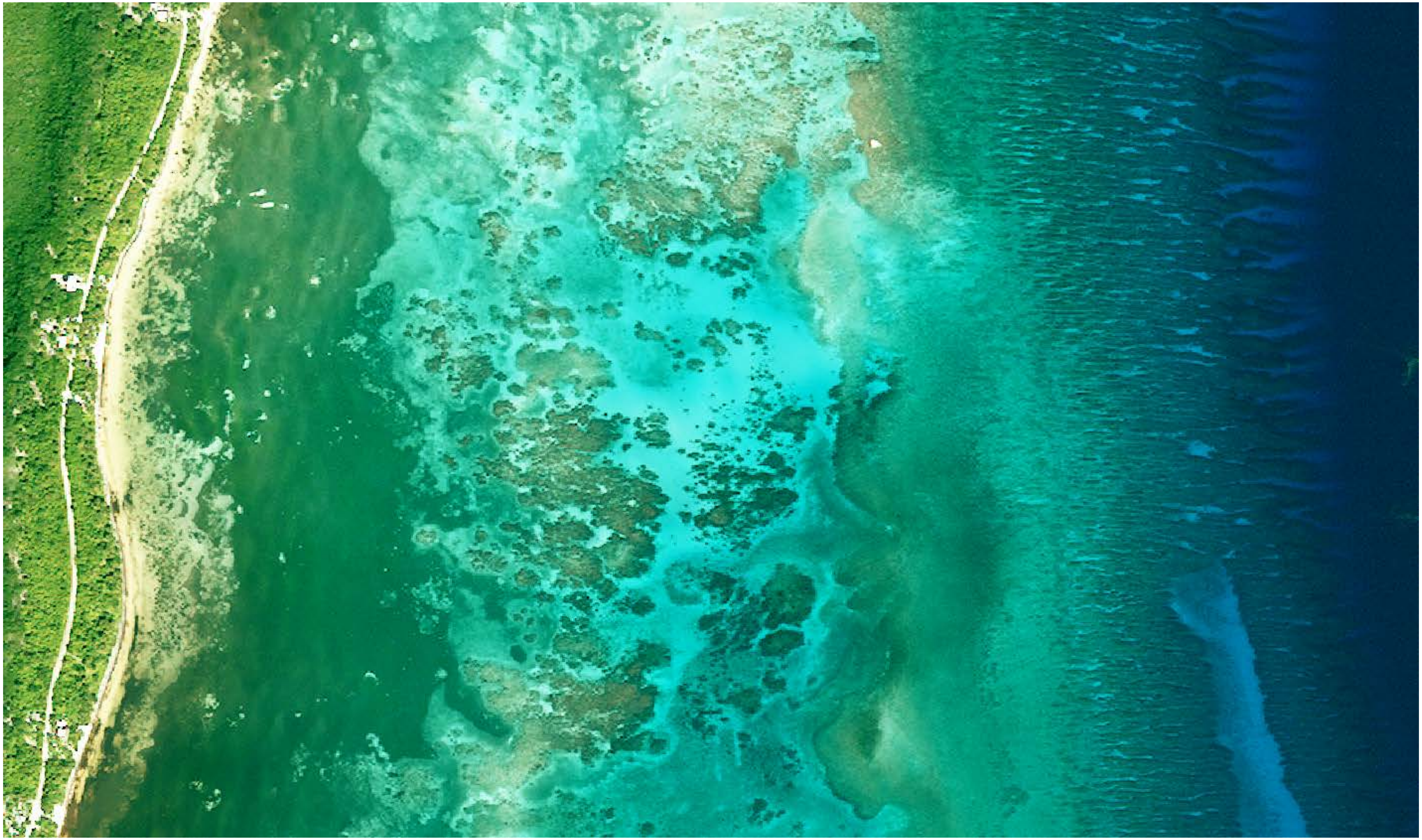
- Spatial ecology (science)
- MPA design (resource mapping)
- Assessing ecosystem services
  - coastal protection and stabilisation
  - fisheries, local subsistence
  - blue carbon
  - tourism

Applications on coral reefs and similar environments



- ➢ Need higher spatial resolution than typical ocean colour satellites

Hedley et al. 2016, *Remote Sensing*, 8, 118; doi:10.3390/rs8020118
Hedley et al. 2018, *RSE* Sentinel-2 special issue (in press, probably)



(c) DigitalGlobe

WorldView-2 image of Yucatan coast, Mexico (15 Feb 2008)
(pixels < 2 m, 8 bands, ~5 usable)

High Spatial Resolution Imagery

Pixel size < 5 m

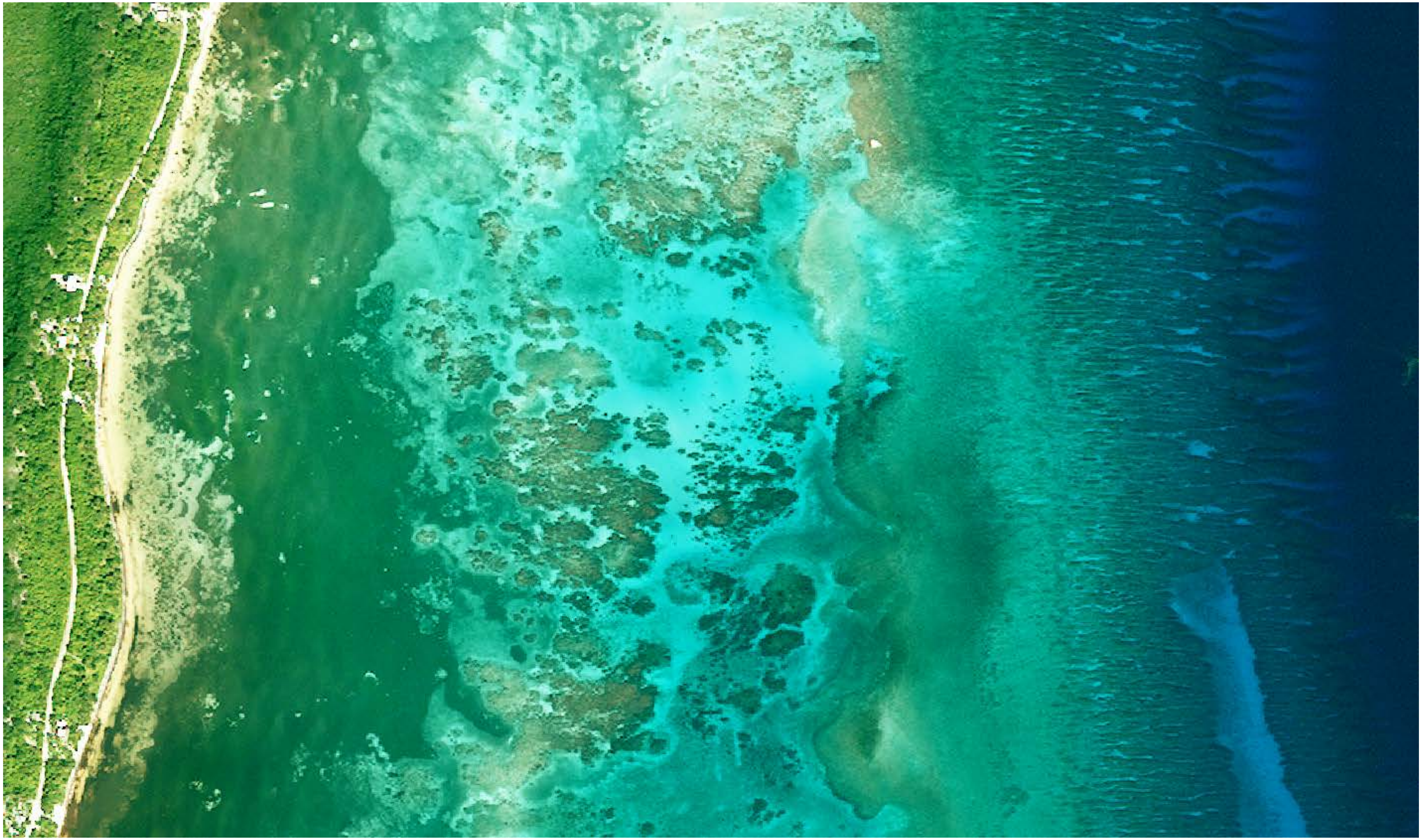
- Many past and present (archive imagery still available)
- Pleiades, WorldView-2, 3, QuickBird, GeoEye, IKONOS, RapidEye, Kompsat
- Typically 4 bands, R, G, B and NIR, but WorldView has 8 bands

Pixel size 10 - 30 m

- SPOT (various)
- Landsat 8 (30 m)
- Sentinel 2 (10 m in four bands)

Notes:

- Radiometric calibration on commercial satellites is usually not as good as on space agency satellites.
- For these sensors bands are spectrally wide, not narrow as with ocean colour satellites
  - not always appropriate to just use centre wavelength
  - may need to integrate over wavelength



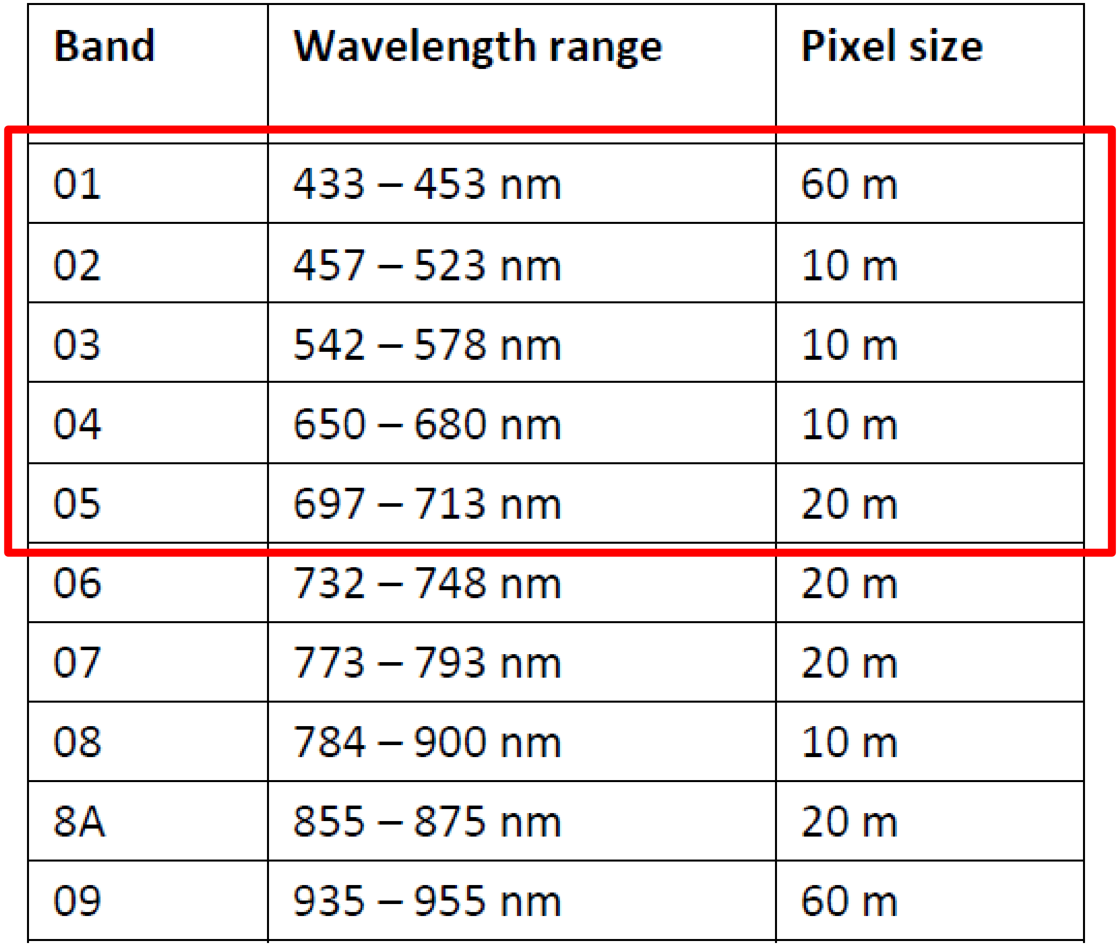
(c) DigitalGlobe

WorldView-2 image of Yucatan coast, Mexico (15 Feb 2008)
(pixels < 2 m, 8 bands, ~5 usable)

ESA / Copernicus

Sentinel-2 image of Yucatan coast, Mexico (17 April 2018)
(pixels 10 m, ~5 usable bands)

Sentinel 2 - useful bands are at different resolutions



Band	Wavelength range	Pixel size
01	433 – 453 nm	60 m
02	457 – 523 nm	10 m
03	542 – 578 nm	10 m
04	650 – 680 nm	10 m
05	697 – 713 nm	20 m
06	732 – 748 nm	20 m
07	773 – 793 nm	20 m
08	784 – 900 nm	10 m
8A	855 – 875 nm	20 m
09	935 – 955 nm	60 m

→ Interesting potential issues / artefacts

Methods for bottom mapping and/or bathymetry

Many and very diverse – overlap with terrestrial methods

Empirical, image based, requires training from in-situ data

- Classification, depth invariant indices
- Bathymetry by regression methods

Physics based

- Radiative transfer model inversion

Hybrid

- Object orientated techniques - classificaton combined with rules which can take data from other remote sensing and physics based methods
- e.g. depth, wave energy (wind)

Empirical image based methods (e.g. bathymetry)

- Usually assume exponential attenuation of light with depth (i.e. constant K_d)
- Requires training of points from imagery (deep water, known depths etc.)
- Similar methods for water column correction, change detection, etc.

Lyzenga 1978

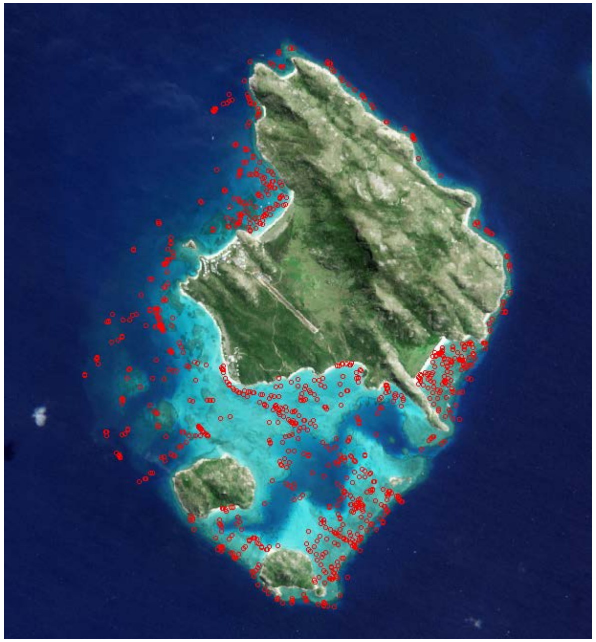
$$X_i = \ln(L_i - L_{si}),$$
$$Z = a_0 + a_i X_i + a_j X_j$$

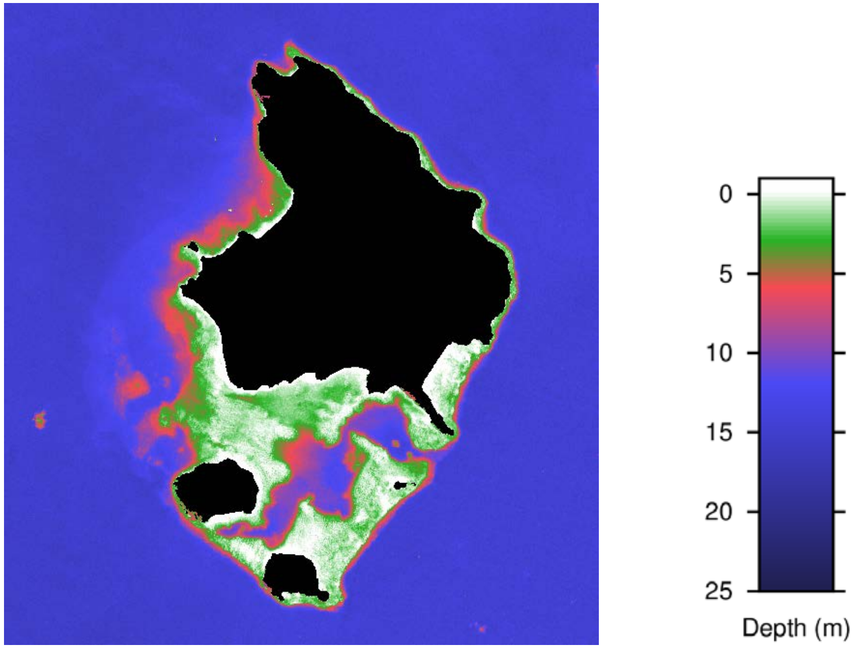
a0, a1, a2 from regression

Stumpf et al. 2003

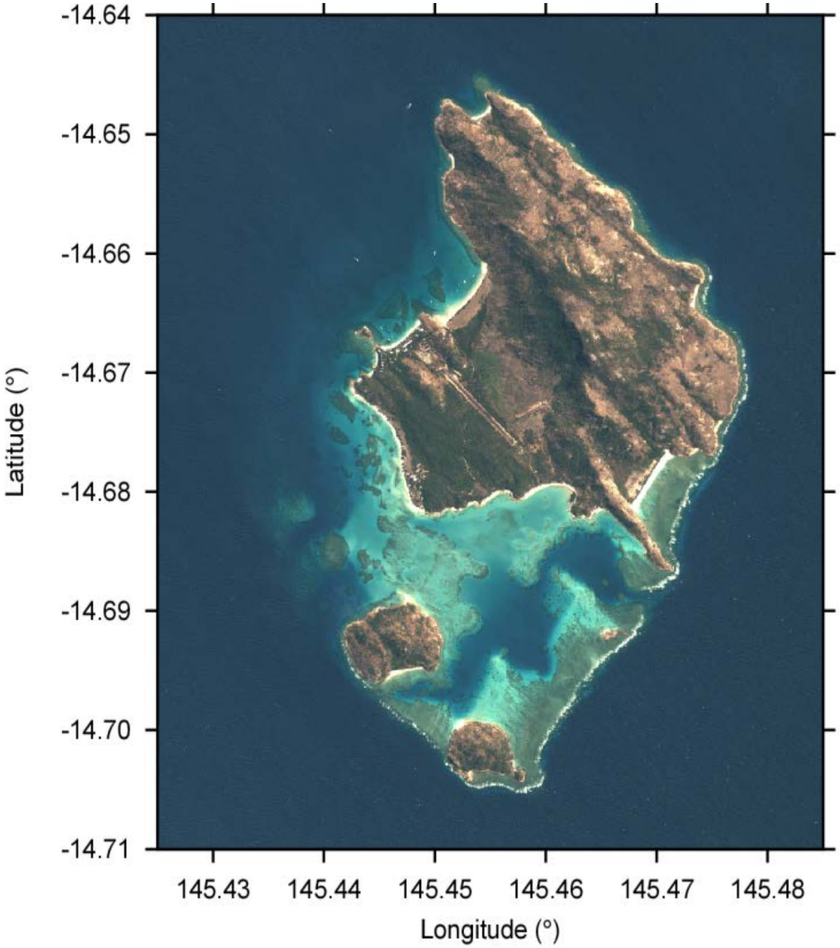
$$z = m_1 \frac{\ln(nR_w(\lambda_i))}{\ln(nR_w(\lambda_j))} + m_0$$

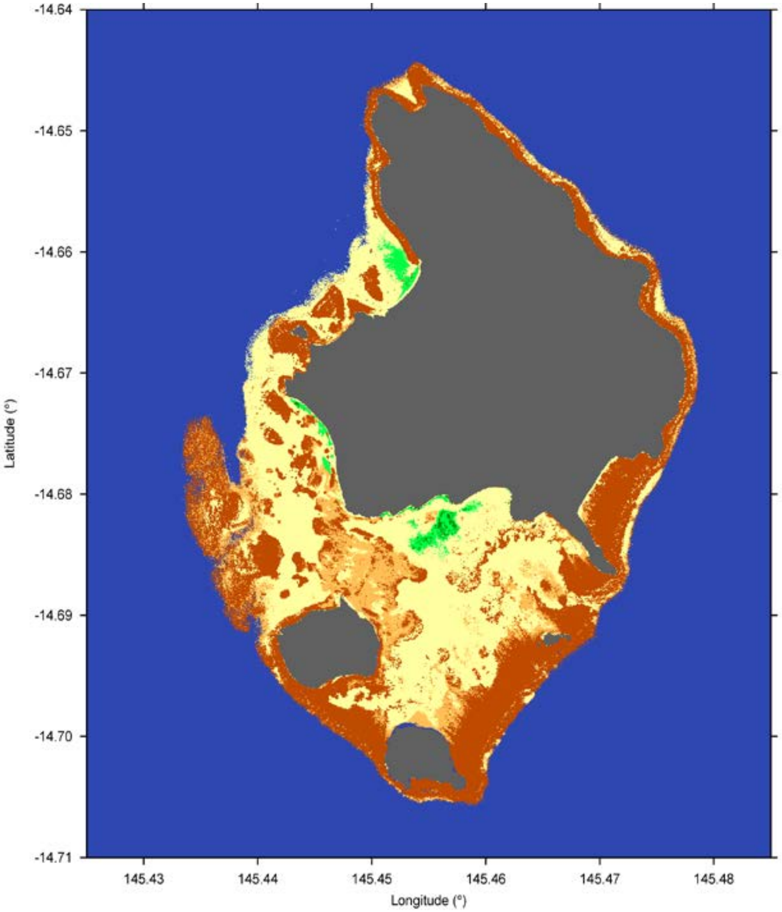
m0, m1, from regression





Benthic classification example, Lizard Island, GBR

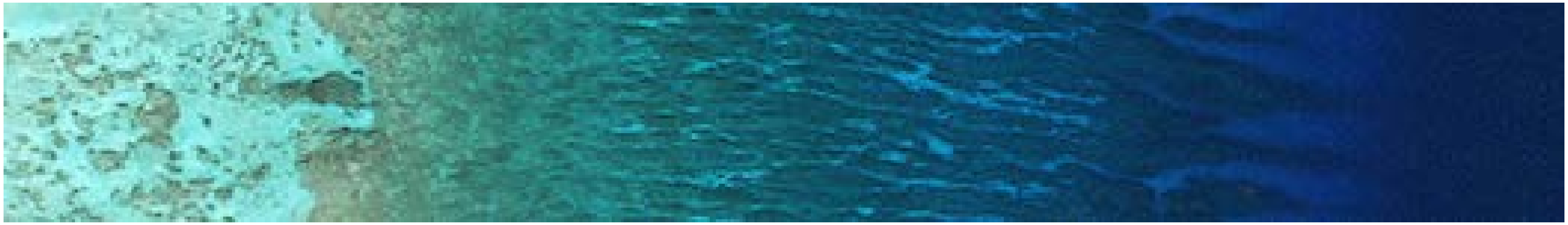




Key:

🟦	Deep Water	🟩	Medium Seagrass	🟧	Rubble / Sparse Coral
🟨	Sand	🟩	Dense Seagrass	🟫	Reef Matrix
⬜	Land				

Classification



- Works by identifying pixels that have similar spectral reflectances
- Supervised or unsupervised
- Need for water column correction

One method - depth invariant indices

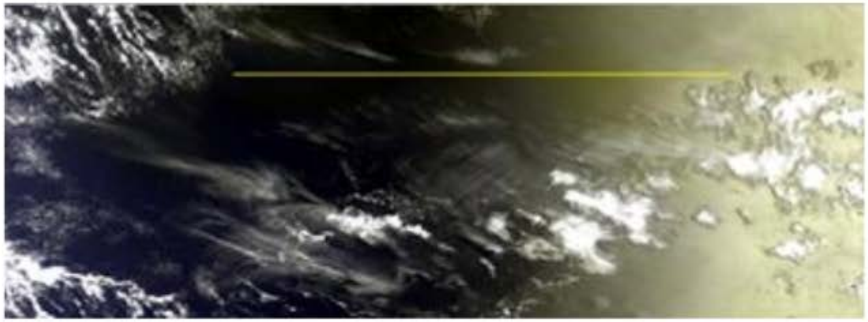
$$X_i = \ln(R_i - R_i^{\text{deep}})$$

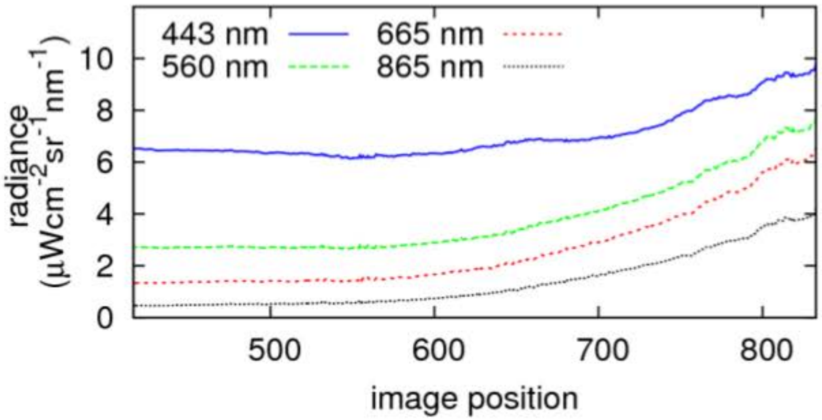
$$X_i = \boxed{\frac{k_i}{k_j}} X_j + d_{ij}$$

only need <u>ratio</u> of attenuation coefficients
can extract from image using sand at different depths

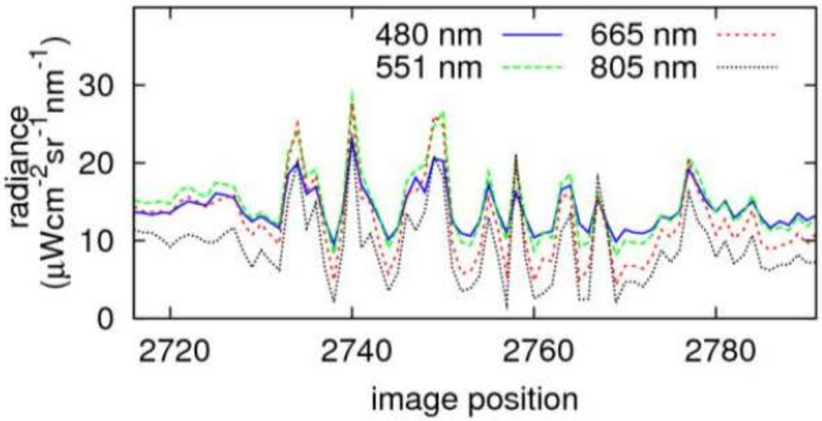
Sun-glint : different types of glint dependent on spatial scale

Large images e.g. MERIS, pixels > 100 m
→ function of solar-view geometry and sea state





High spatial resolution, pixels < 10 m
→ individual waves



Eg. IKONOS, QuickBird, WorldView 2, Sentinel 2

Atmospheric contribution and surface glint

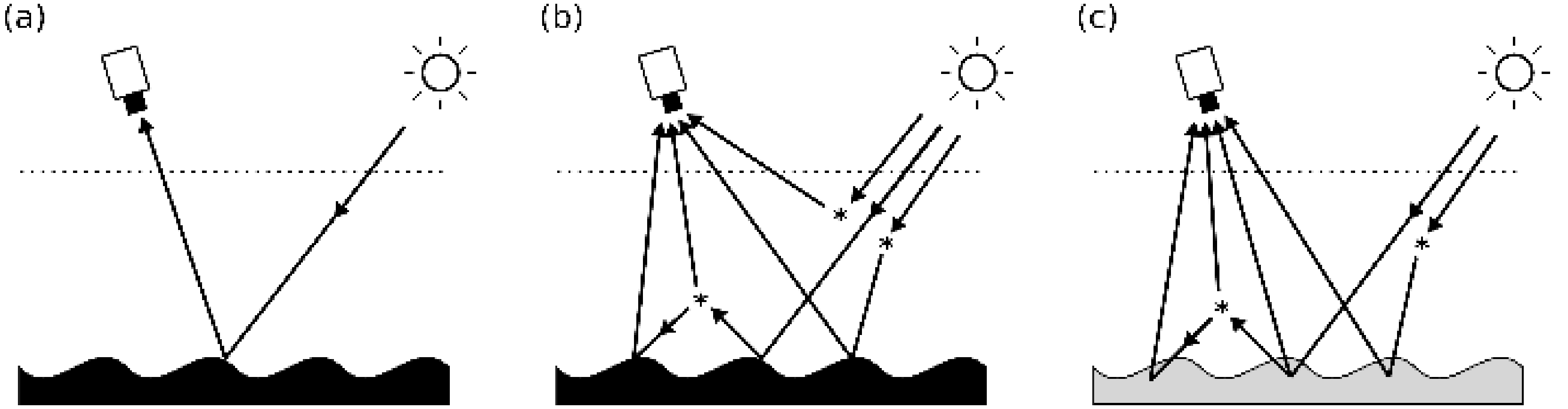


Figure 1: Three-way decomposition of photon paths underlying the atmospheric correction algorithm, * - indicates a scattering event. (a) Direct transmission and reflection from a black ocean; (b) Path radiance over a black ocean; (c) Total transmission of water penetrating photons. Note that a combination of multiple bottom boundary interactions from (b) and (c) is also possible.

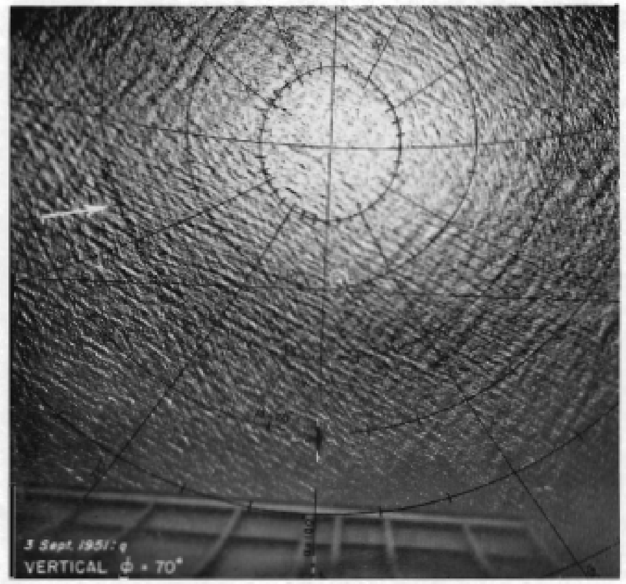
1) Direct Glint **2) Atmospheric Reflectance** **3) Part We Want**

Glint prediction and correction - large scale

Cox and Munk equations

- 1950s - based on photographs of surface glitter
- Many subsequent studies: all agree

Cox & Munk (1956) Slopes of the Sea Surface Deduced from Photographs of Sun Glitter. *Scripps Inst. Oceanogr. Bull*. 6(9): 401–88



Result is statistical model of the sea surface:

Mean square slope = 0.003 + 0.00512 U_{10}

wind speed ms^{-1}

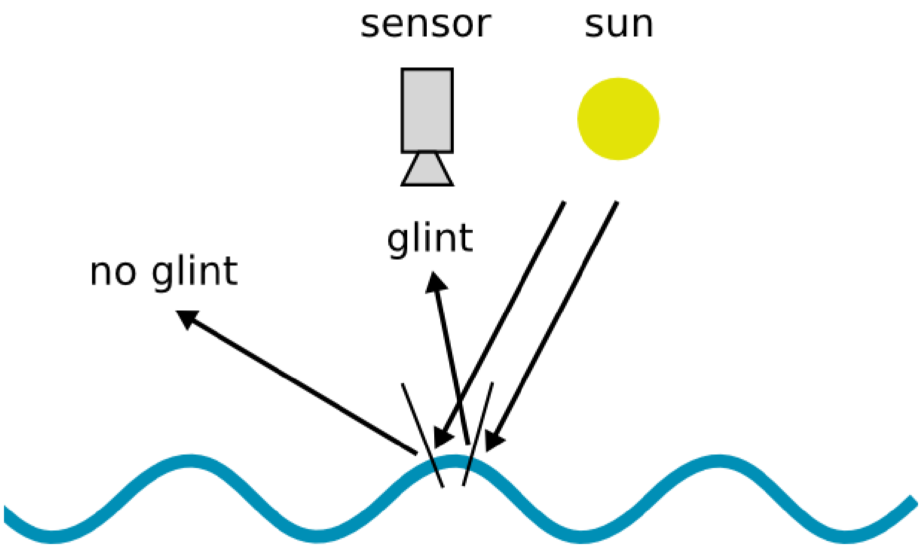
Sun-glint depends only on:

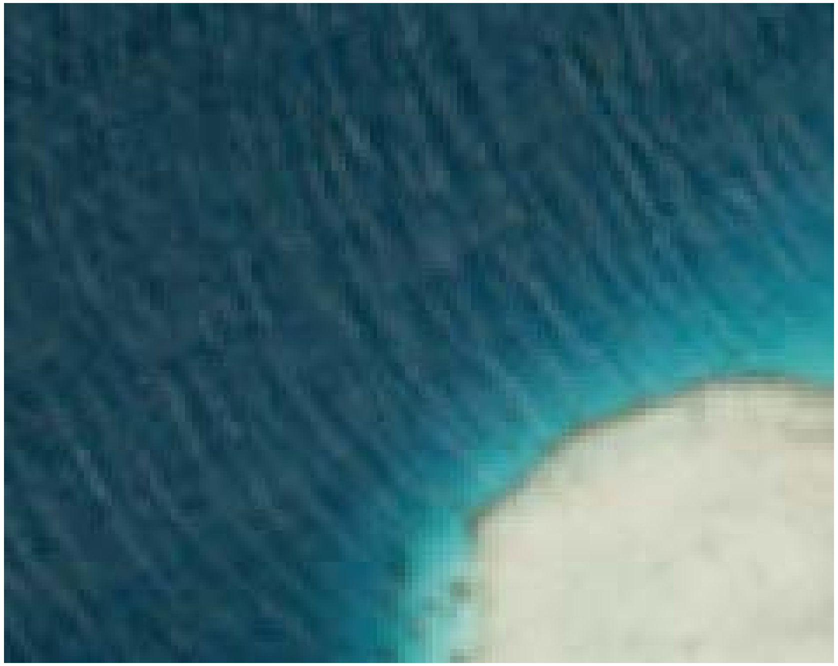
1) sun position
2) sensor position
3) wind speed (and to a small extent wind direction)

- Statistical description at large scales and open ocean → large pixels (100s m)
- No use for high resolution imagery and shallow areas

High spatial resolution

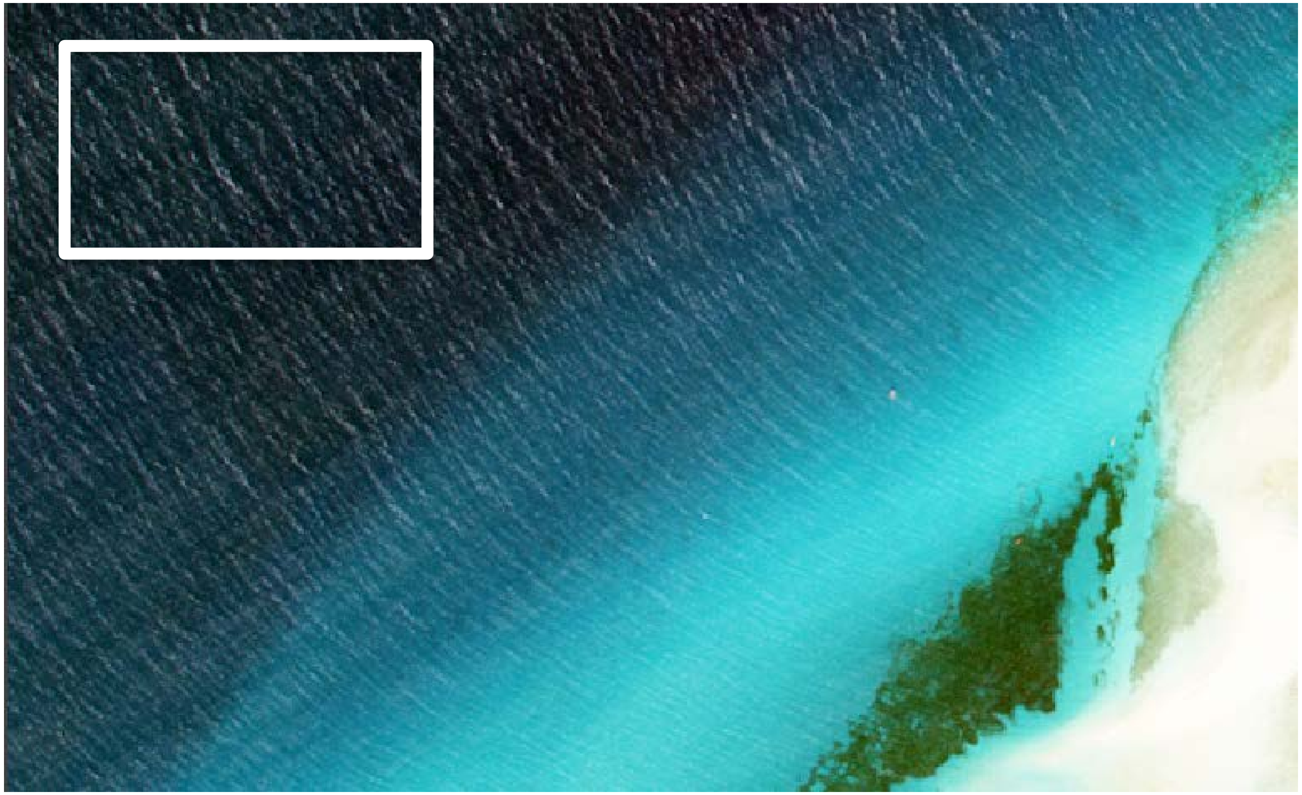
- Atmospheric contribution may be assumed uniform over the area of interest
- Surface glint is not uniform





Glint correction or “deglint” of high spatial resolution images

- Can correct using a Near-Infra Red (NIR) band to assess the glint
- **Assumption 1** - Glint has a uniform spectral signature
- **Assumption 2** - NIR from below the water surface is zero



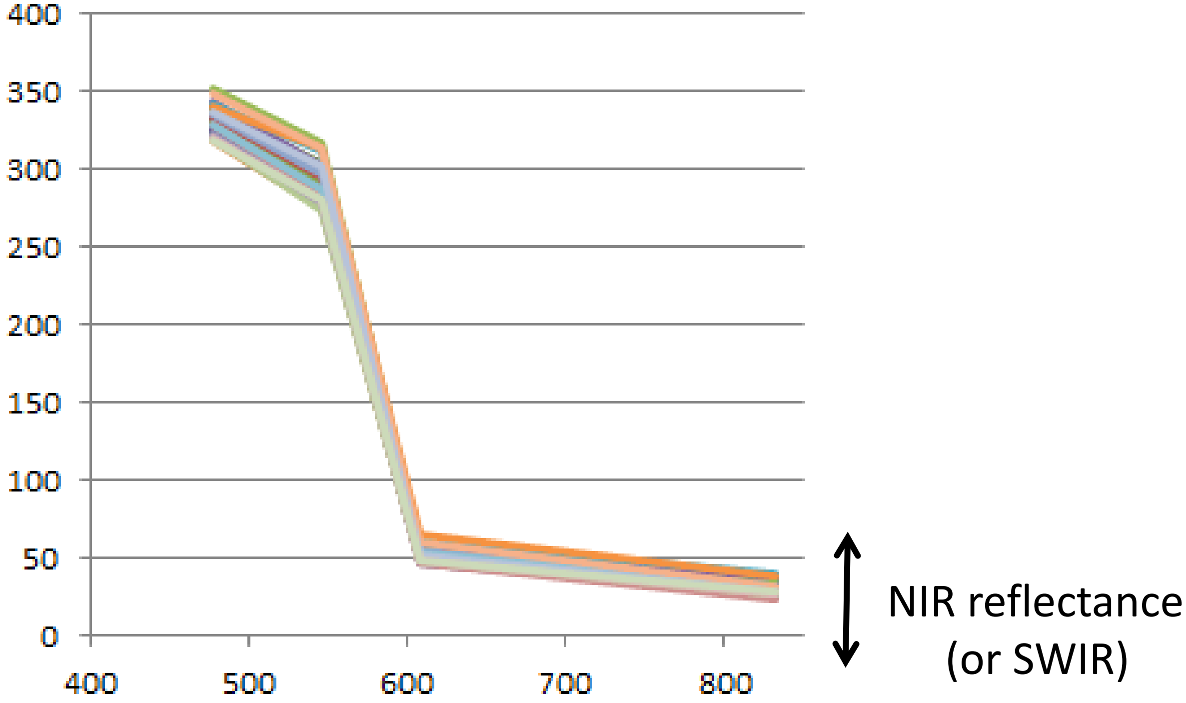
WorldView-2 Image
(c) DigitalGlobe

pixels ~2 m

- Start with a sample of pixels over deep water, where it is assumed there is no sub-surface variation in reflectance

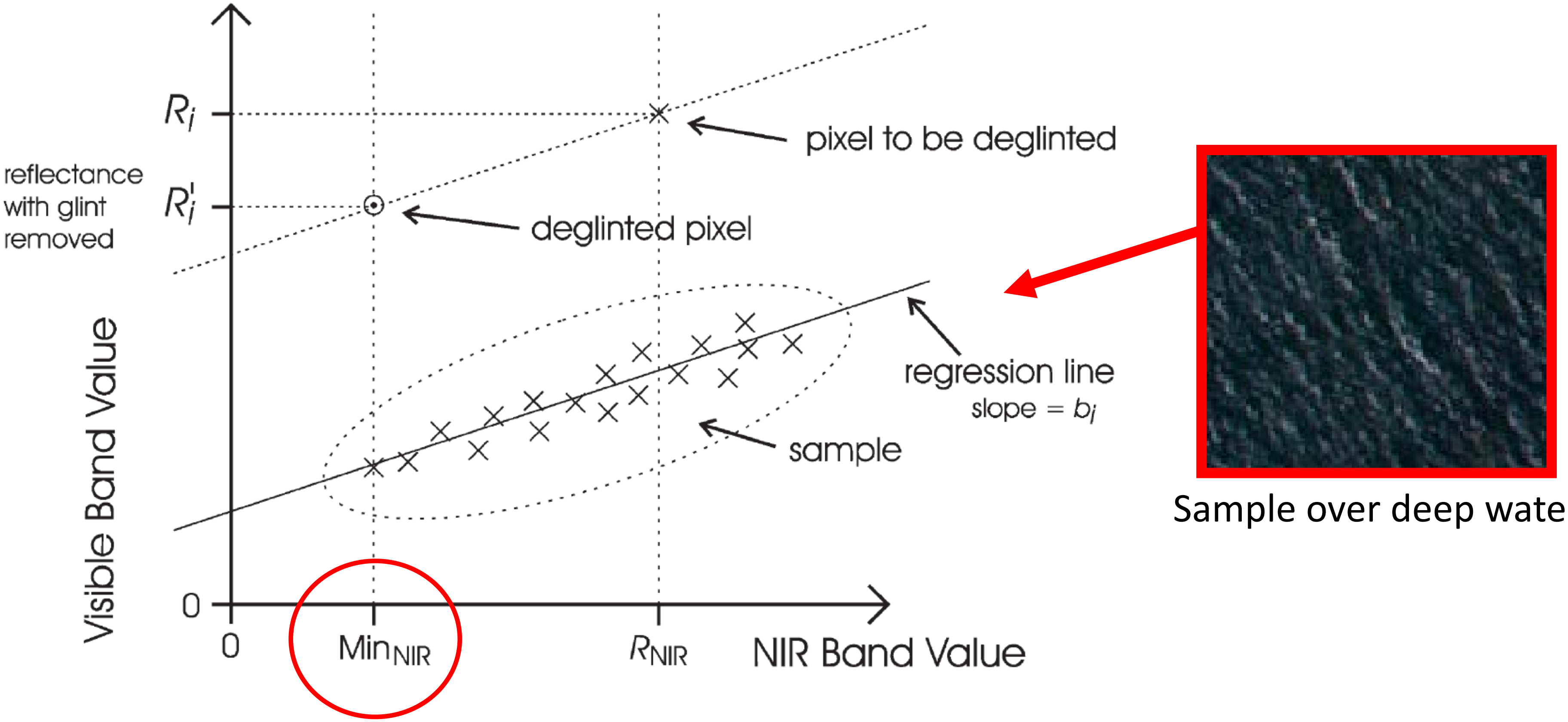
Glint correction or "deglint" of high spatial resolution images

Sample over deep water



Hedley et al. (2005) *International Journal of Remote Sensing* 26: 2107-2112
and other similar methods - see Kay et al. (2009) *Remote Sensing* 1: 697-730

Glint correction or “deglint” of high spatial resolution images

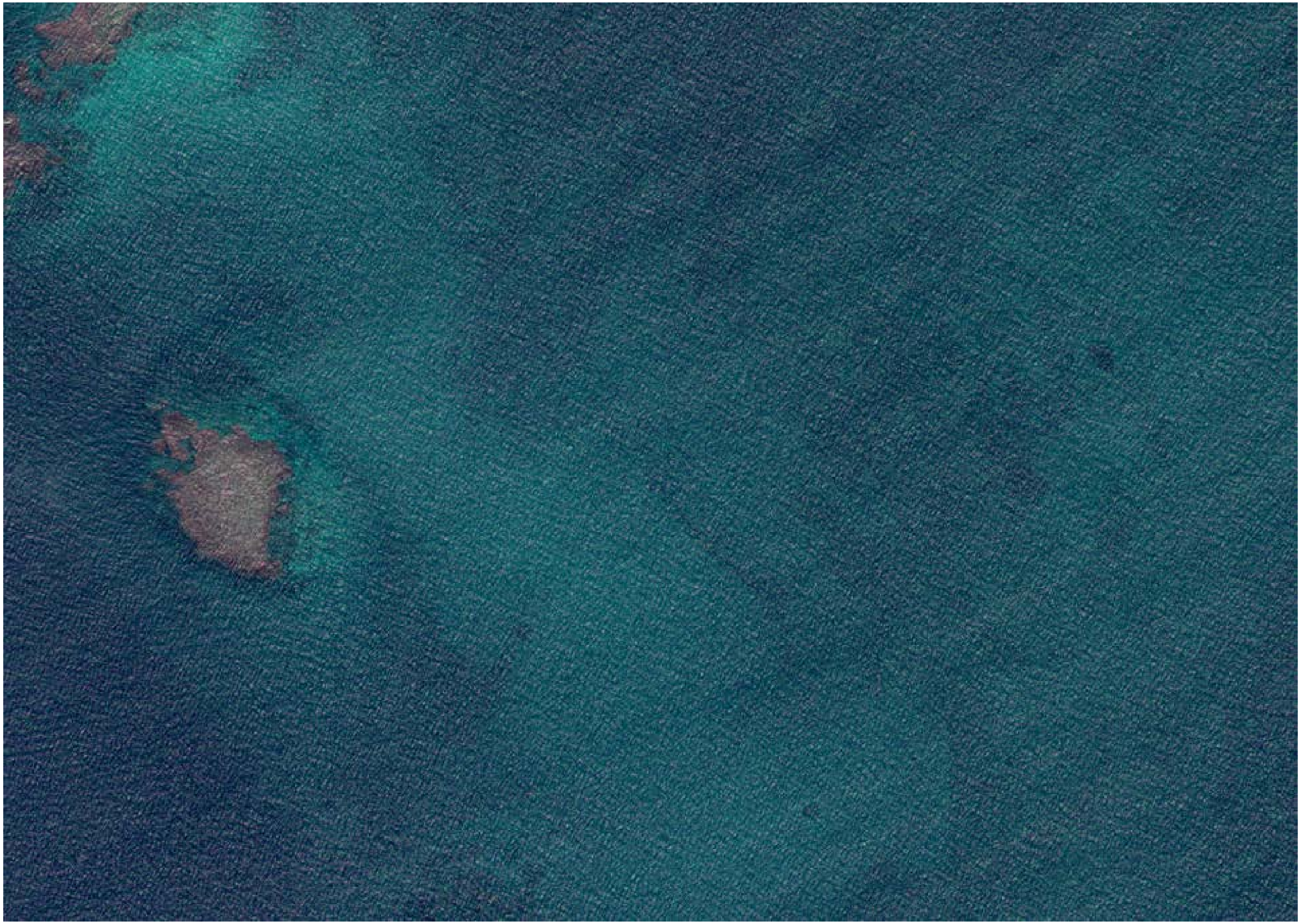


Sample over deep water

$$R_i' = R_i - b_i(R_{\mathrm{NIR}} - \mathrm{Min}_{\mathrm{NIR}})$$

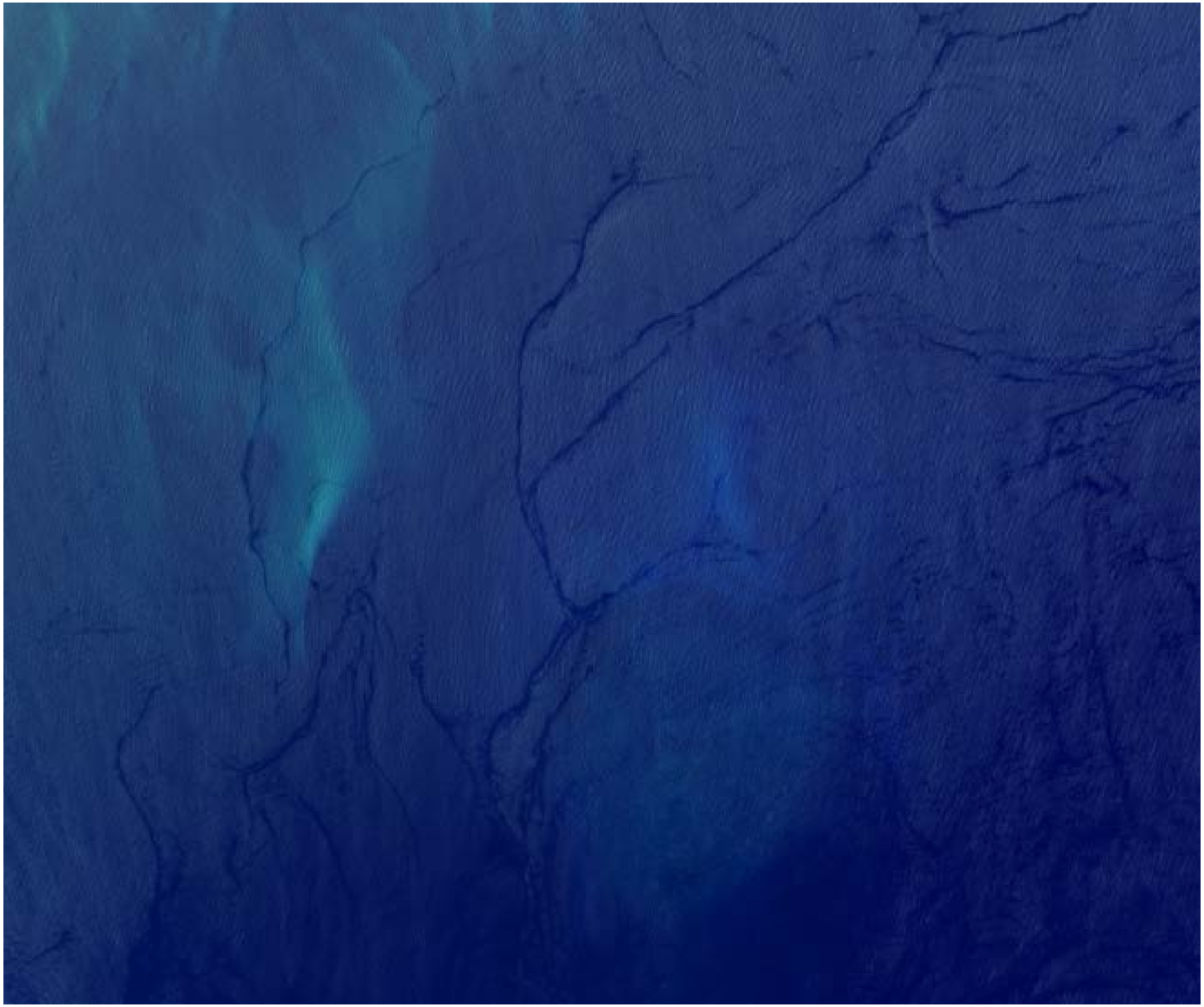
- Before or after atmospheric correction? – using minimum NIR reflectance means it probably doesn’t matter if you assume uniform atmospheric contribution

Before deglint

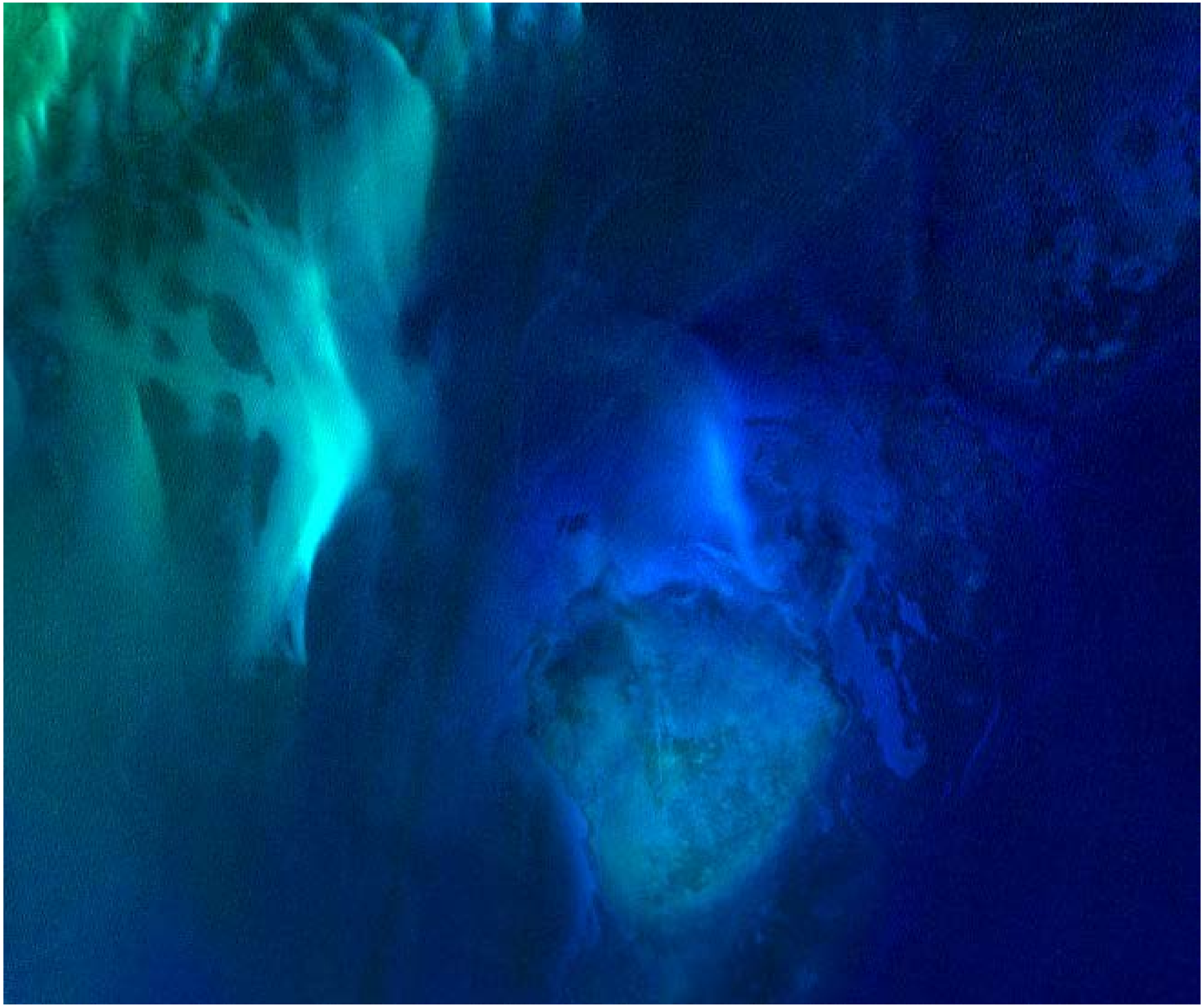


After deglint

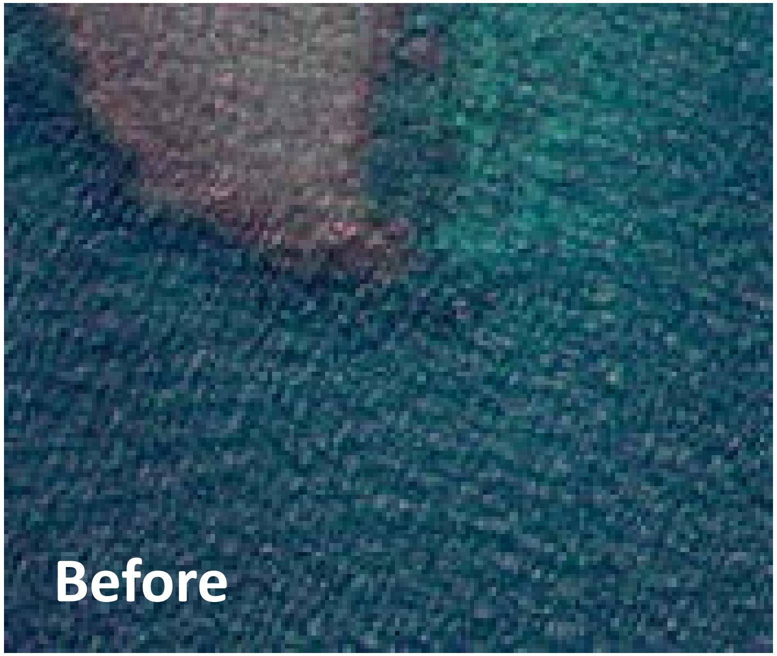
Deglint example (Landsat 8)



Deglint example (Landsat 8)



Note 1: Glint corrected images are quite noisy



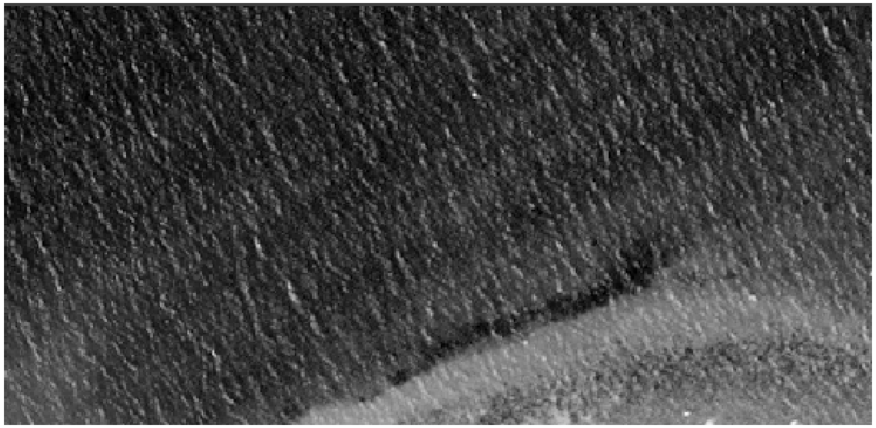
1) Signal to noise issue - take a big signal away to leave a small signal, but noise was on the big signal.
2) Also, combining noise from two bands - visible band and NIR band.
3) Process is not perfect - band alignment, etc.

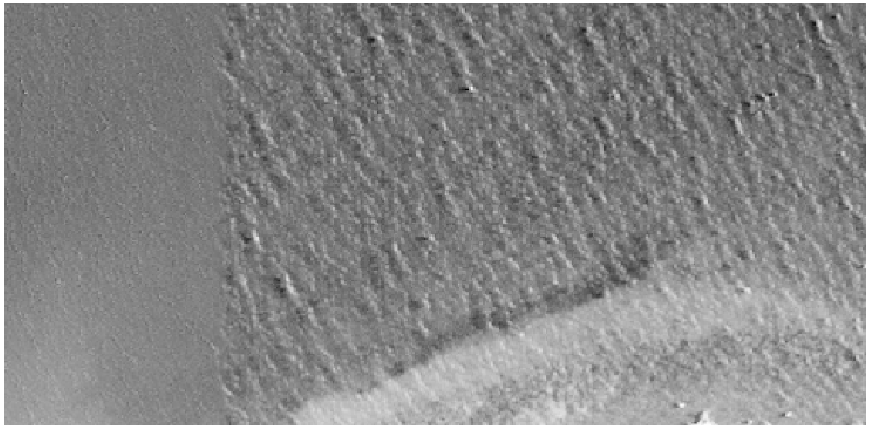
→ Spatial filtering (smoothing) may be useful

Pixel-to-pixel noise

Note 2: The need for precise band alignment

- Image bands are not always perfectly spatially aligned
- Causes serious problems for glint removal algorithm
- WorldView-2 has various striping artefacts



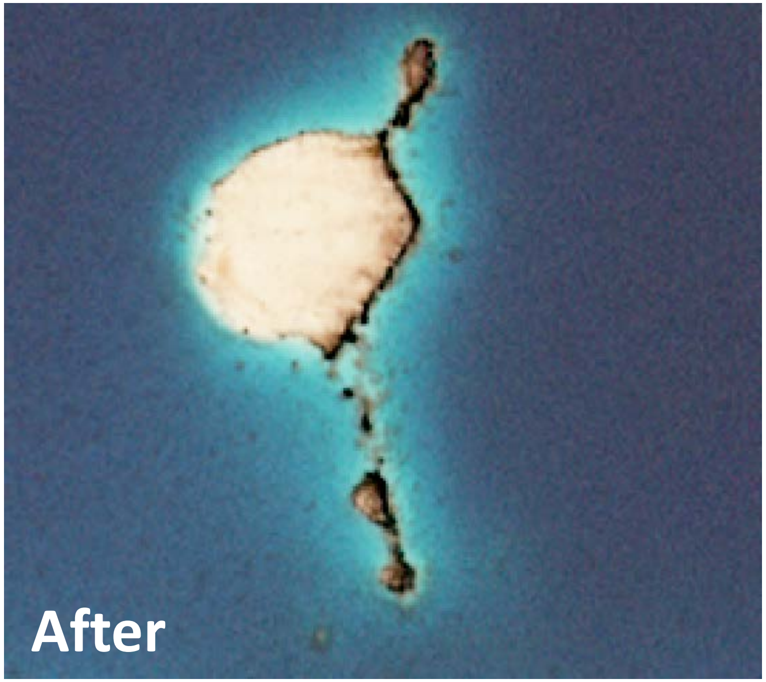


- ➢ glint corrected
- ➢ band alignment on right side is bad

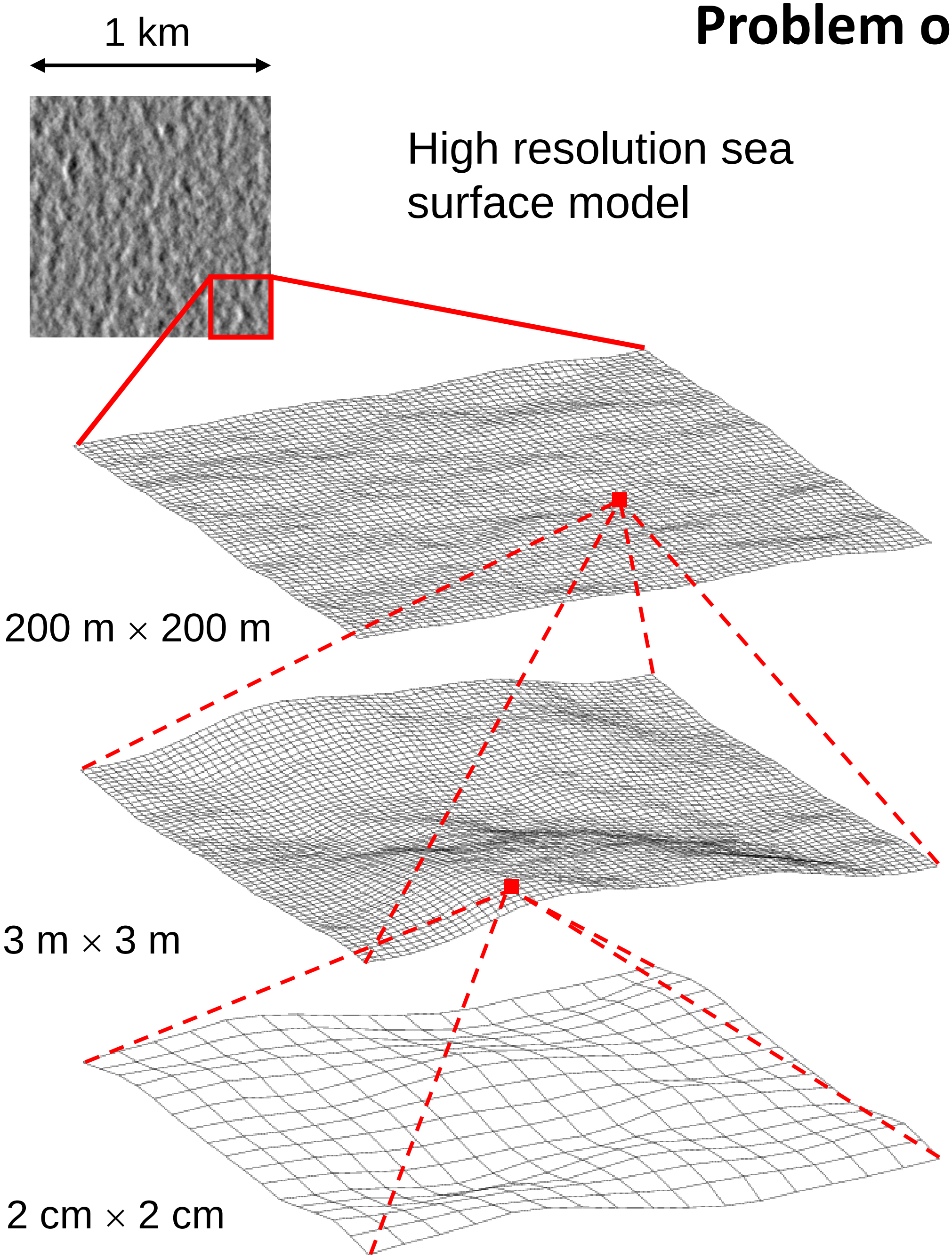
- Sentinel-2 detector edges – similar problems

Note 3: Over-correction when NIR below surface is not zero

- Assumption of zero NIR from below the water is not valid in shallow water
- Result is “dark halo” effect around land features
- Causes problems for subsequently applied algorithms



Problem of sub-pixel glint (Sentinel-2)

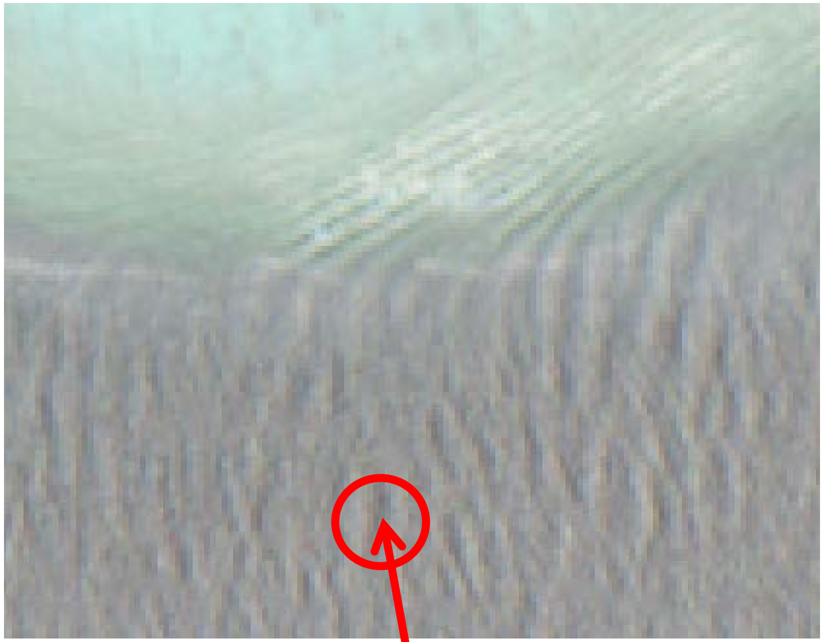


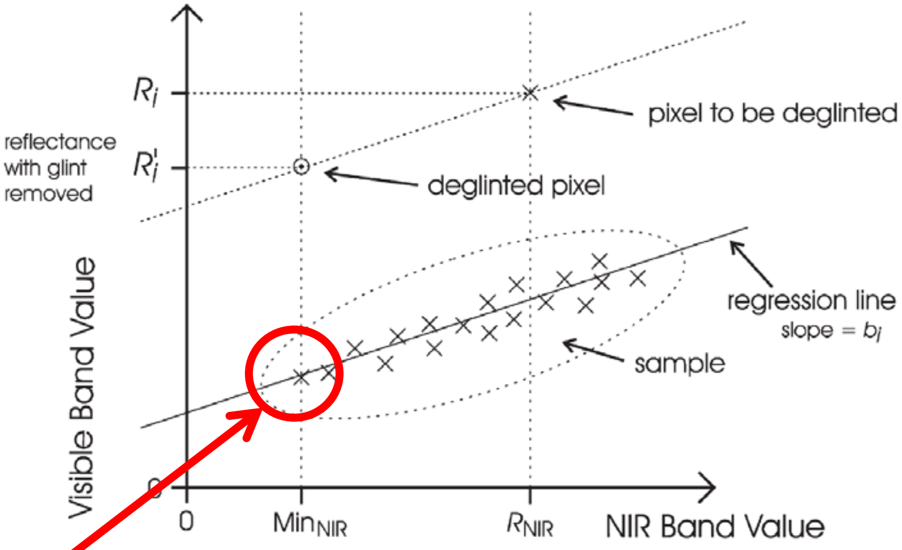
Sea surface undulations occur at multiple scales

- From 100’s metres to millimetres
- 10 m pixels may still contain slopes contributing to the glint within them

Specific challenges with Sentinel-2

PIxel size means hard to get a “no glint” reference

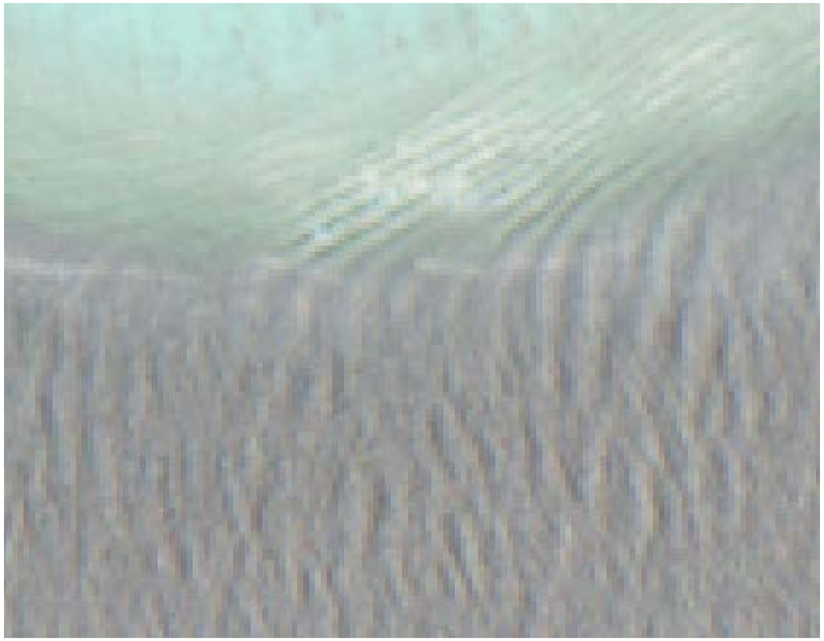


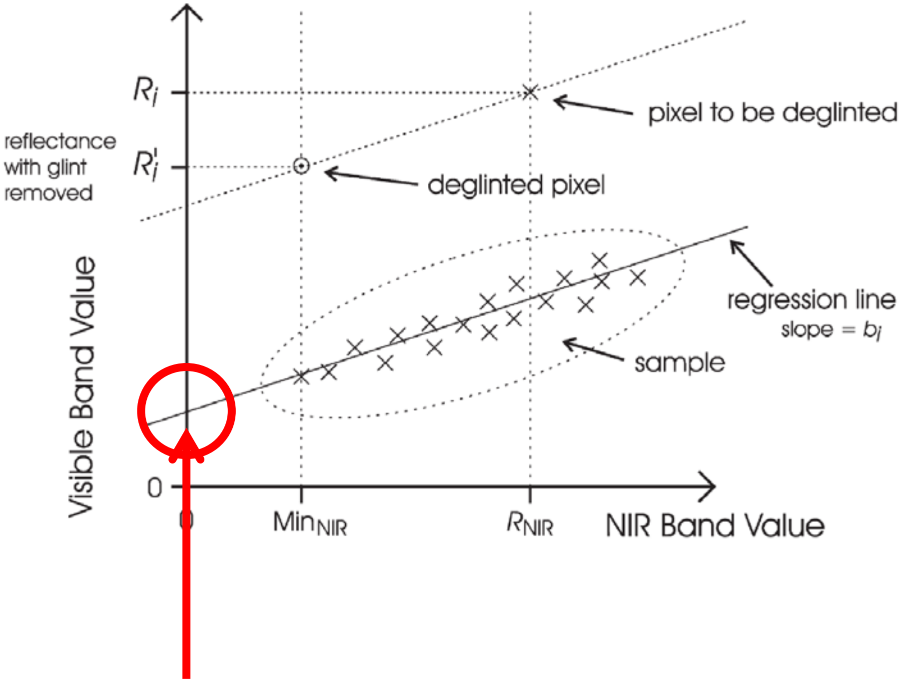


The darkest pixels probably still contain some glint
So glint correction is incomplete and there remains a glint contribution

Specific challenges with Sentinel-2

PIxel size means hard to get a “no glint” reference





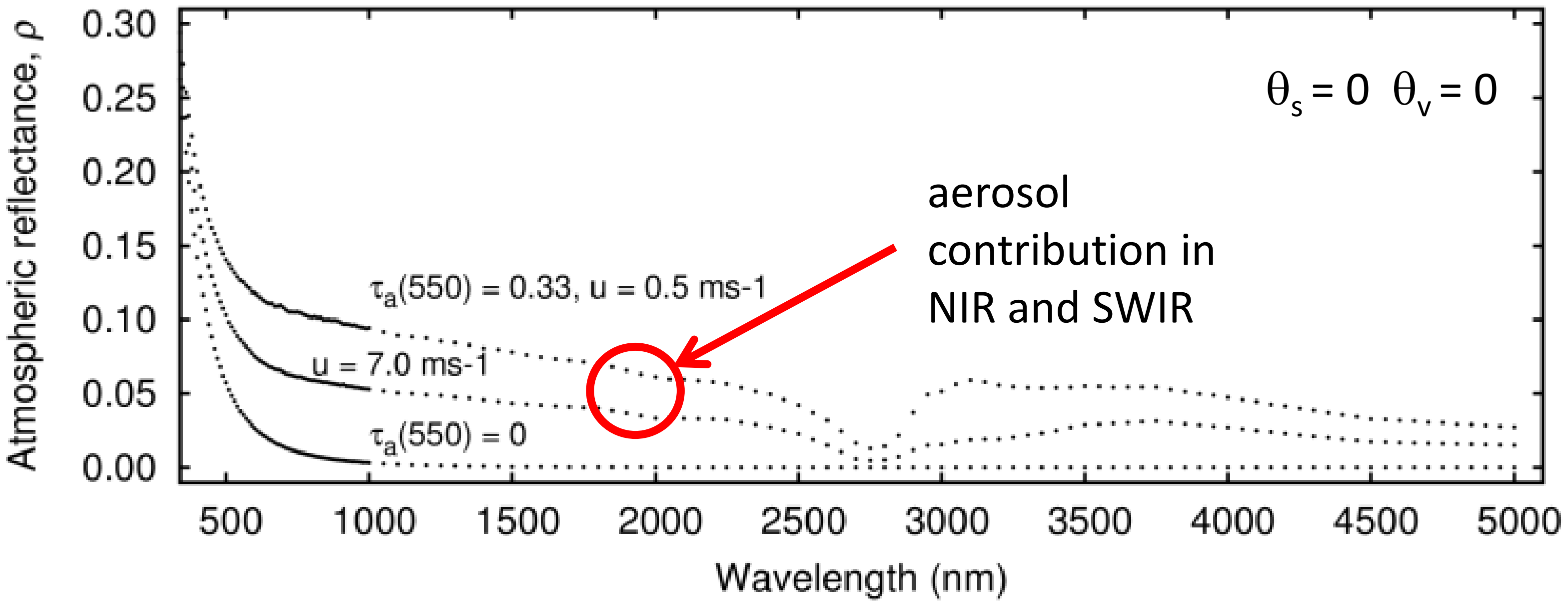
Force correction to assume zero NIR reflectance rather than empirical minimum

<u>But</u> that assumes NIR really should be zero

- i.e. atmospheric correction has removed any aerosol contribution in the NIR
- but atmospheric corrections often use NIR to estimate aerosol!

➢ Very difficult to disentangle glint from aerosol contribution in Sentinel-2 imagery - without additional information

Atmospheric reflectance, Marine 99% RH aerosol model (libRadtran)



$\theta_s = 0 \quad \theta_v = 0$

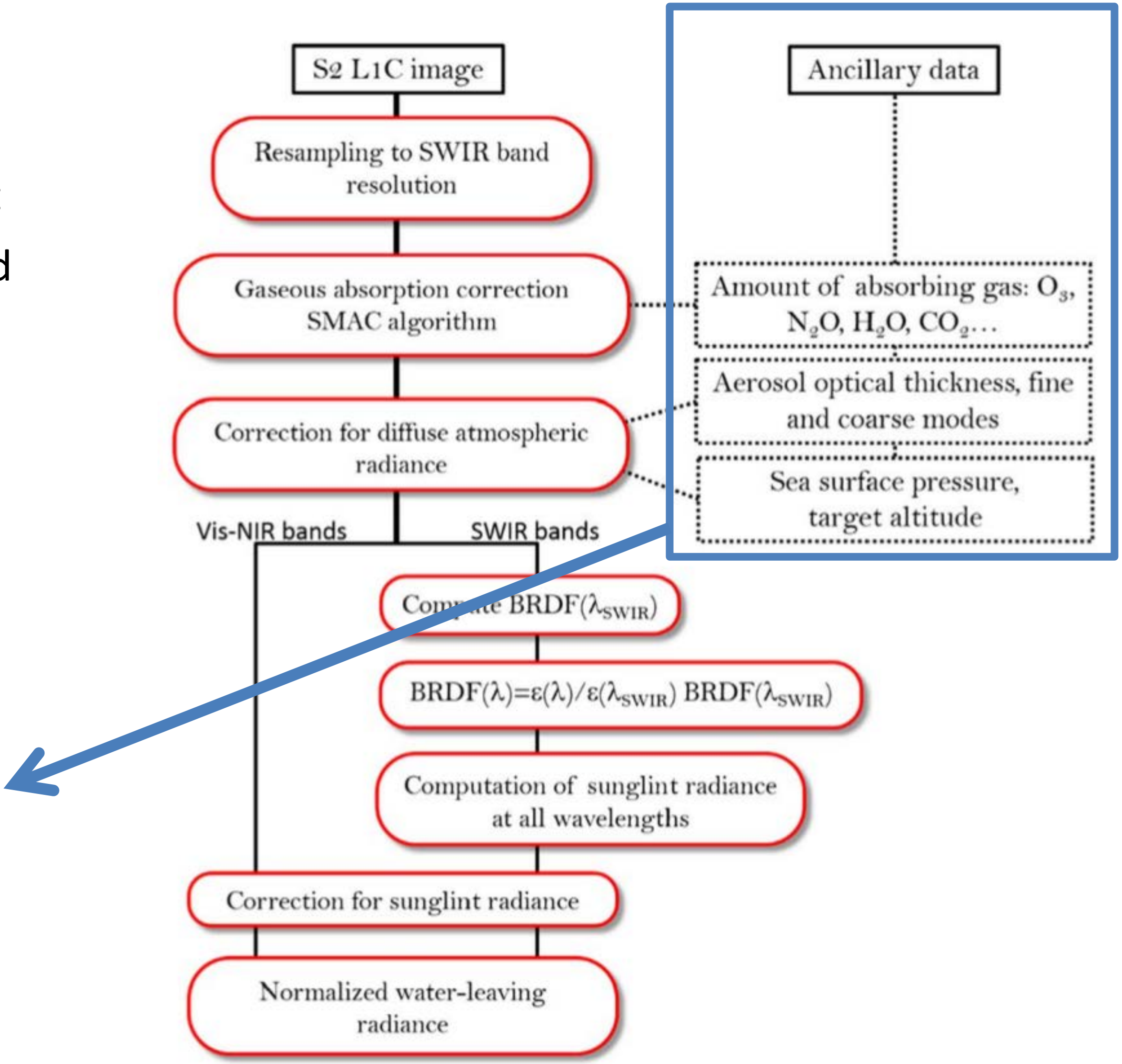
aerosol contribution in NIR and SWIR

- In this plot sun and view are directly overhead (zenith and nadir)
- Indirect surface reflectance but no direct glint included
- Top two lines include aerosols, bottom line Rayleigh only

SWIR doesn’t help much - there still is an aerosol and glint contribution

Harmel et al. 2018

- Glint correction for Sentinel-2
- Uses SWIR to characterise glint
- Wavelength dependence based on refractive index of water
- <u>But</u> still relies on a-priori separation of atmospheric reflectance from surface glint

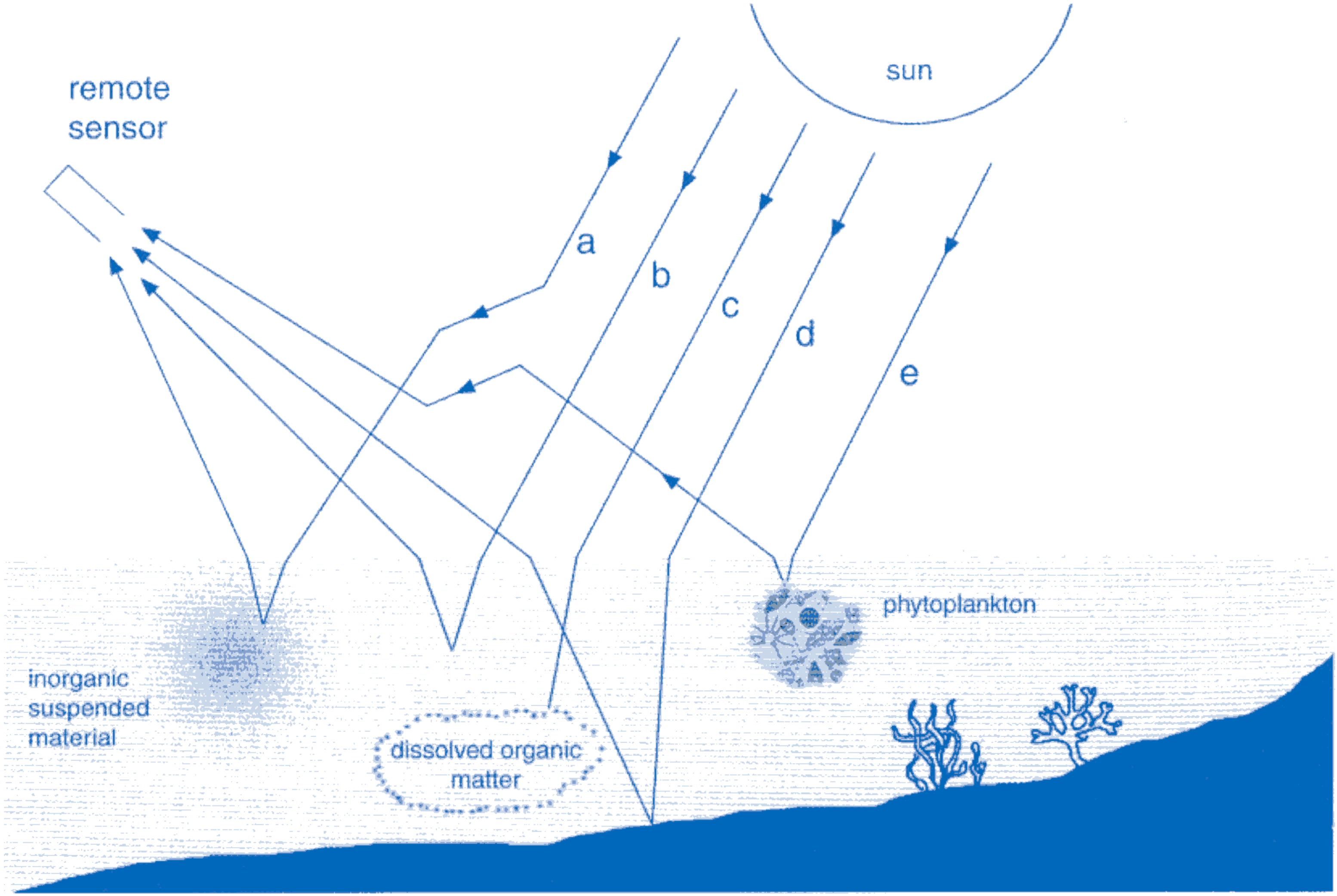


Need this data for atmospheric correction, e.g. from AERONET station.

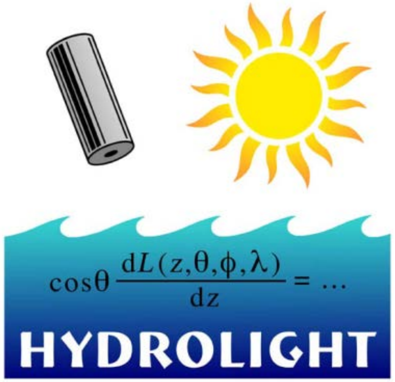
Effectively this adds information to reduce uncertainty between aerosol and glint

Harmel T. et al. (2018) *Remote Sensing of Environment*, 204: 308-321 doi: 10.1016/j.rse.2017.10.022

Inversion methods for shallow water applications



Shallow water models for R_{rs}



1) HydroLight-EcoLight

Build look-up tables for different depths, water column optical properties and bottom reflectances

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

2) Semi-analytical models

Develop a simpler conceptual model and estimate coefficients or parameters from a physically exact model such as HydroLight

Results in a forward model that is faster to compute

Lee et al. (1998) *Applied Optics* 37, 6329-6338

Lee et al's semianalytical model for shallow water reflectance

$$r_{\mathrm{rs}}(\lambda) \approx f(P, G, X, H, \rho(\lambda), \lambda)$$

$$a(\lambda) = a_{\mathrm{w}}(\lambda) + [a_0(\lambda) + a_1(\lambda)\ln P]\,P + G\exp[-0.015\,(\lambda - 440)]$$

$$b_{\mathrm{b}}(\lambda) = b_{\mathrm{bw}}(\lambda) + X\,(400/\lambda)^{Y}$$

$$u(\lambda) = b_{\mathrm{b}}(\lambda)/\left[a(\lambda) + b_{\mathrm{b}}(\lambda)\right], \qquad \kappa(\lambda) = a(\lambda) + b_{\mathrm{b}}(\lambda)$$

$$r_{\mathrm{rs}}^{\mathrm{dp}}(\lambda) \approx [0.084 + 0.170u(\lambda)]\,u(\lambda)$$

$$D_{\mathrm{u}}^{\mathrm{C}}(\lambda) \approx 1.03\sqrt{1 + 2.4u(\lambda)} \qquad D_{\mathrm{u}}^{\mathrm{B}}(\lambda) \approx 1.04\sqrt{1 + 5.4u(\lambda)}$$

remote sensing reflectance

$$r_{\mathrm{rs}}(\lambda) \approx r_{\mathrm{rs}}^{\mathrm{dp}}(\lambda)\left(1 - \exp\left\{-\left[\frac{1}{\cos\theta_{\mathrm{w}}} + \frac{D_{\mathrm{u}}^{\mathrm{C}}(\lambda)}{\cos\theta}\right]\kappa(\lambda)H\right\}\right) + \frac{1}{\pi}\rho(\lambda)\exp\left\{-\left[\frac{1}{\cos\theta_{\mathrm{w}}} + \frac{D_{\mathrm{u}}^{\mathrm{B}}(\lambda)}{\cos\theta}\right]\kappa(\lambda)H\right\}$$

bottom reflectance

H = depth in metres
P = phytoplankton concentration (proxy)
G = dissolved organic matter concentration (proxy)
X = backscatter
Y = (spectral slope of backscatter) is fixed at 1

Also incorporates sun and view zenith angles

Various factors derived from HydroLight

Inversion of the model

This is a **forward model** it describes what can occur in every individual pixel based on what is in the pixel

$$r_{\mathrm{rs}}(\lambda) \approx f(\underline{P, G, X, H, m, E})(\lambda)$$

Six values describe every pixel

But we start with this
and wish to deduce this

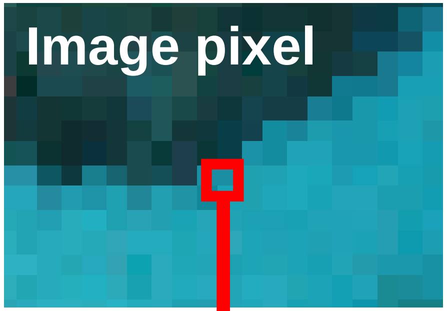
1) Look-Up Tables - just try every combination of *P*, *G*, *X*, *H*, *m*, *E* within their bounds and find which produces the best match for the pixel $r_{\mathrm{rs}}(\lambda)$

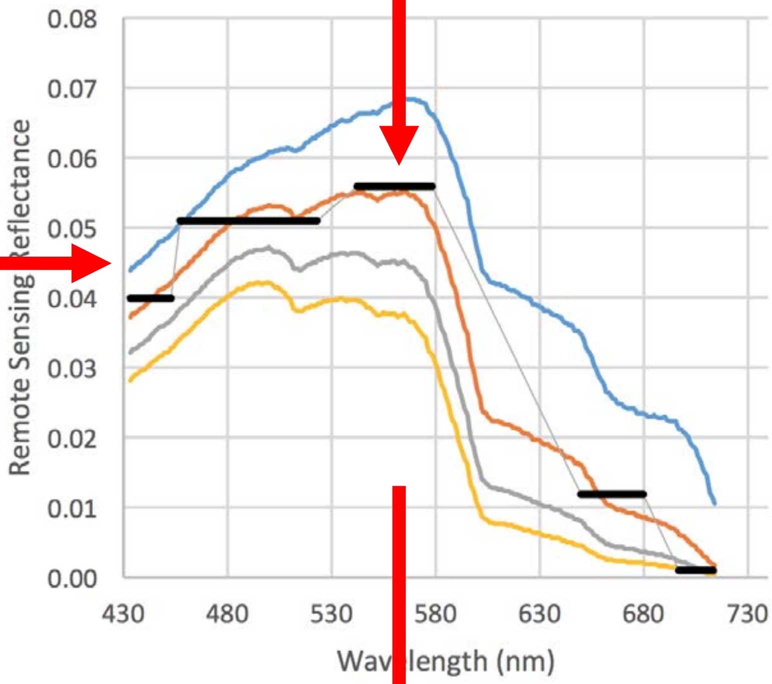
2) Successive approximation technique such as the Levenberg-Marquardt algorithm, keeps adjusting solution to try and improve it.

LUT (look-up table)

Depth,	Phytoplankton,	CDOM, … etc
1 m	0.1 mg m^{-3}	
2 m	0.1 mg m^{-3}	
3 m	0.1 mg m^{-3}	
4 m	0.1 mg m^{-3}	
1 m	0.2 mg m^{-3}	
2 m	0.2 mg m^{-3}	
3 m	0.2 mg m^{-3}	
4 m	0.2 mg m^{-3}	
1 m	0.4 mg m^{-3}	
2 m	0.4 mg m^{-3}	
3 m	0.4 mg m^{-3}	
4 m	0.4 mg m^{-3}	

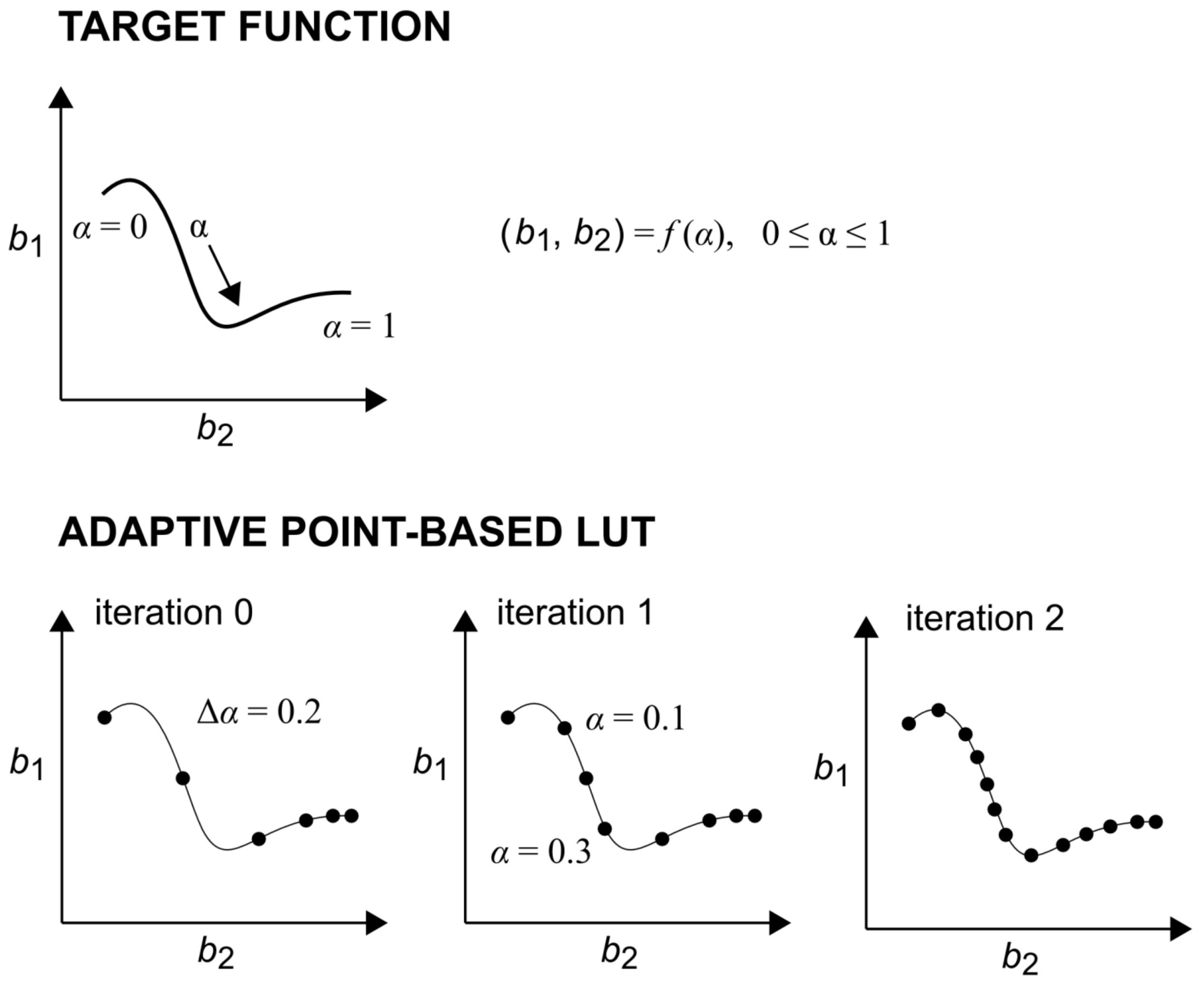
MODEL





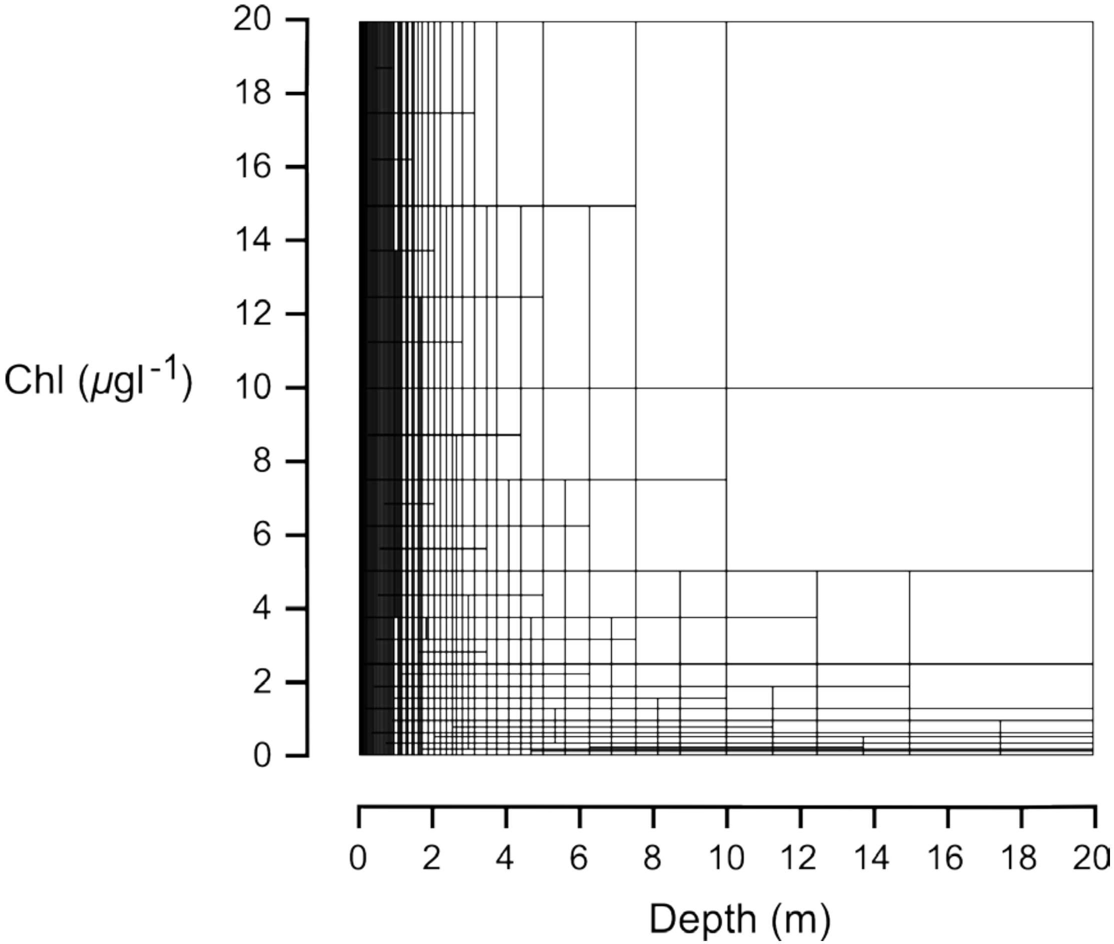
Estimate:
Depth = 2 m
Phytopankton = 0.2 mg m^{-3}
... etc

Adaptive LUT construction



Hedley et al. 2009, *Remote Sens. Environ.*

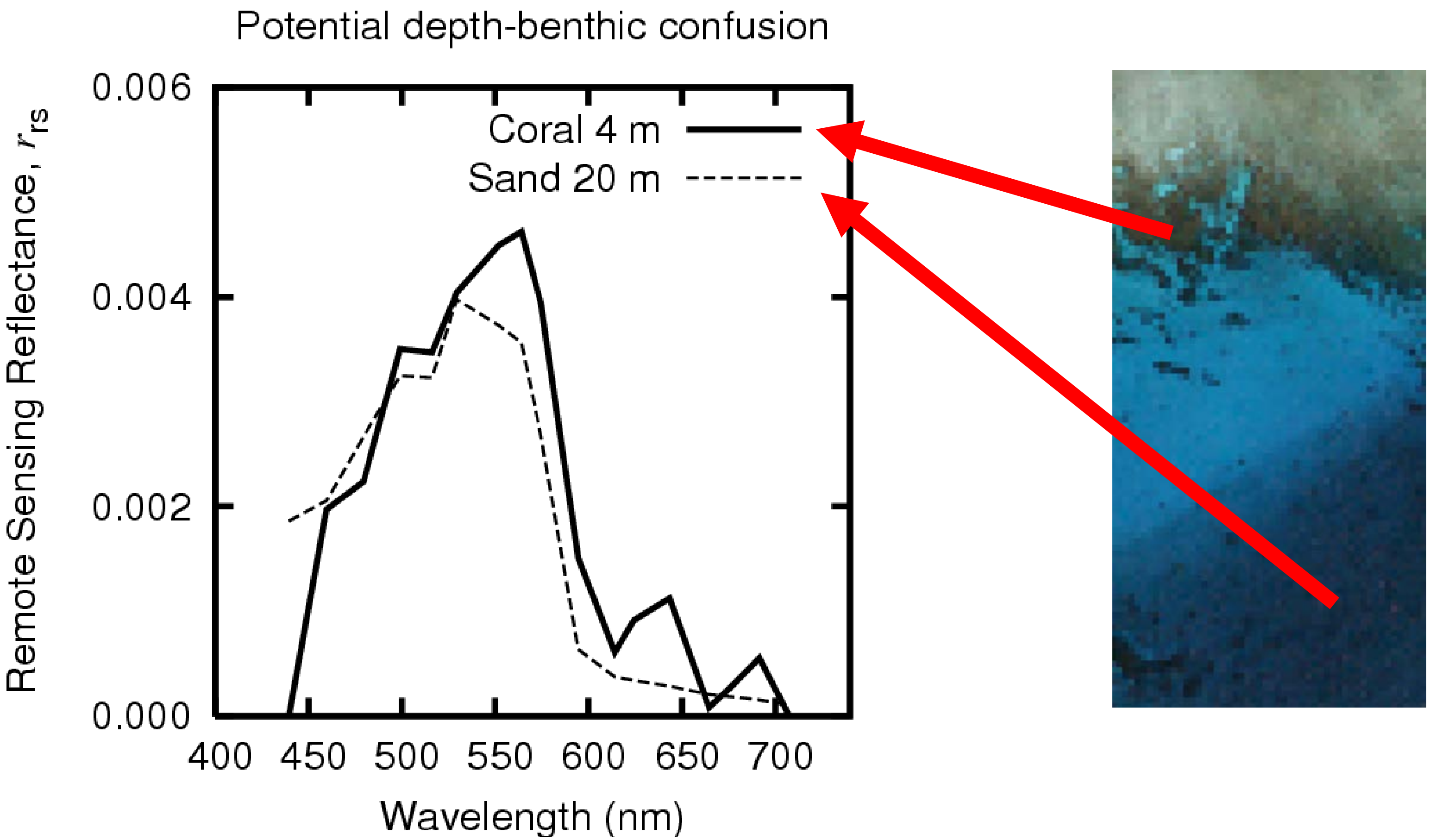
Example slice through ALUT structure



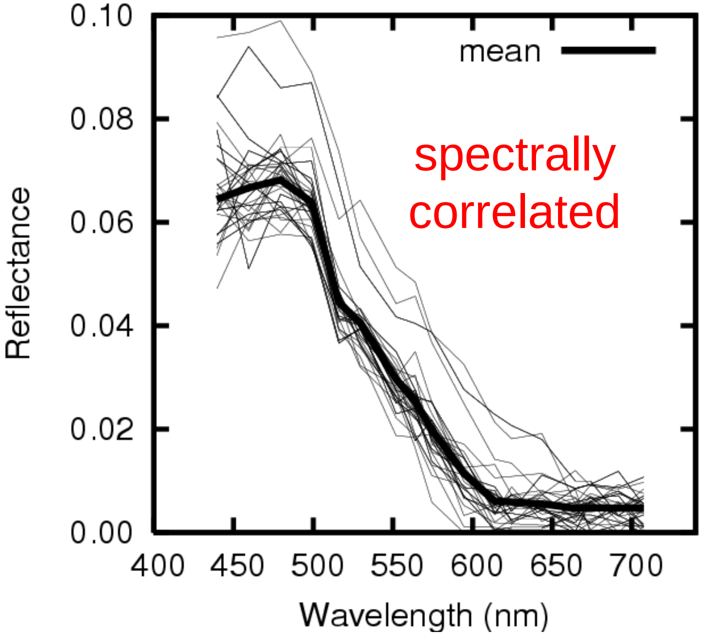
Uncertainty Propagation

Fundamental uncertainty

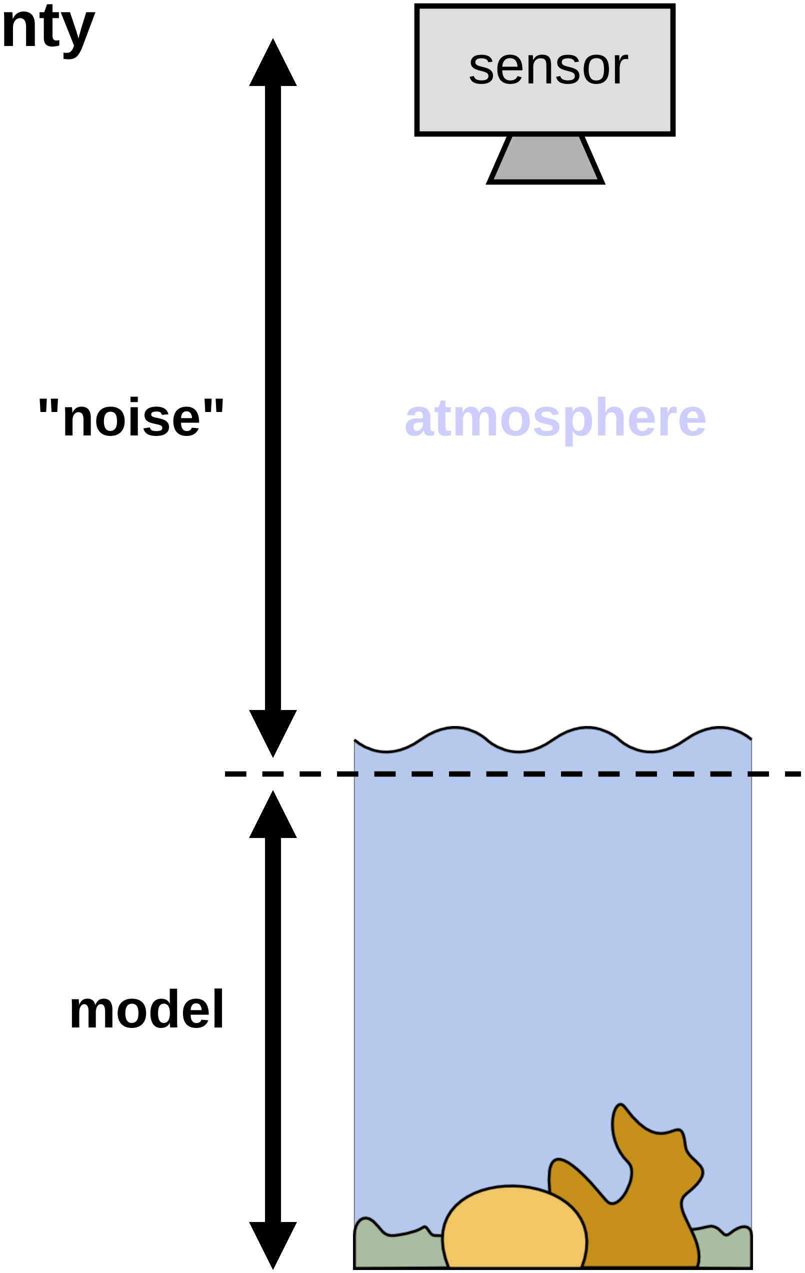
→ similar spectra from differing parameters



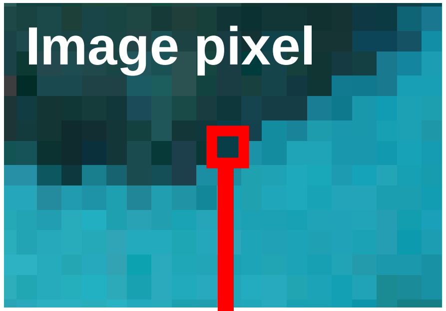
Sources of "noise" → uncertainty



Hyperspectral deep water pixels



Propagation through inversion



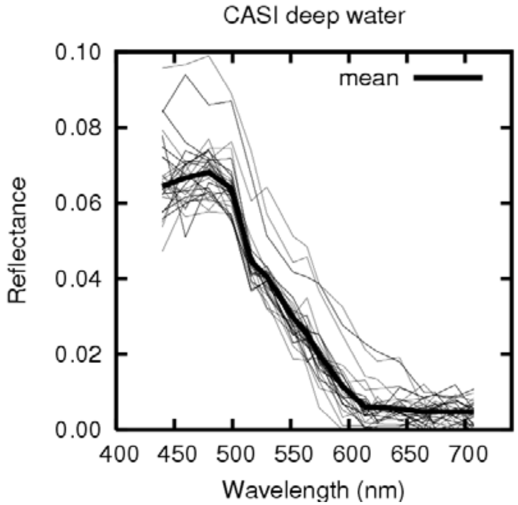


image noise

(multivariate normal)

subtract random noise term × 20 times

20 reflectance spectra

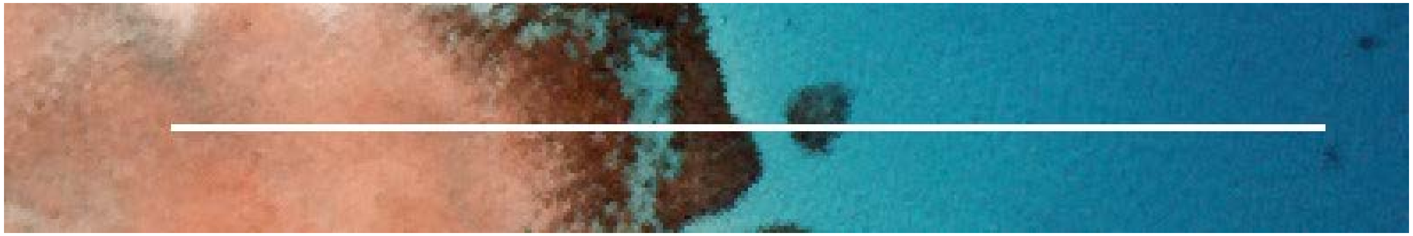
invert to retrieve parameter estimations

discard upper and lower tails to give 90% conf. intervals

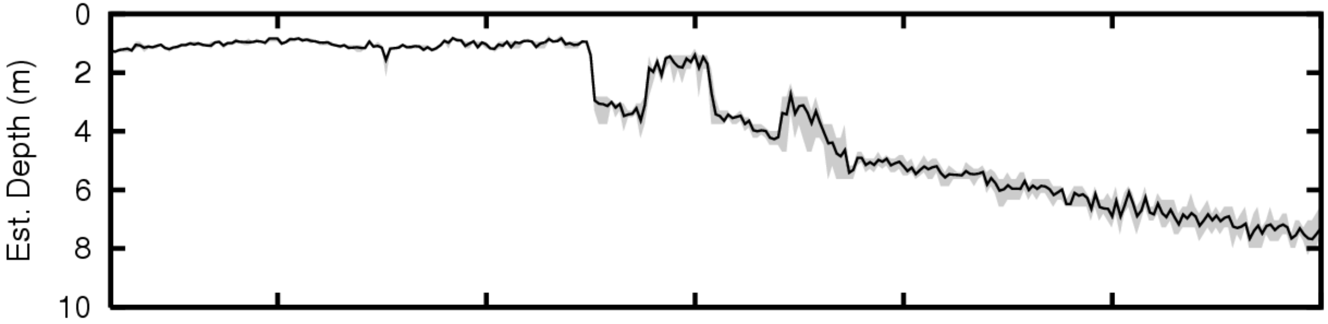
use mean for actual result

- better than direct result
- spatially smoother

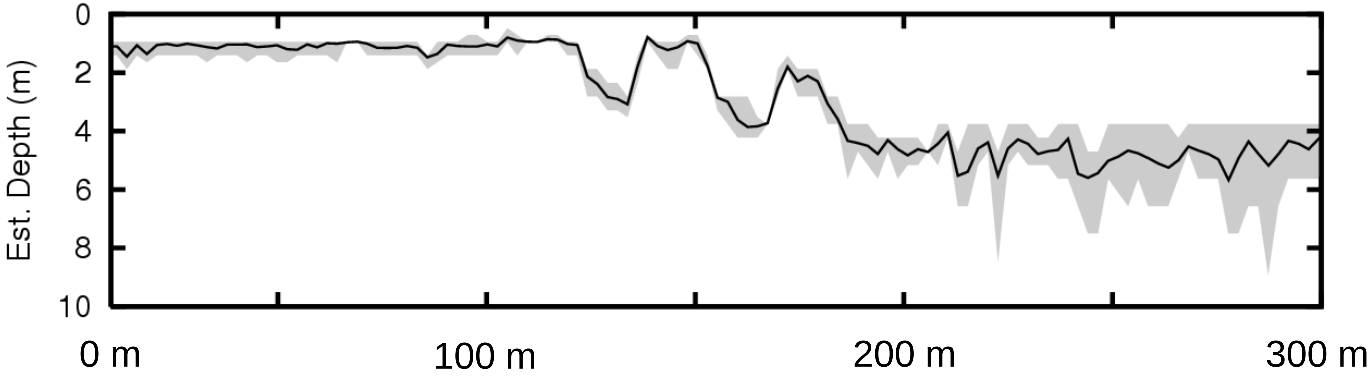
Bathymetry estimation with uncertainty



CASI



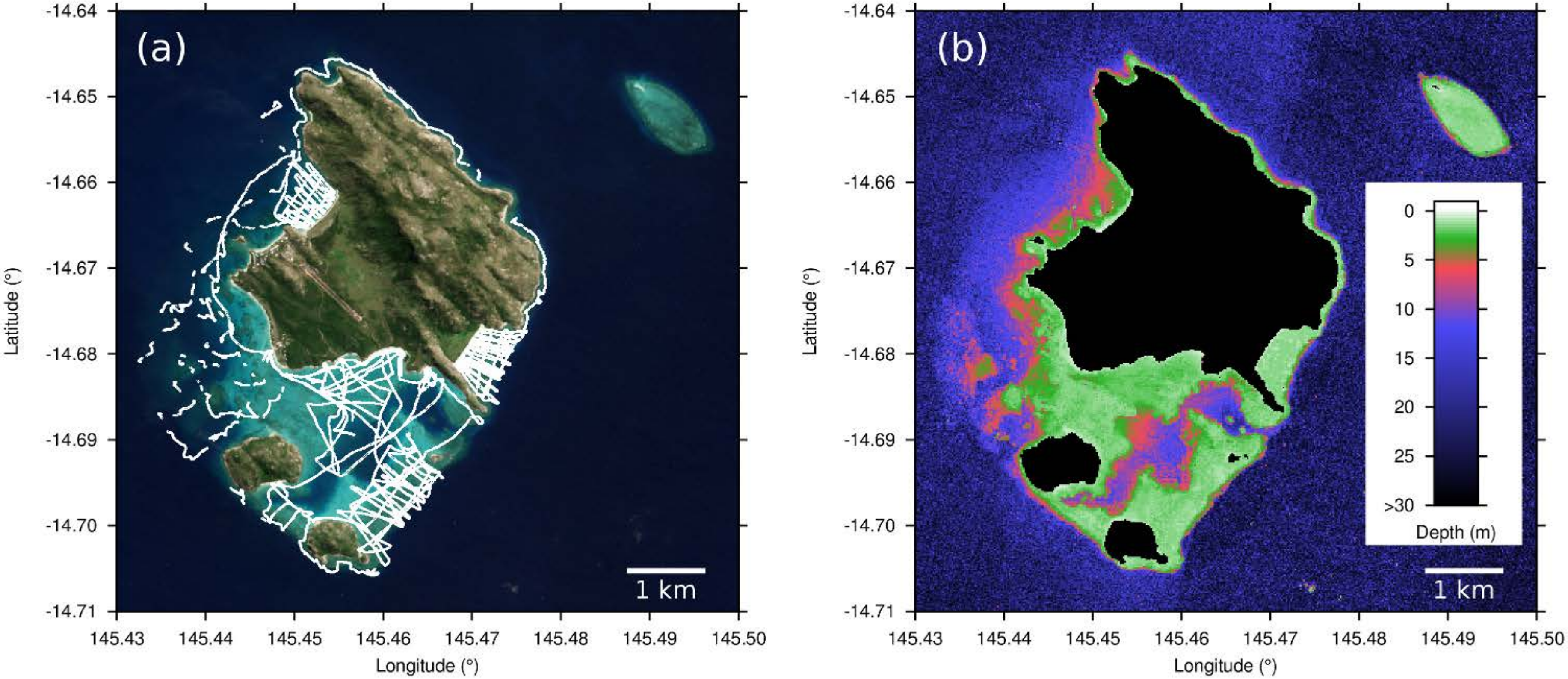
Quickbird



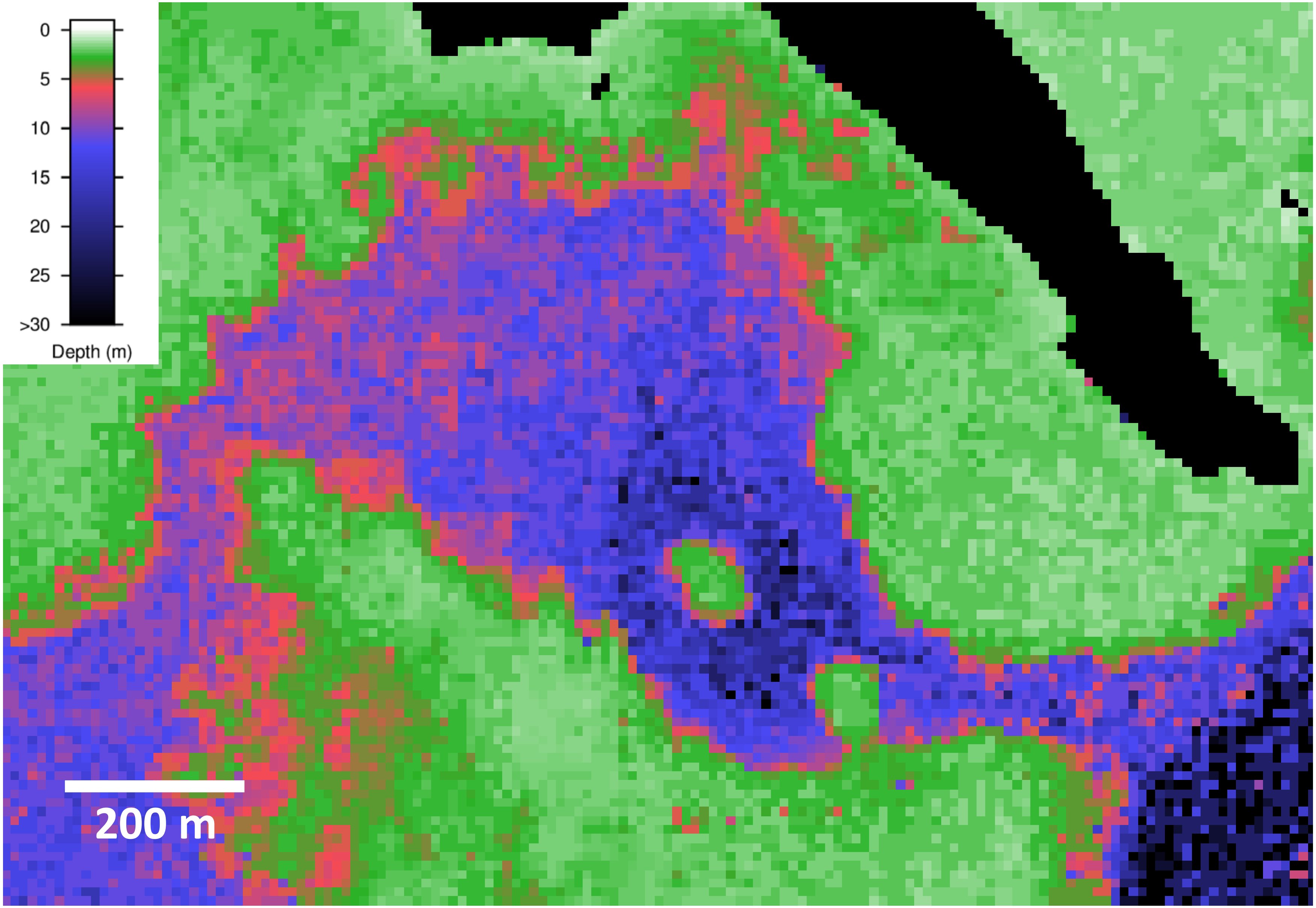
▨ = 90% confidence interval

Sentinel-2 bathymetry of Lizard Island (GBR) by model inversion

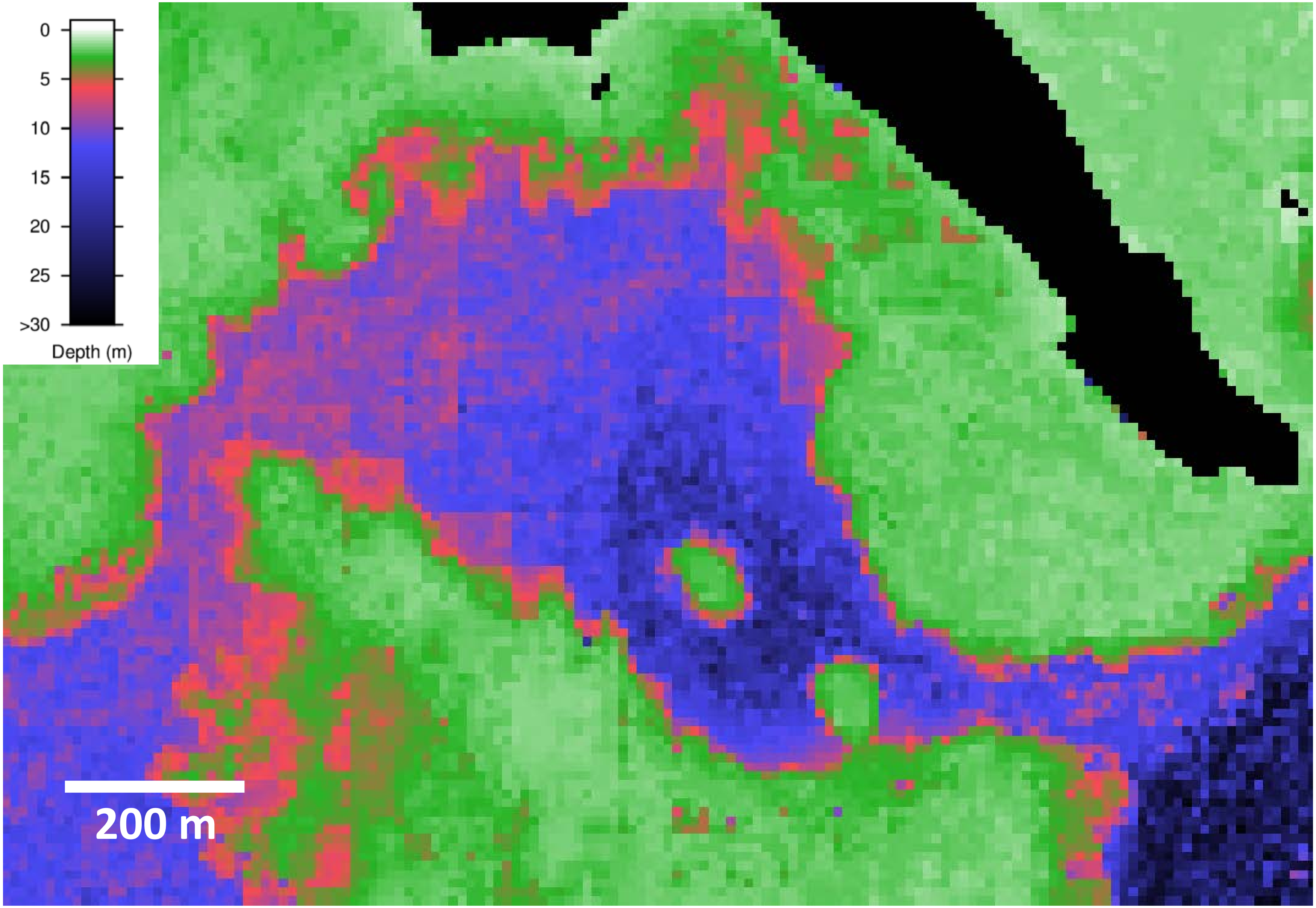
- Uses bands 1, 2, 3, 4 and 5
- ALUT inversion of Lee et al. equations
- In-situ echo-sound data for comparison



Direct result (single inversion)

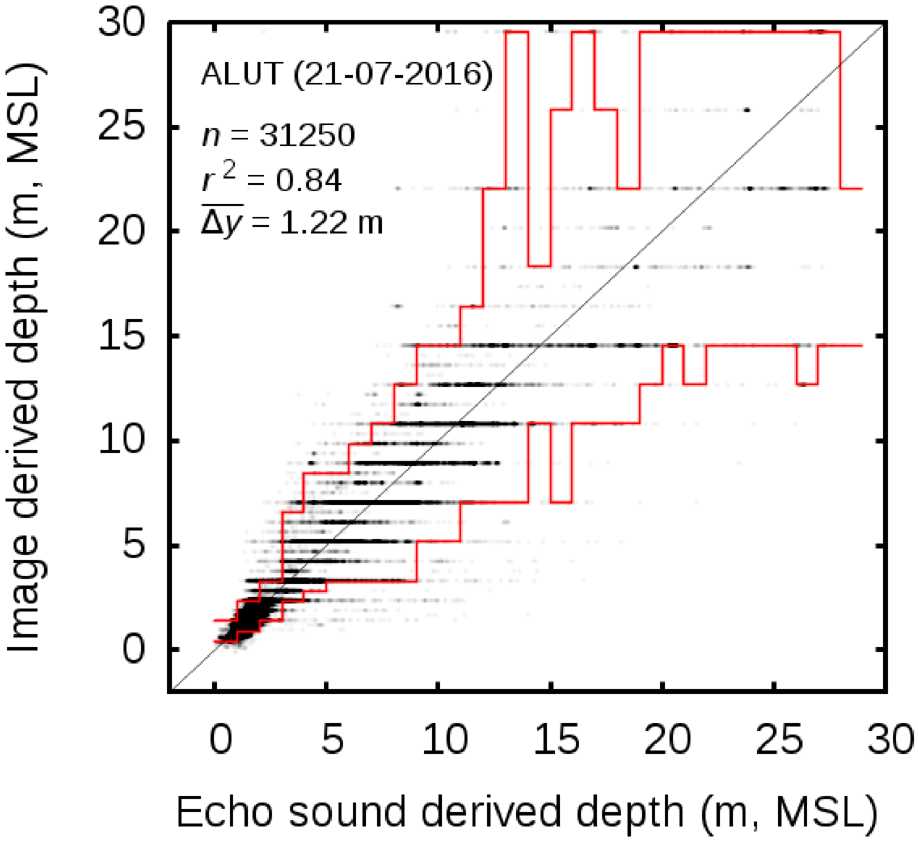


Mean of 20 noise perturbed results

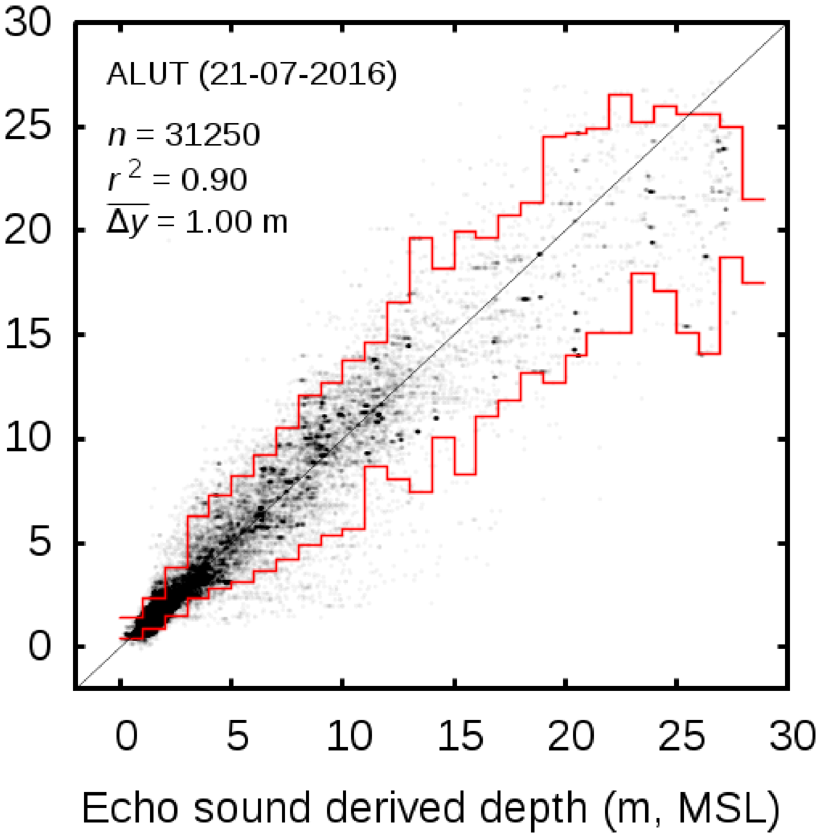


Single inversion vs. mean of noise perturbed inversions

Direct result (single inversion)

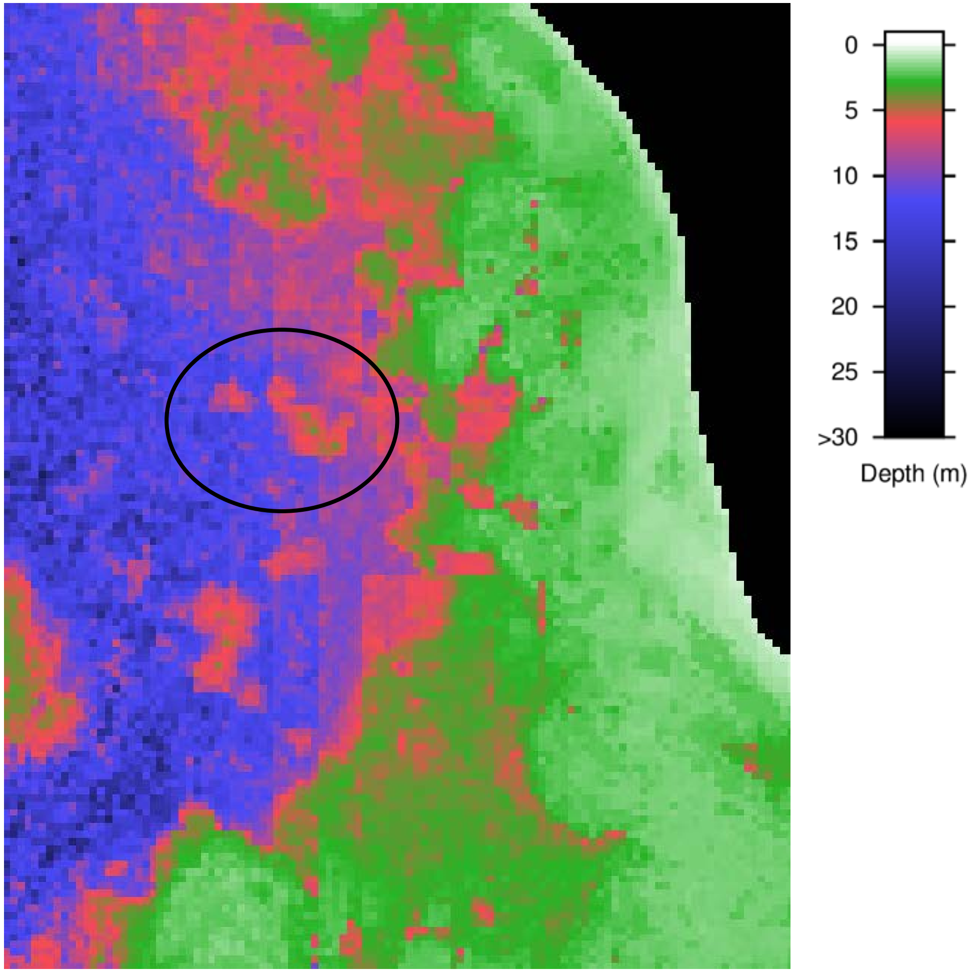


Mean of 20 noise perturbed results



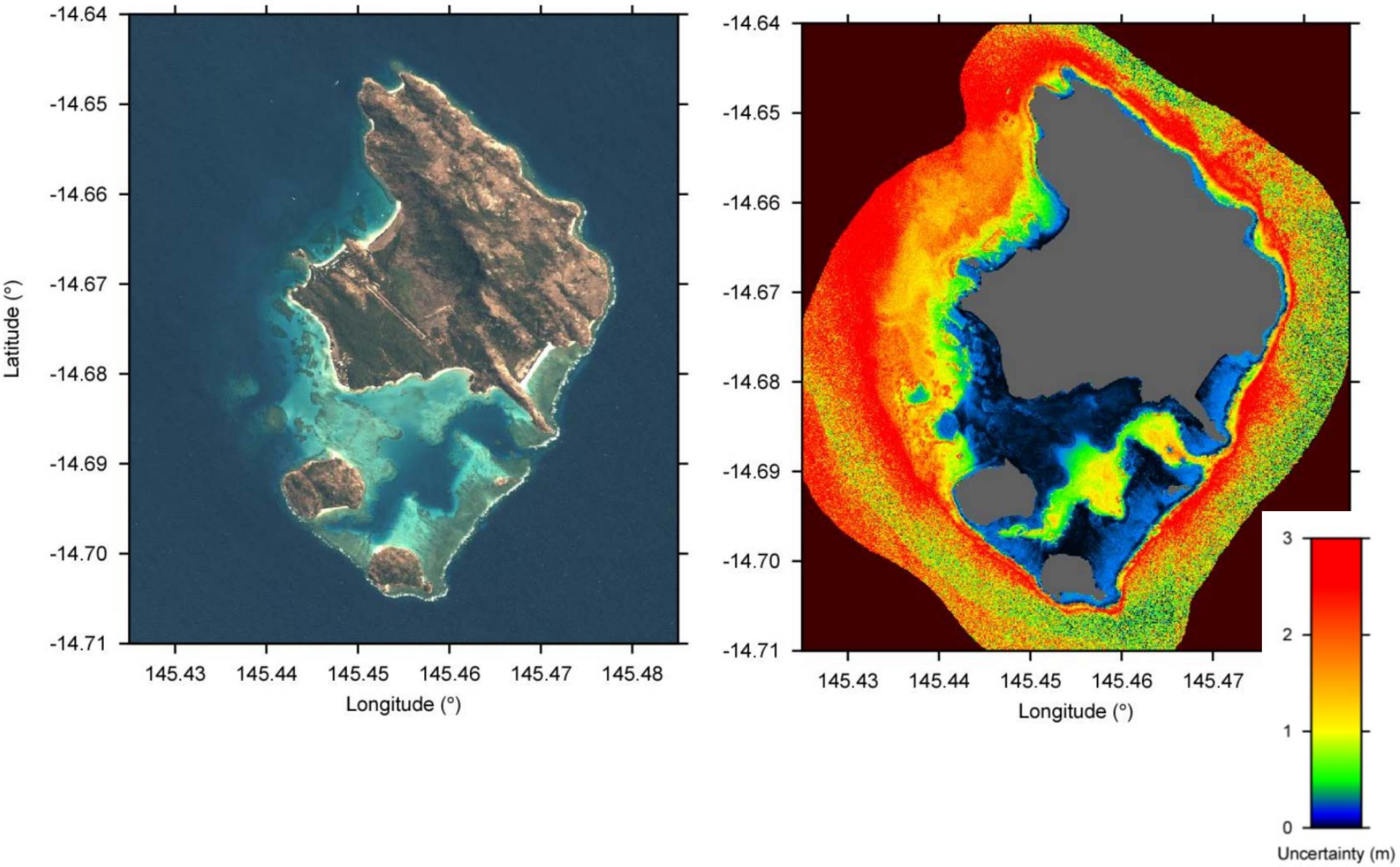
- Marginally better statistics, r-squared, mean absolute residual, etc.
- Cosmetically better (spatially smoother)

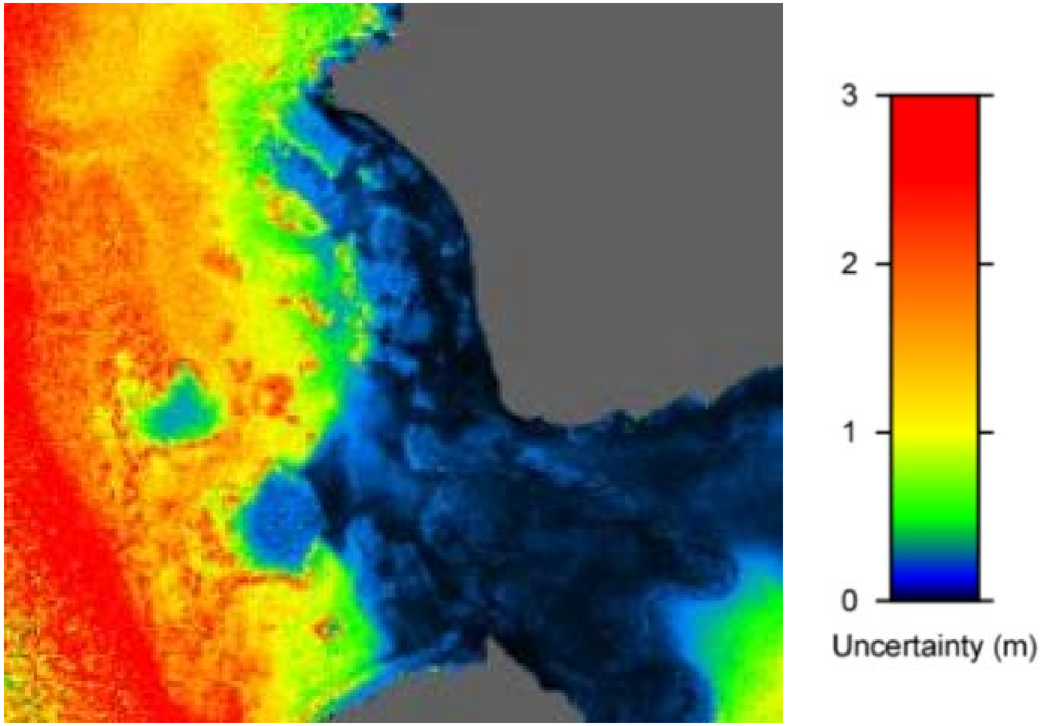
Shallow (upstanding) coral heads



- Correctly identified as being shallow even though are dark pixels
- Benefit of variable bottom reflectance in the forward model.

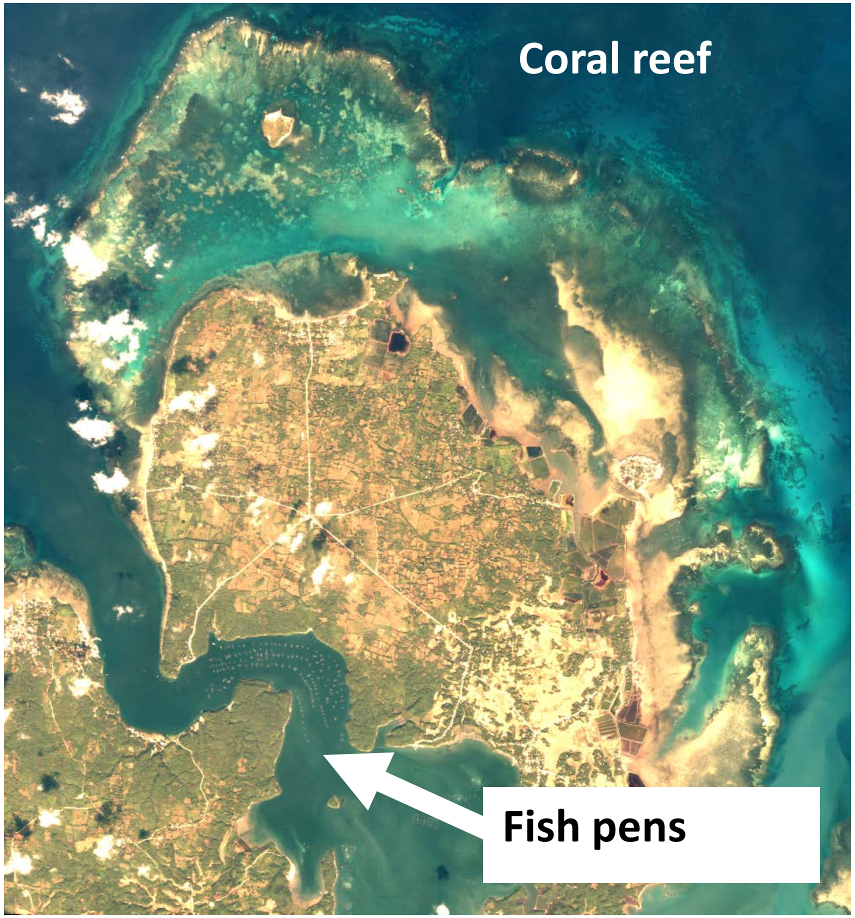
Uncertainty (Quickbird image)





- Dark patches (coral heads) have relatively higher uncertainty in depth
- Because there reflectance is similar to that of deeper pixels, within the bounds defined by the noise model

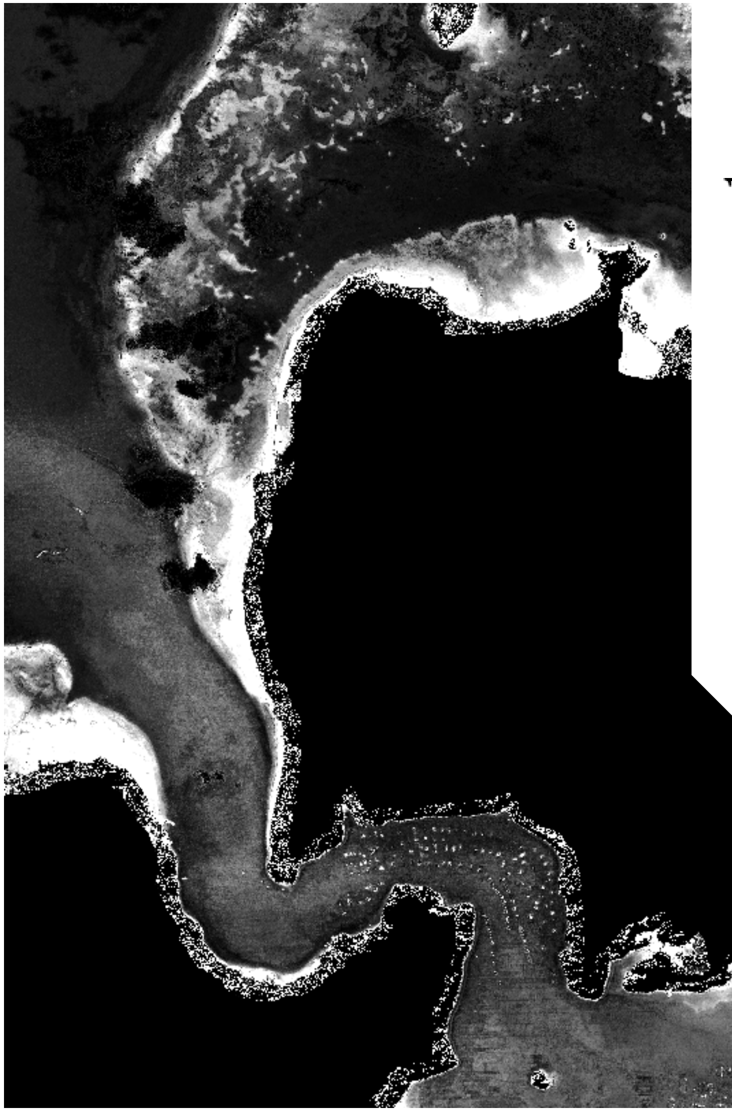
Bolinao, Philippines (QuickBird image)



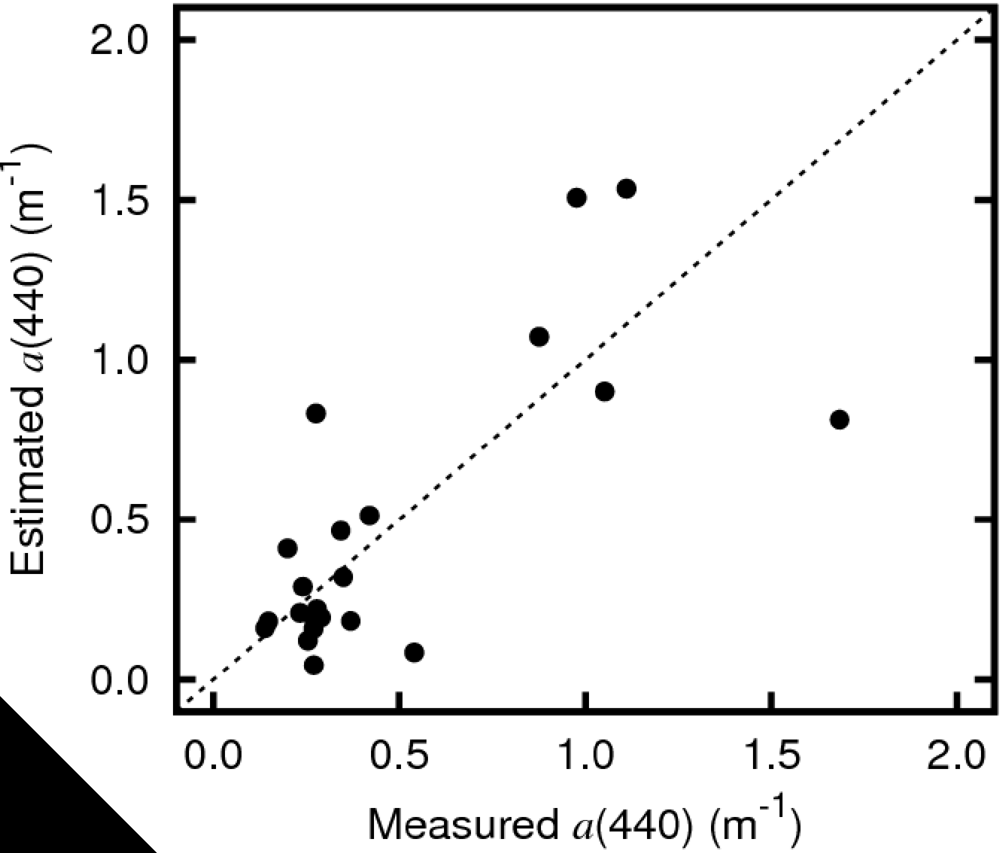
Coral Reef Targeted Research & Capacity Building for Management

MSI

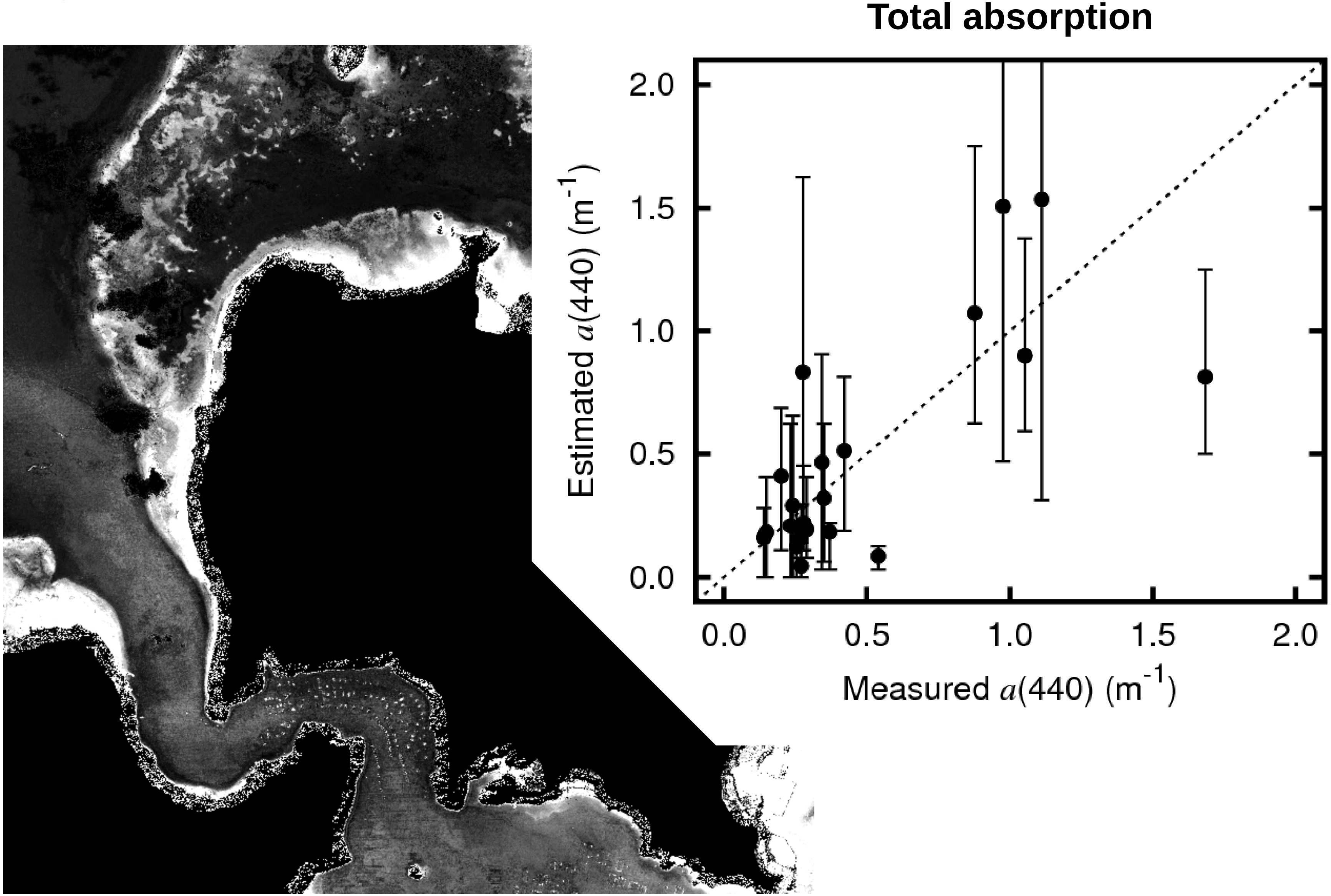
Light absorption due to CDOM



Total absorption

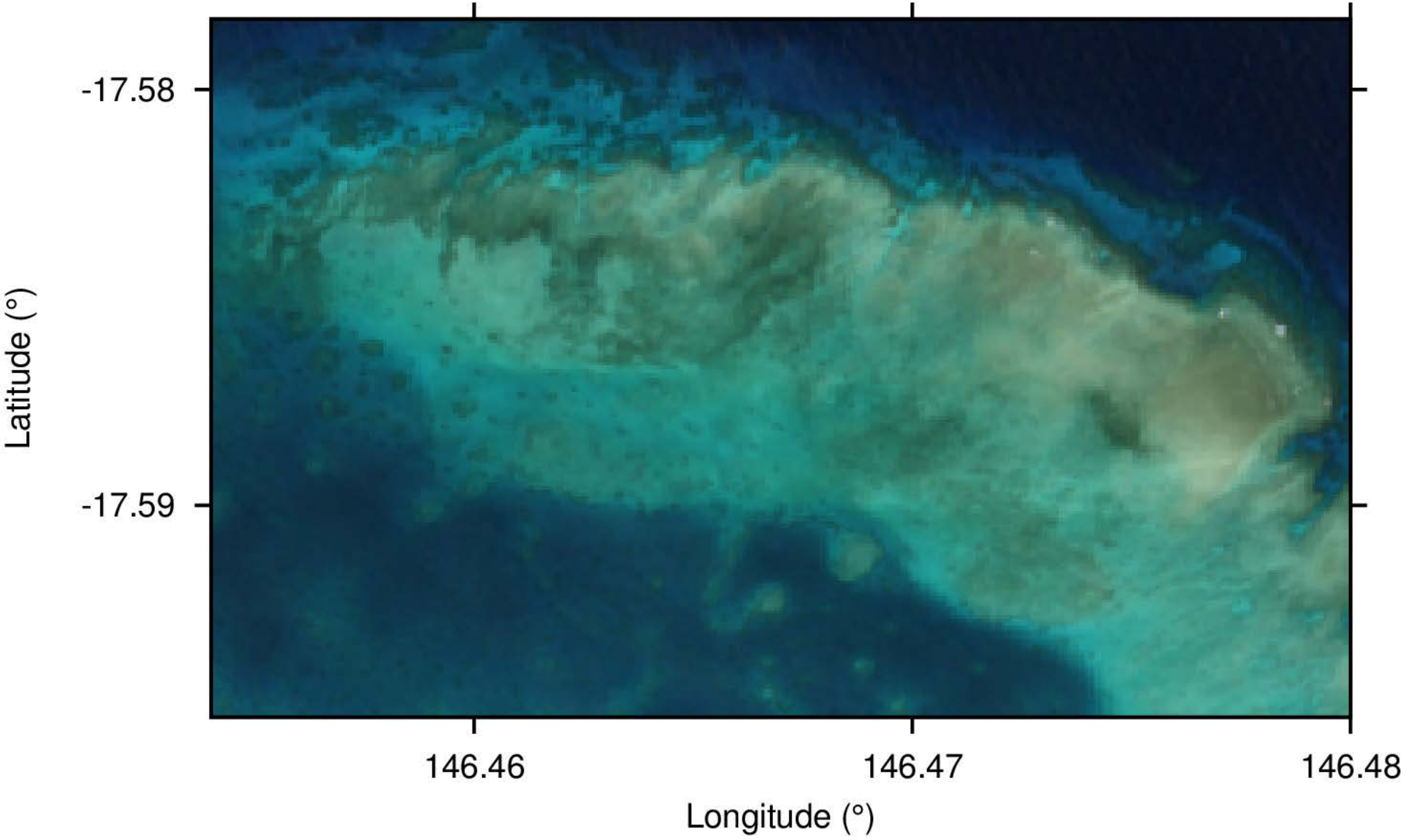


Light absorption due to CDOM



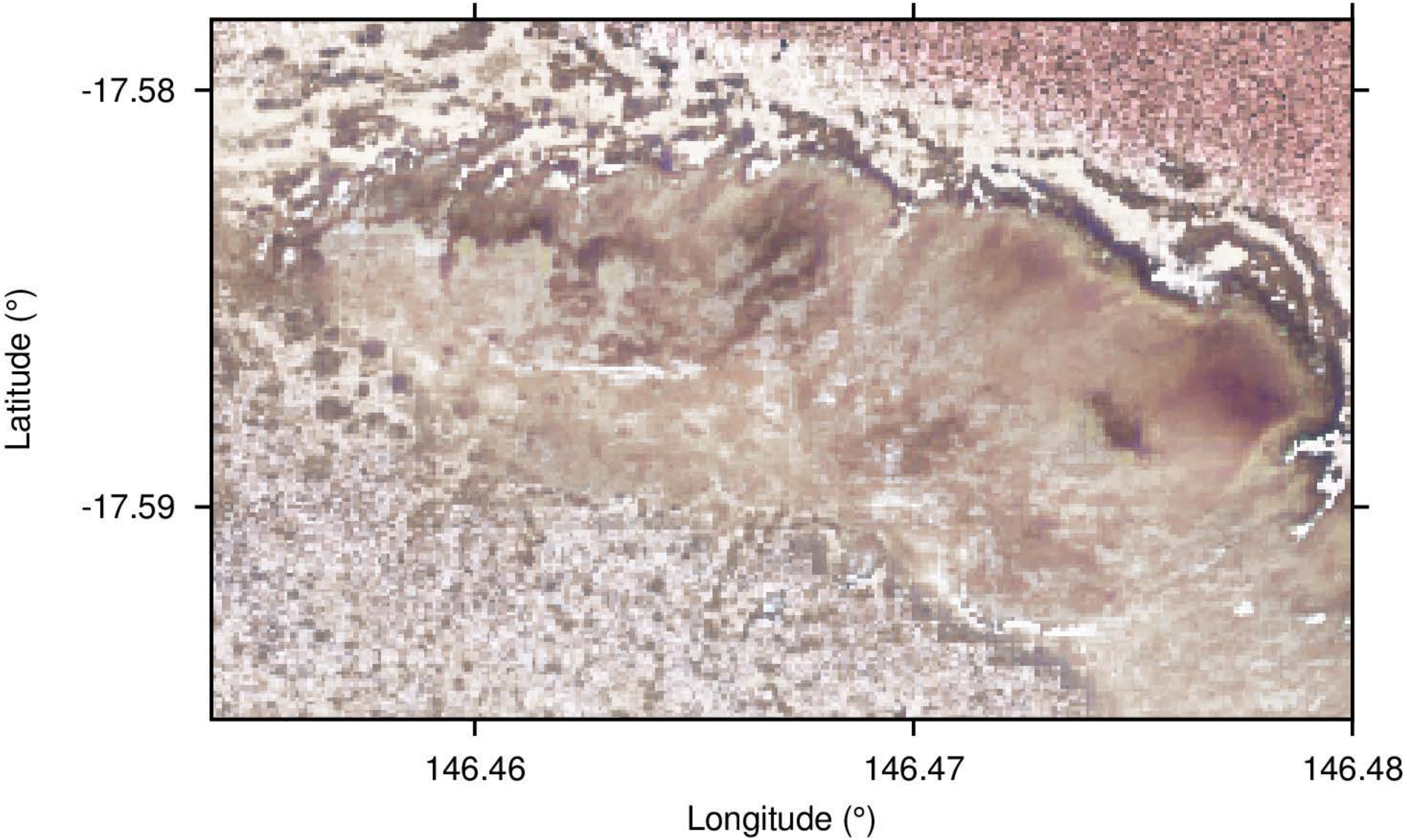
Bottom reflectance

- Use the bathymetry estimate and water optical properties to make water column correction



Bottom reflectance

- Use the bathymetry estimate and water optical properties to make water column correction

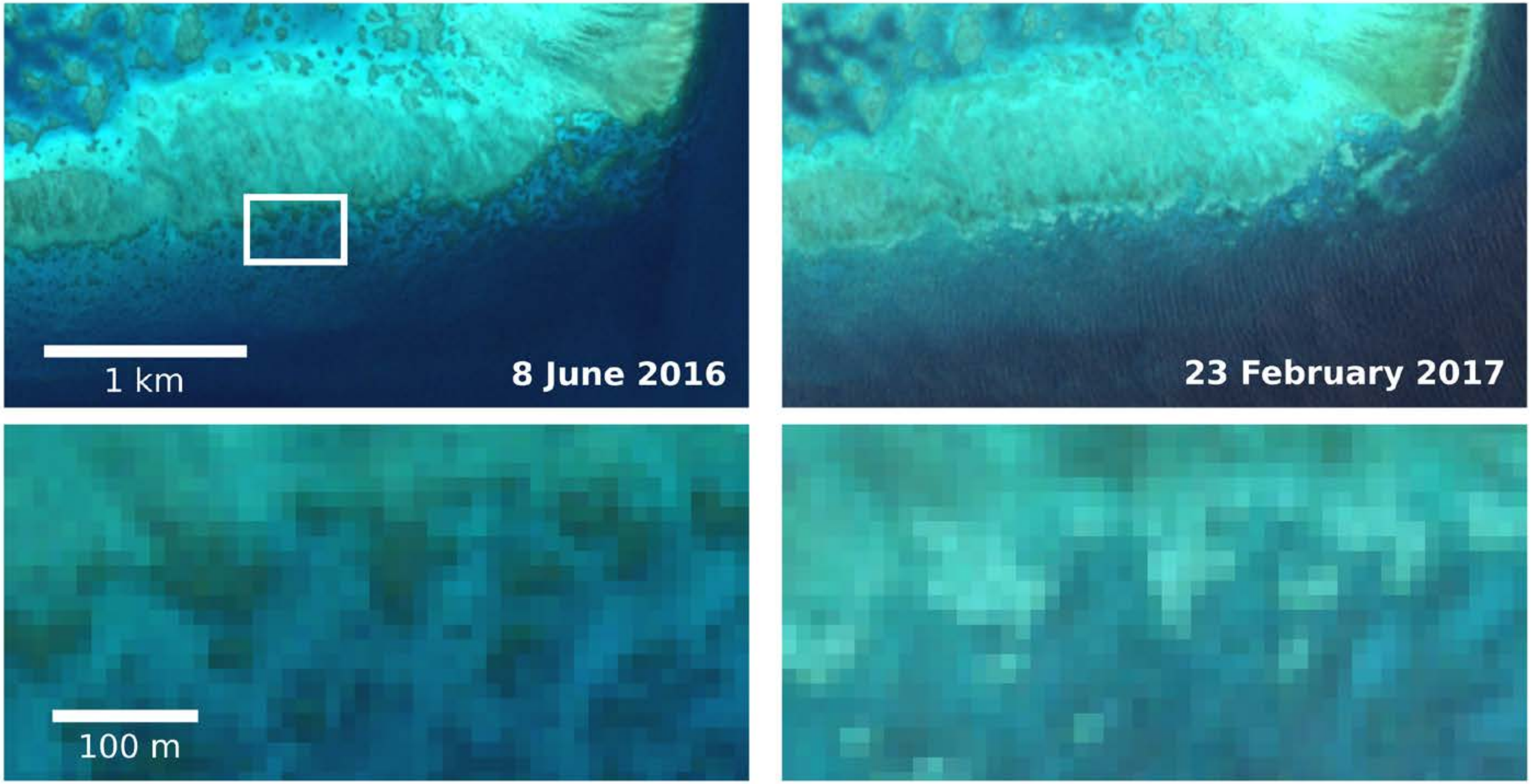


Coral Bleaching

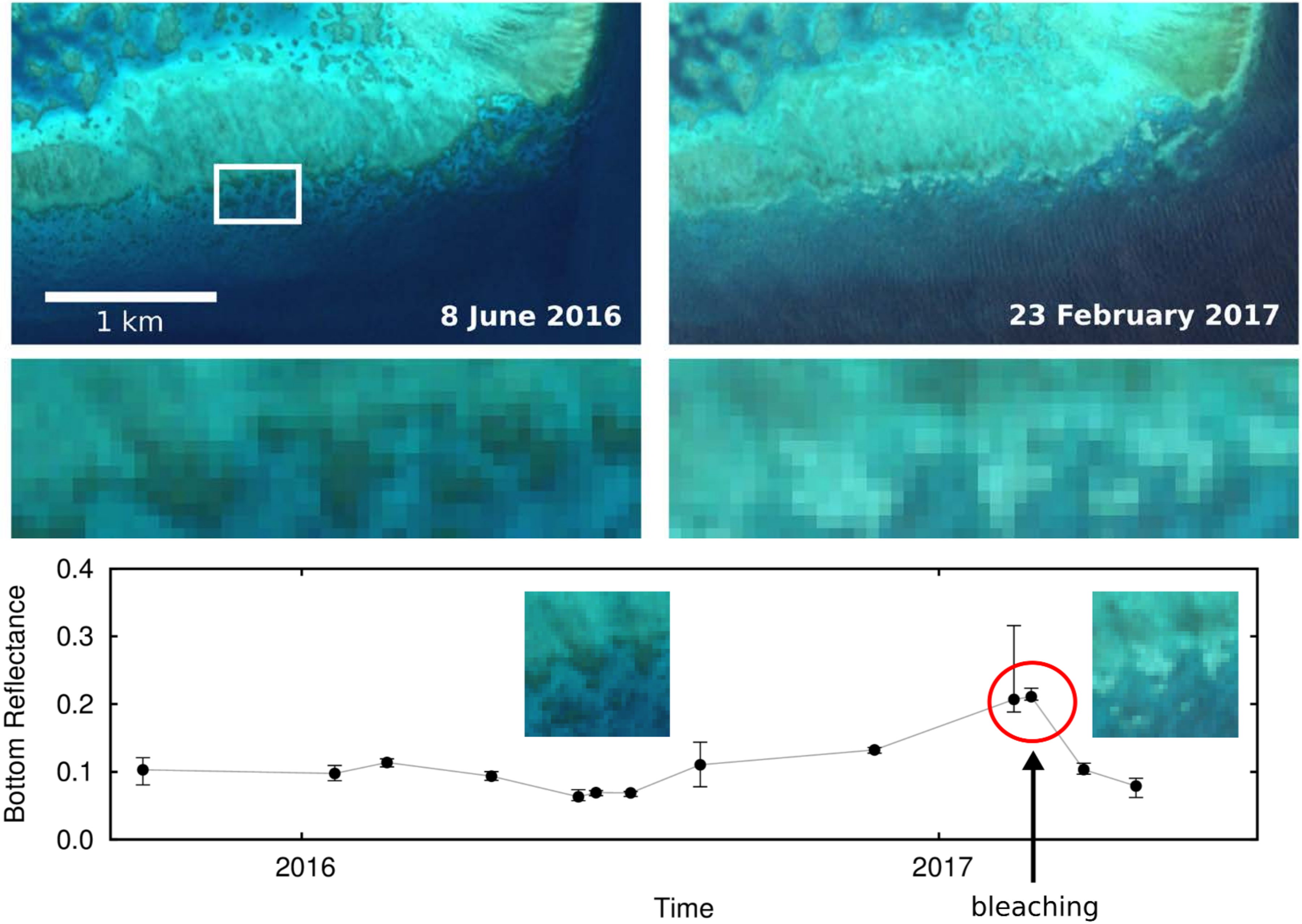
(photo, P. Mumby)

- Corals turn temporarily white when stressed by elevated temperature
- Key indicator of climate change stresses on coral reefs

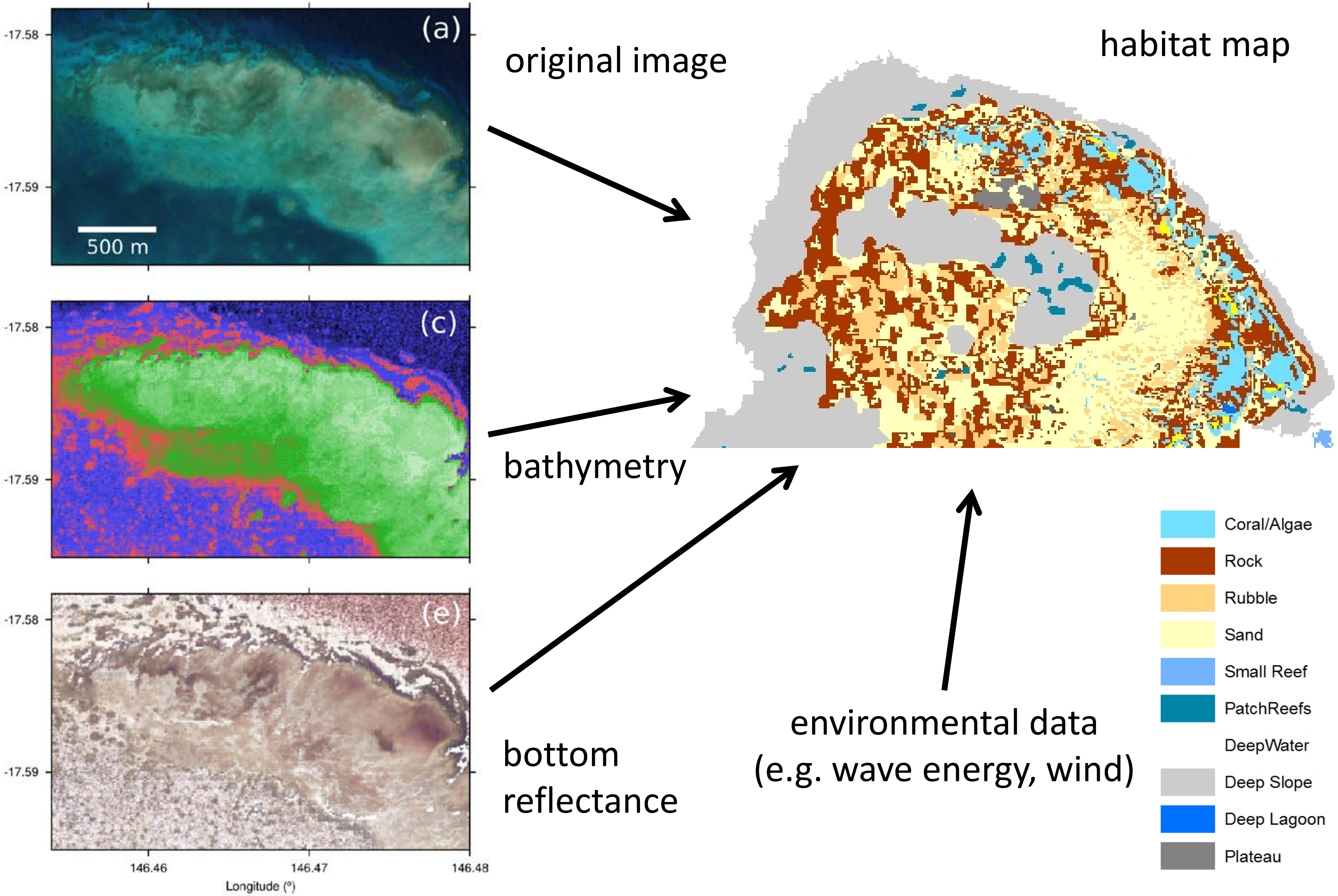
Coral Bleaching Detection (Sentinel-2)



Coral Bleaching Detection (Sentinel-2)



Object-orientated / machine learning techniques



original image

habitat map

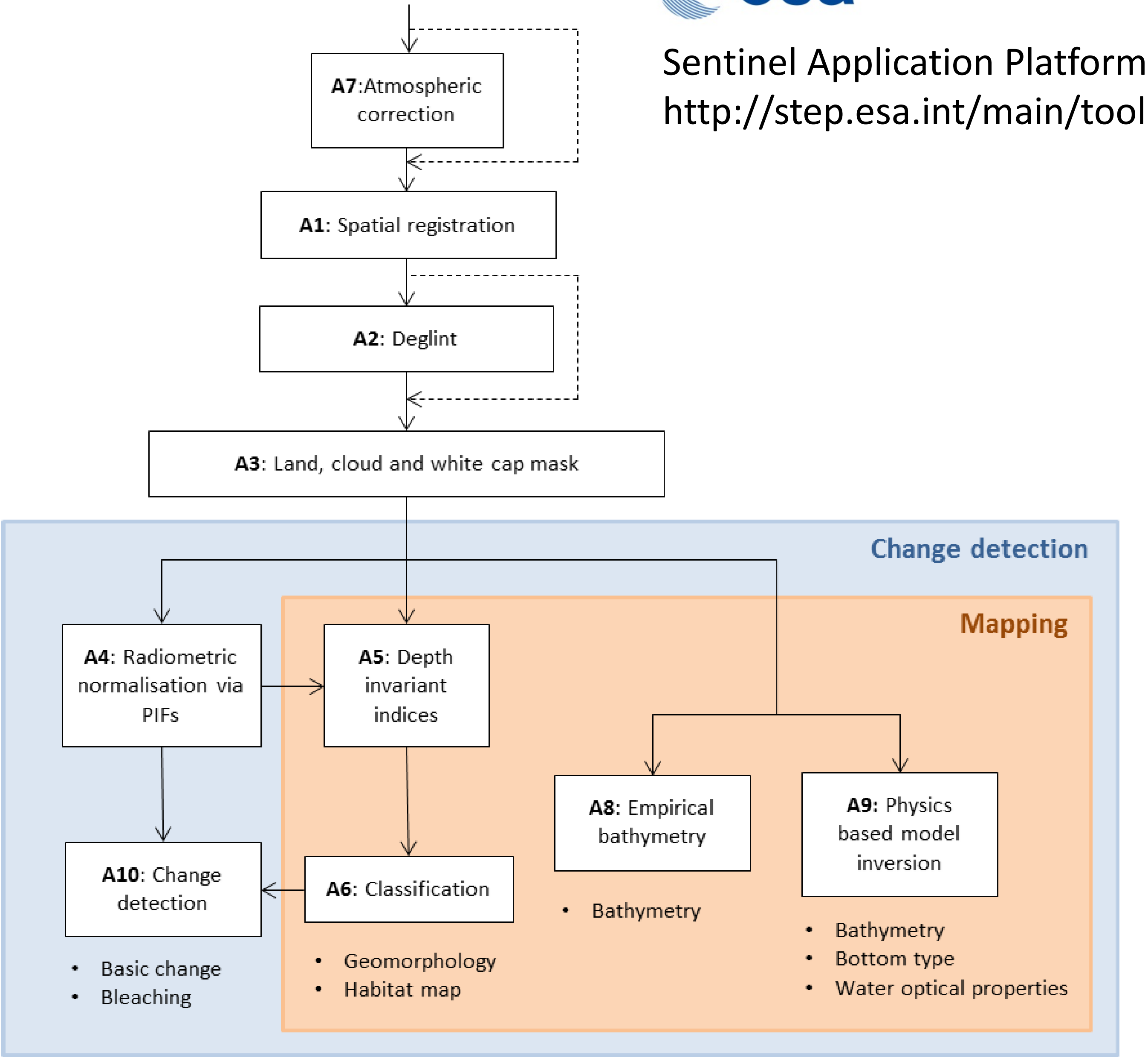
bathymetry

bottom
reflectance

environmental data
(e.g. wave energy, wind)

Sen2Coral Toolkit in SNAP

Sentinel Application Platform
http://step.esa.int/main/toolboxes/snap/



A7:Atmospheric correction

A1: Spatial registration

A2: Deglint

A3: Land, cloud and white cap mask

Change detection

Mapping

A4: Radiometric normalisation via PIFs

A5: Depth invariant indices

A8: Empirical bathymetry

- Bathymetry

A9: Physics based model inversion

- Bathymetry
- Bottom type
- Water optical properties

A10: Change detection

- Basic change
- Bleaching

A6: Classification

- Geomorphology
- Habitat map

Questions…