Shallow Water Remote Sensing

John Hedley, IOCCG Summer Class 2024

- Overview
- High spatial resolution imagery and Sentinel-2
- Empirical methods / machine learning
- Sun-glint correction of high spatial resolution images
- Model inversion methods
- Canopy modelling
- Uncertainty propagation
- Multi image analysis and statistical tests
- ICESat-2 space-bourne LIDAR

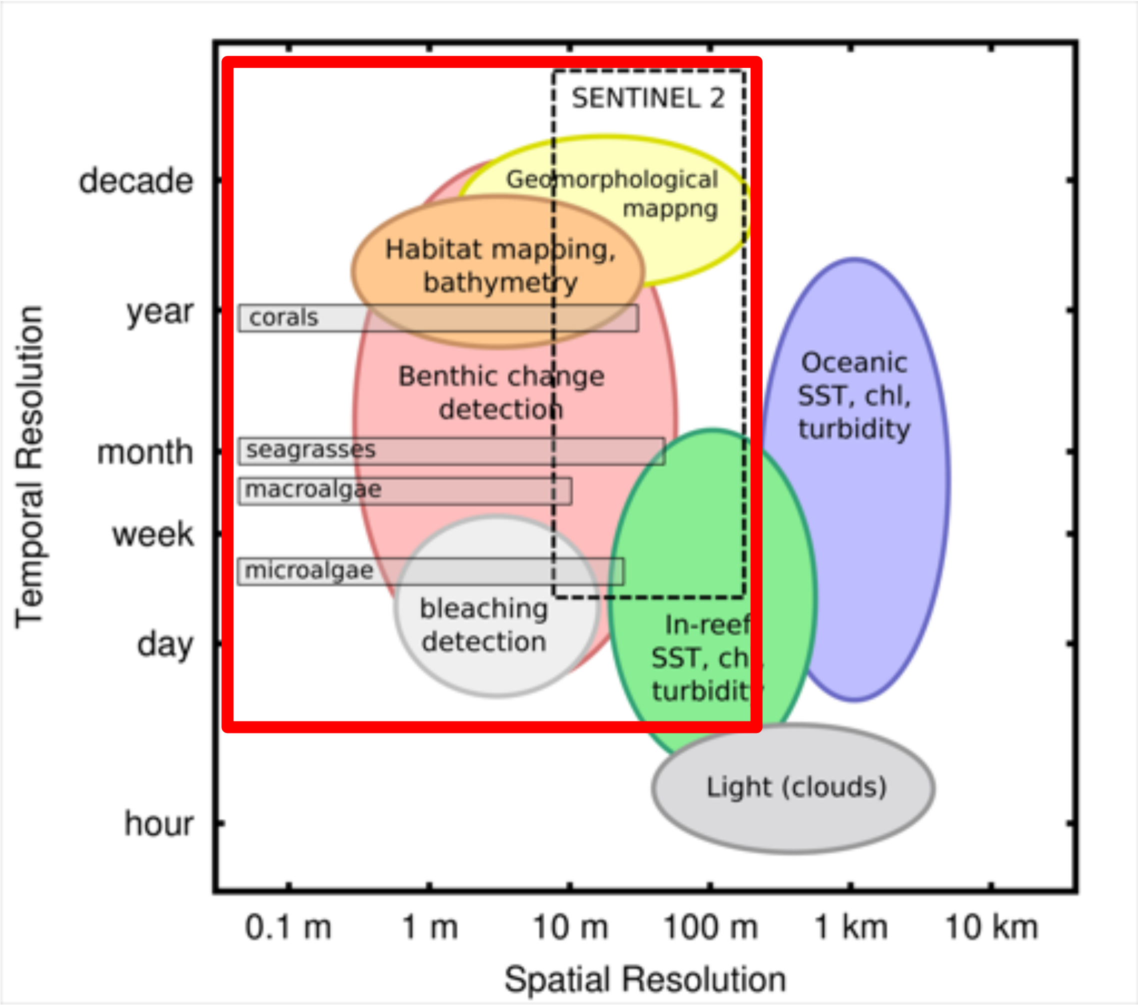
Objectives of shallow water remote sensing

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

Applications

- Spatial ecology (science)
- Resource mapping, MPA design, impact assessments
- Assessing ecosystem services
  - coastal protection and stabilisation
  - fisheries, local subsistence
  - blue carbon
  - tourism
- Hydrography (bathymetry for navigation)

Applications on coral reefs and similar environments



- ➢ Need higher spatial resolution than typical ocean colour satellites

Hedley et al. 2018, *RSE*, 216, 598–614

High Spatial Resolution Imagery

Pixel size < 5 m – typically commercial

- Many past and present (archive imagery still available)
- Pleiades, DigitalGlobe (WorldView-2, 3, 4, GeoEye, IKONOS), Planet (various)
- Typically 4 bands, R, G, B and NIR, but some now have 8 bands

Pixel size 10 - 30 m – typically not focussed on aquatic applications

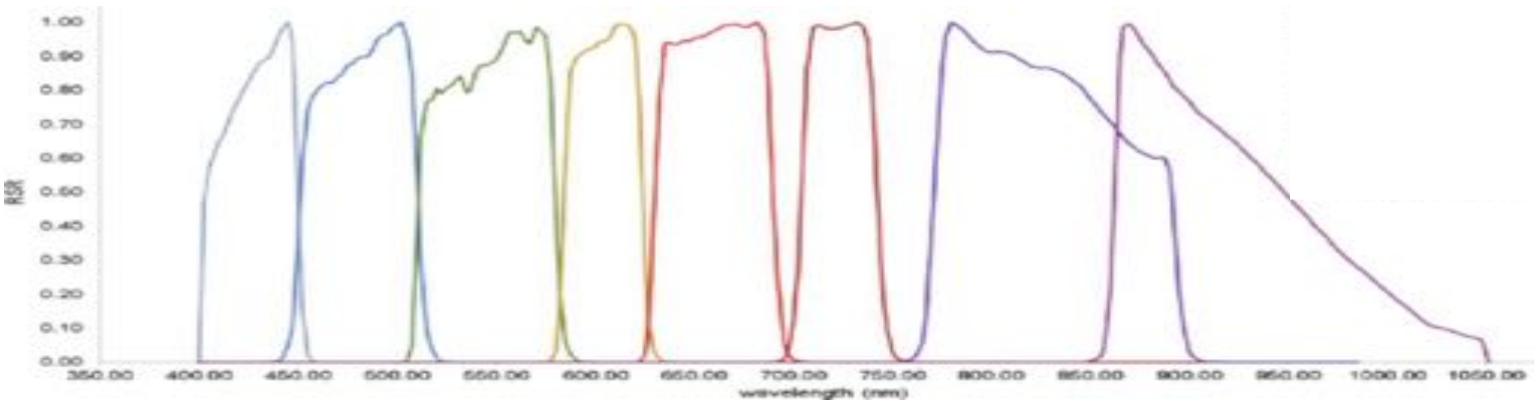
- Landsat 8, 9 (30 m)
- Sentinel 2 (10 m in four bands)

Notes:

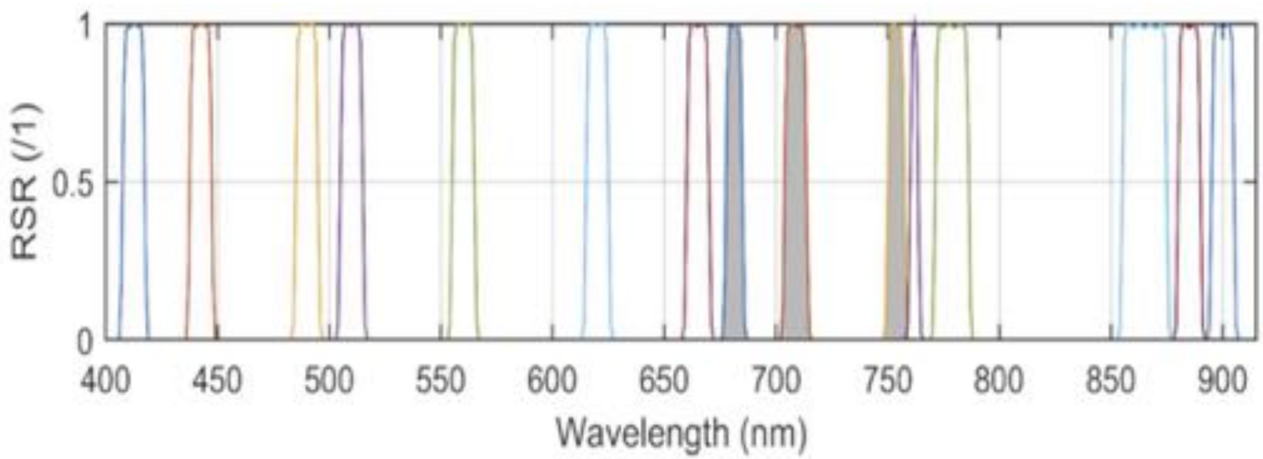
- Radiometric calibration on commercial satellites is often not as good as on space agency satellites.
- For these sensors bands are spectrally wide, not narrow as with ocean colour satellites
  - not always appropriate to just use centre wavelength
  - may need to integrate over wavelength

Band widths are typically wider than ocean colour sensors

Worldview-3



MERIS / OLCI



Smaller pixel means less light energy, wider bands required for acceptable SNR

Martins et al. (2020). doi: 10.1016/j.jag.2020.102215
Zeng et al. doi: 10.3390/rs13173349

(c) DigitalGlobe

WorldView-2 image of Yucatan coast, Mexico (15 Feb 2008)
(pixels < 2 m, 8 bands, ~5 in wavelengths useable for sub-surface applications)

ESA / Copernicus

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

Empirical image based methods (e.g. bathymetry)

- Assume exponential attenuation of light with depth (~ constant K_d and K_{Lu})
- Requires training of points from imagery (deep water, known depths etc.)

Lyzenga 1978

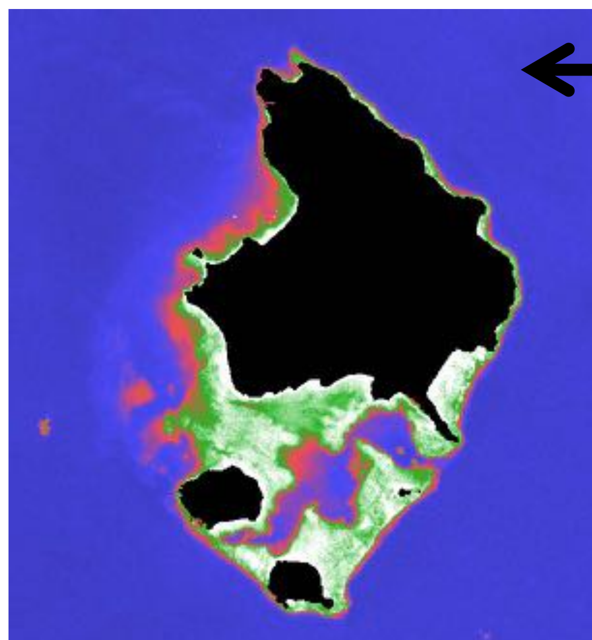
$$X_i = \ln(L_i - L_{si}),$$
$$Z = a_0 + a_i X_i + a_j X_j$$

a0, a1, a2 from regression

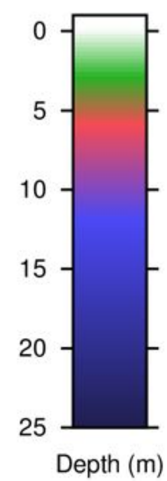
Stumpf et al. 2003

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

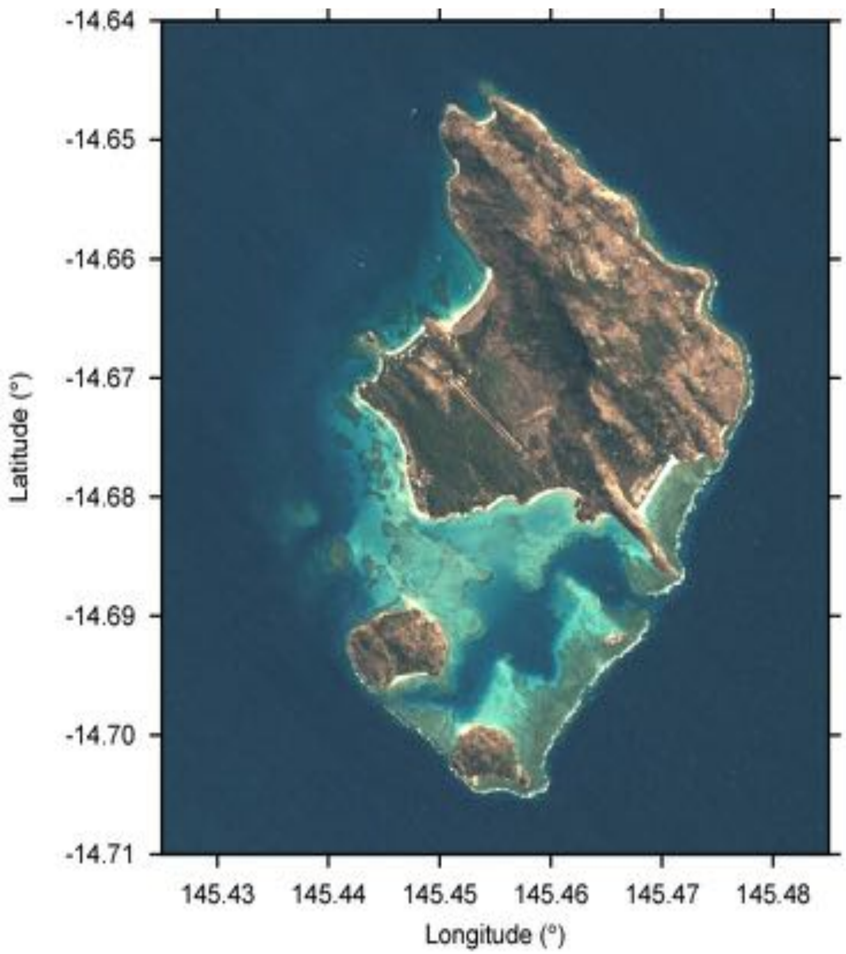
m0, m1, from regression

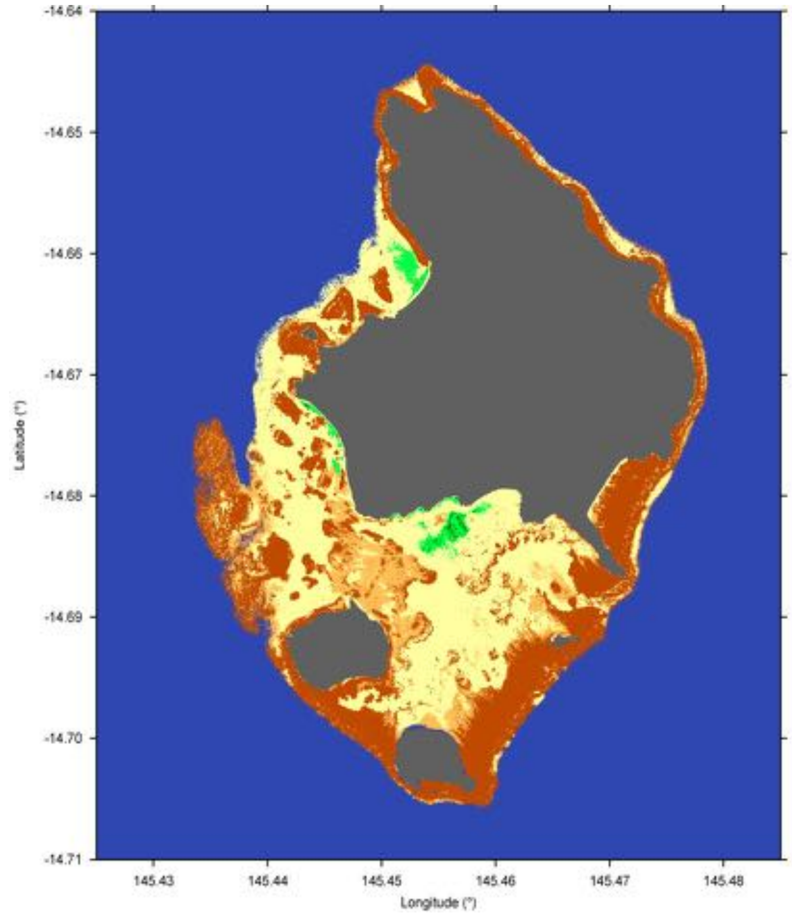


should be deeper than 15m!



Bottom classification – machine learning





Key:

Deep Water	Medium Seagrass	Rubble / Sparse Coral
Sand	Dense Seagrass	Reef Matrix
Land		

- train on dataset
- apply to image

Bottom classification - depth invariant indices

An index that is approximately constant for the same reflectance at different depths

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

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

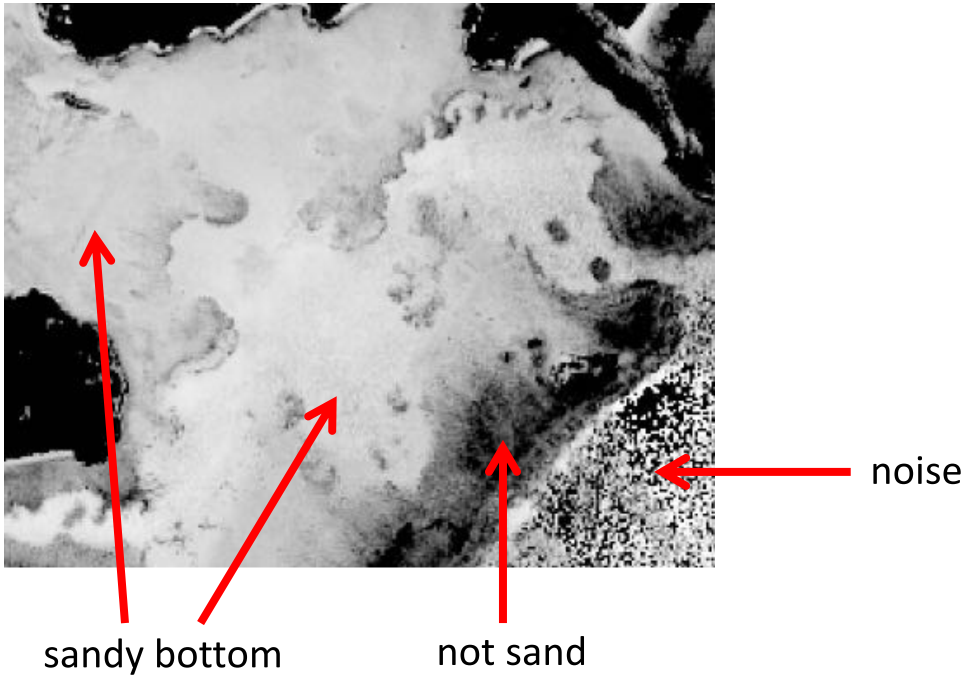
Get one band from each pair of original bands

Need: 1) ratio of attenuation coefficients

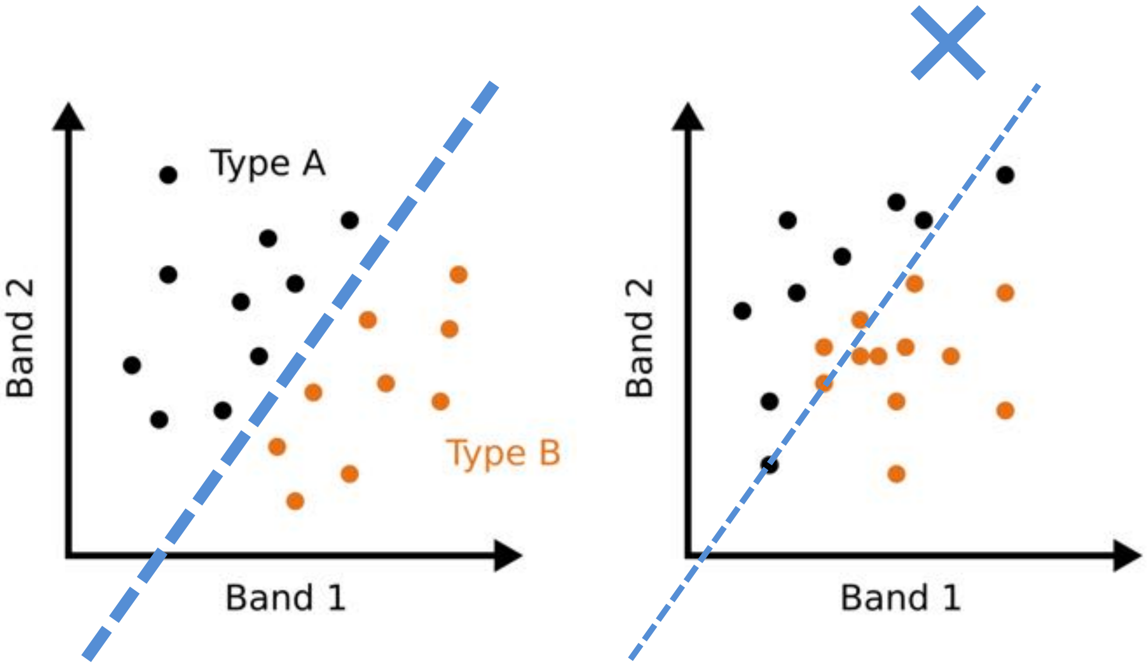
2) deep water reflectance

- can extract from image using sand and deep water

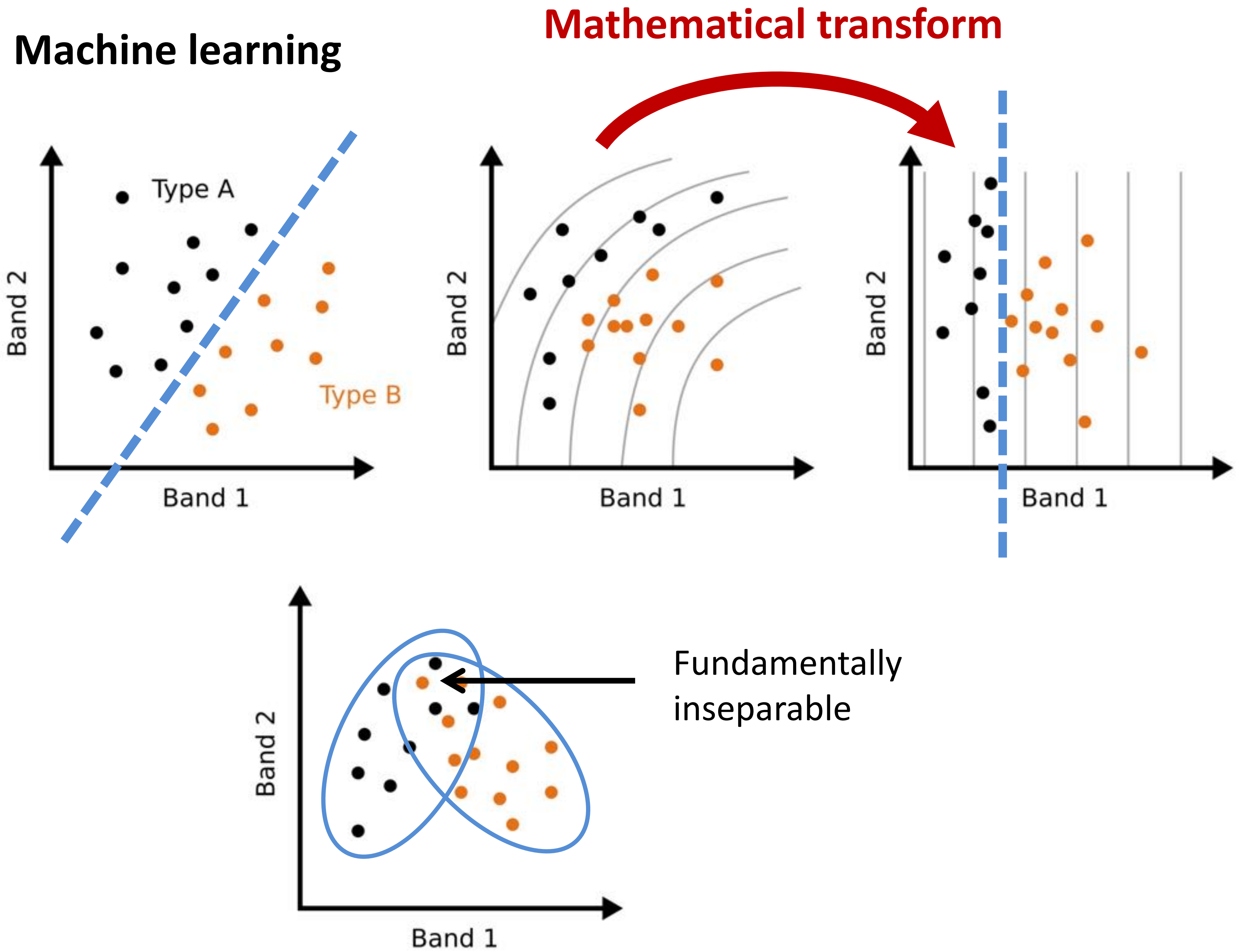
Example from bands 2 and 3 of a Sentinel 2 image of Lizard Island, band “d_{23}”



Machine learning



Machine learning



Machine learning - comparing techniques

Many different techniques

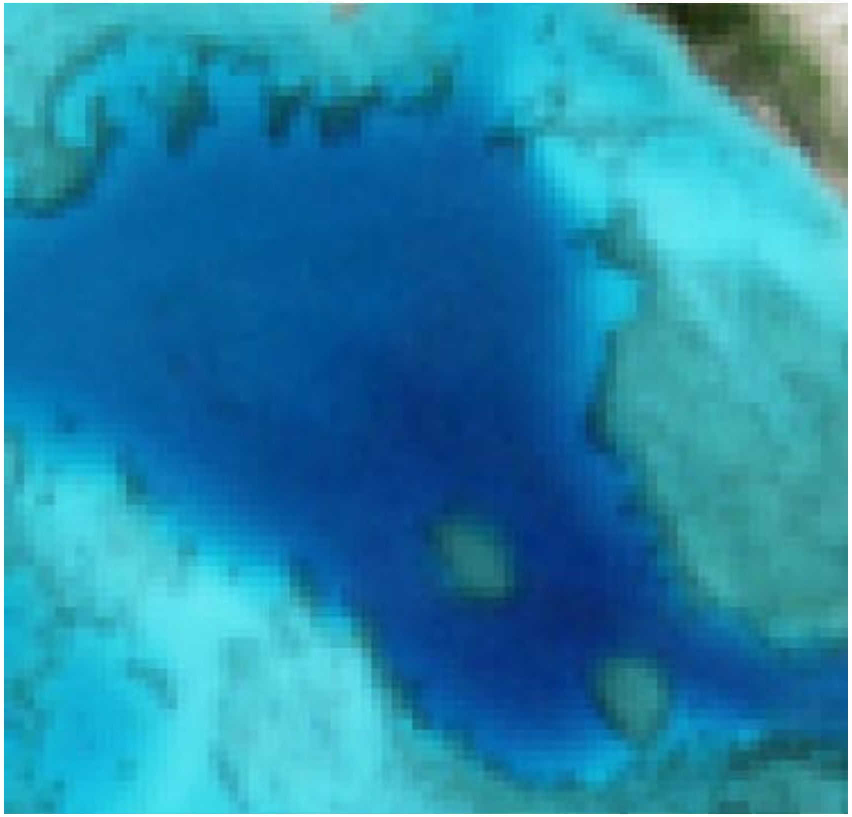
- Support Vector Machines (SVM)
- Neural Networks
- Random Forest
- etc.

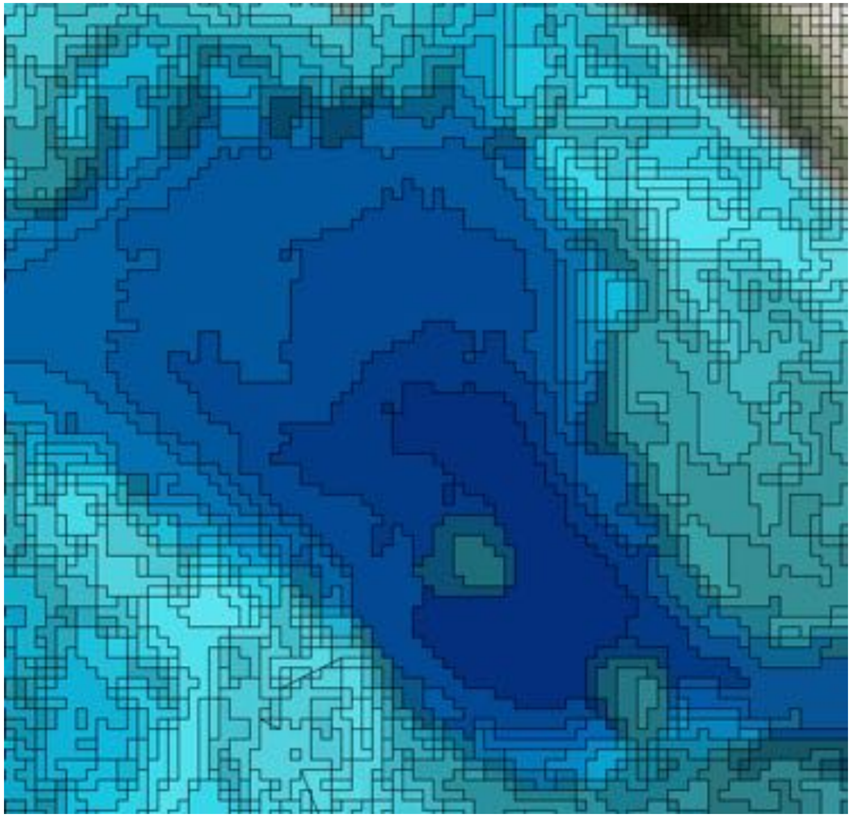
Why do they perform differently? (if they do)

- What does it tell you about the structure of the data?
- Is there a fundamental limitation?
- Can we learn something?

*** These algorithms may appear like “black boxes” but it is possible to look inside them**

Going beyond single pixels - image segmentation

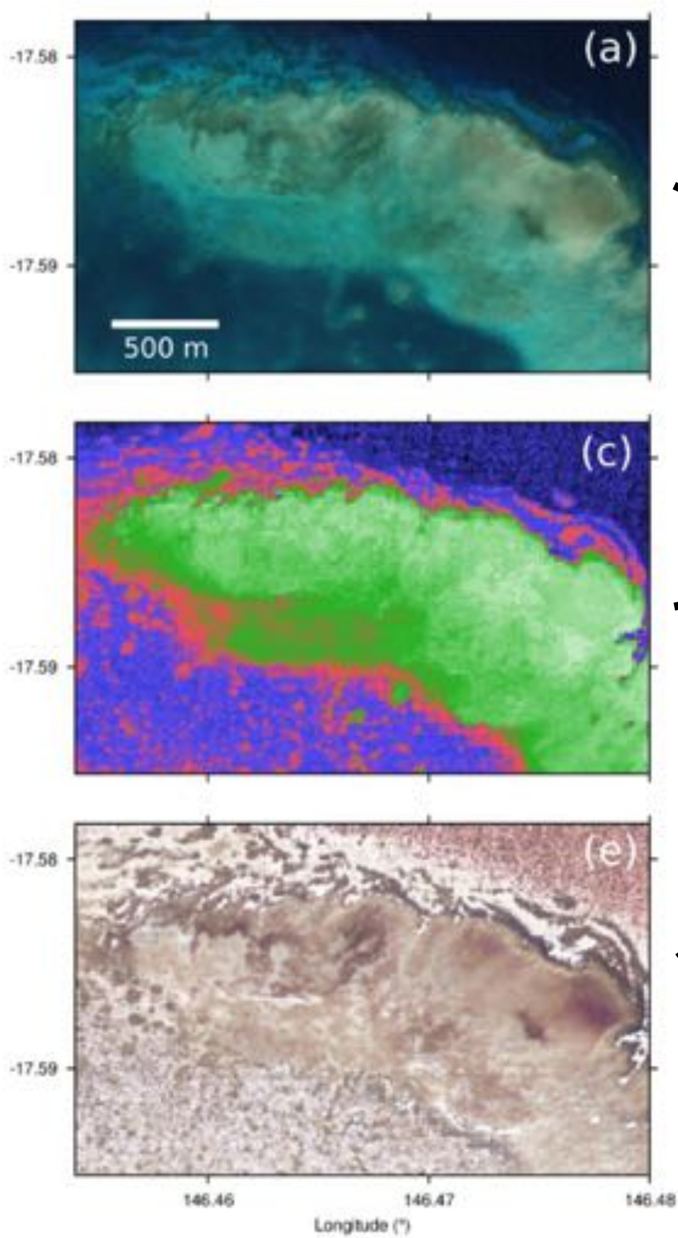




Can input object metrics into classifier, as well as image data:

- size
- shape
- orientation, etc.

Object-orientated machine learning techniques

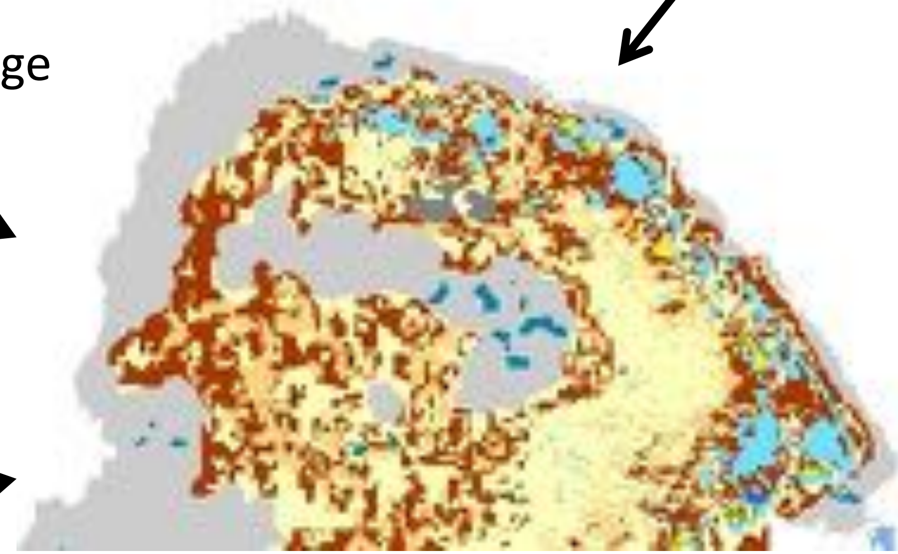


original image

bathymetry

bottom
reflectance

segmented
object metrics



habitat map

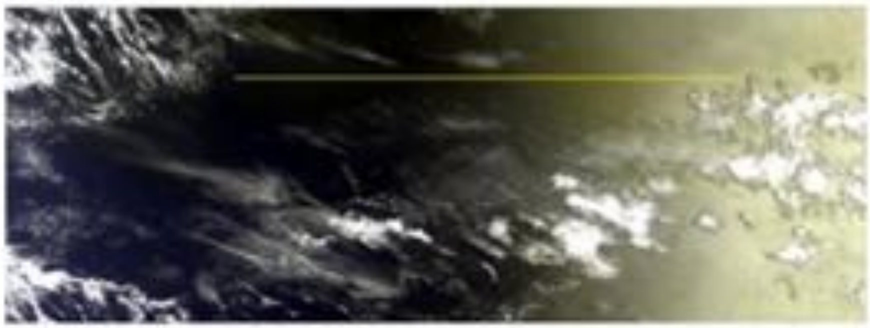
environmental data
(e.g. wave energy, wind)

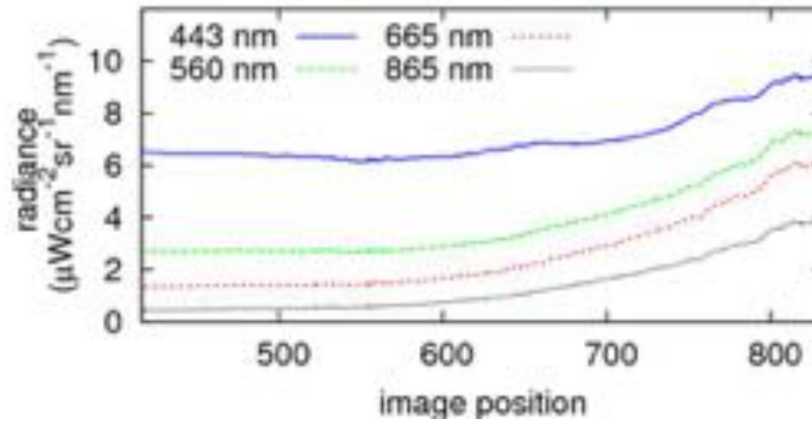
[See papers by Chris Roelfsema et al.]

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

Large images e.g. MERIS, pixels > 100 m

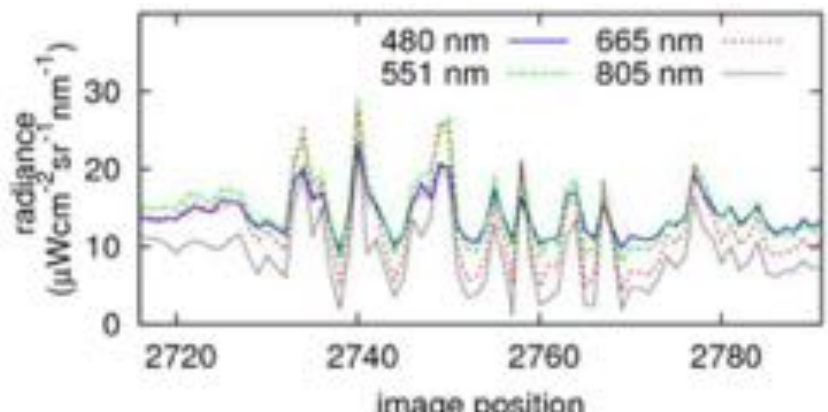
→ function of solar-view geometry and sea state – Cox & Munk equations





High spatial resolution, pixels < 10 m

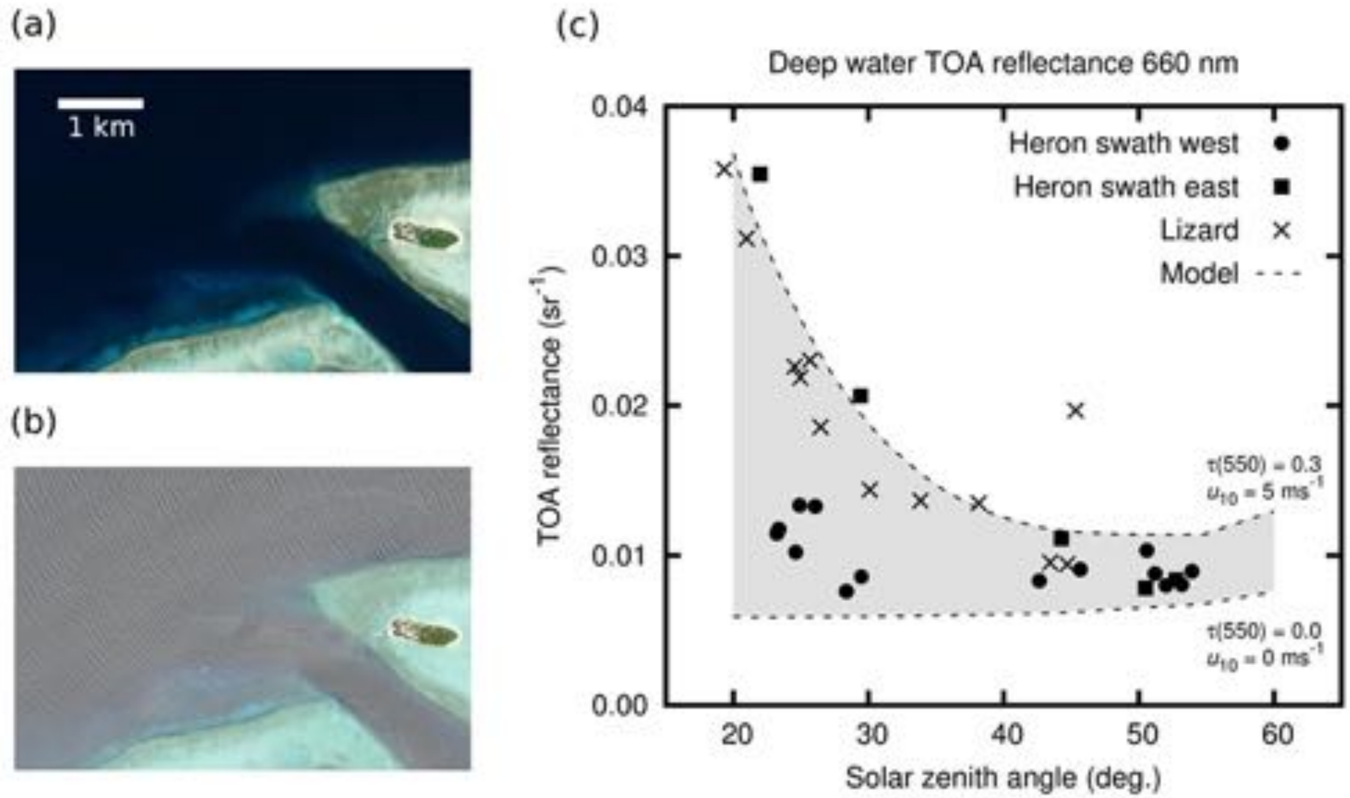
→ individual waves



Kay et al. 2009 *Remote Sens.*, 1(4), 697-730, doi: 10.3390/rs1040697

Avoidance is best, but not always possible

Sun-synchronous orbit means glint occurs frequently in Sentinel-2 imagery



- Solar zenith angle at a specific location varies mostly with season
- East-west position in swath is important (equivalent to tilt, max. ~12°)
- Some places are imaged in two orbits so occur at both east and west edges

Hedley et al. 2018, *RSE*, 216, 598–614

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

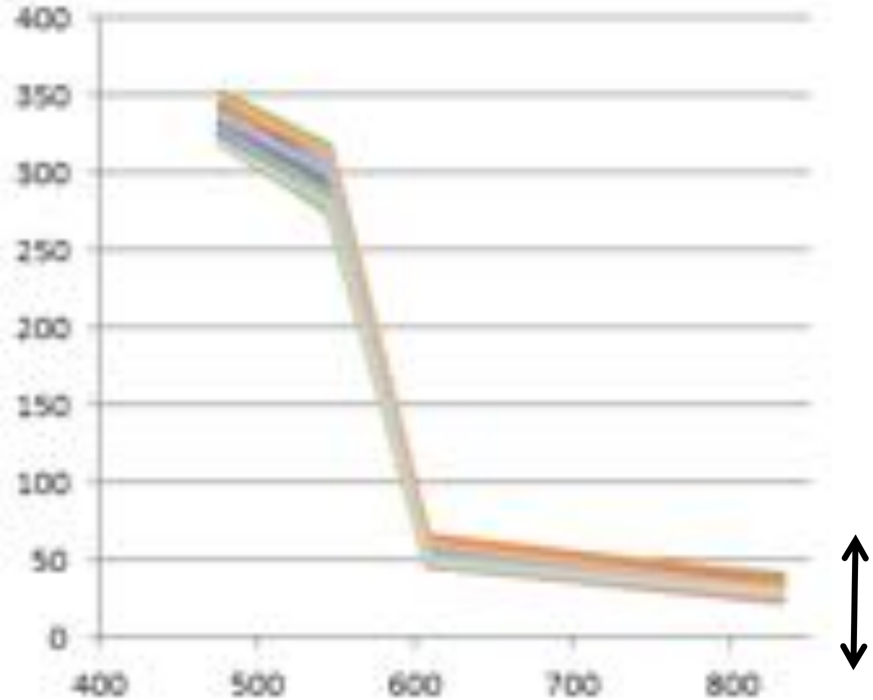
WorldView-2 Image
(c) DigitalGlobe

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

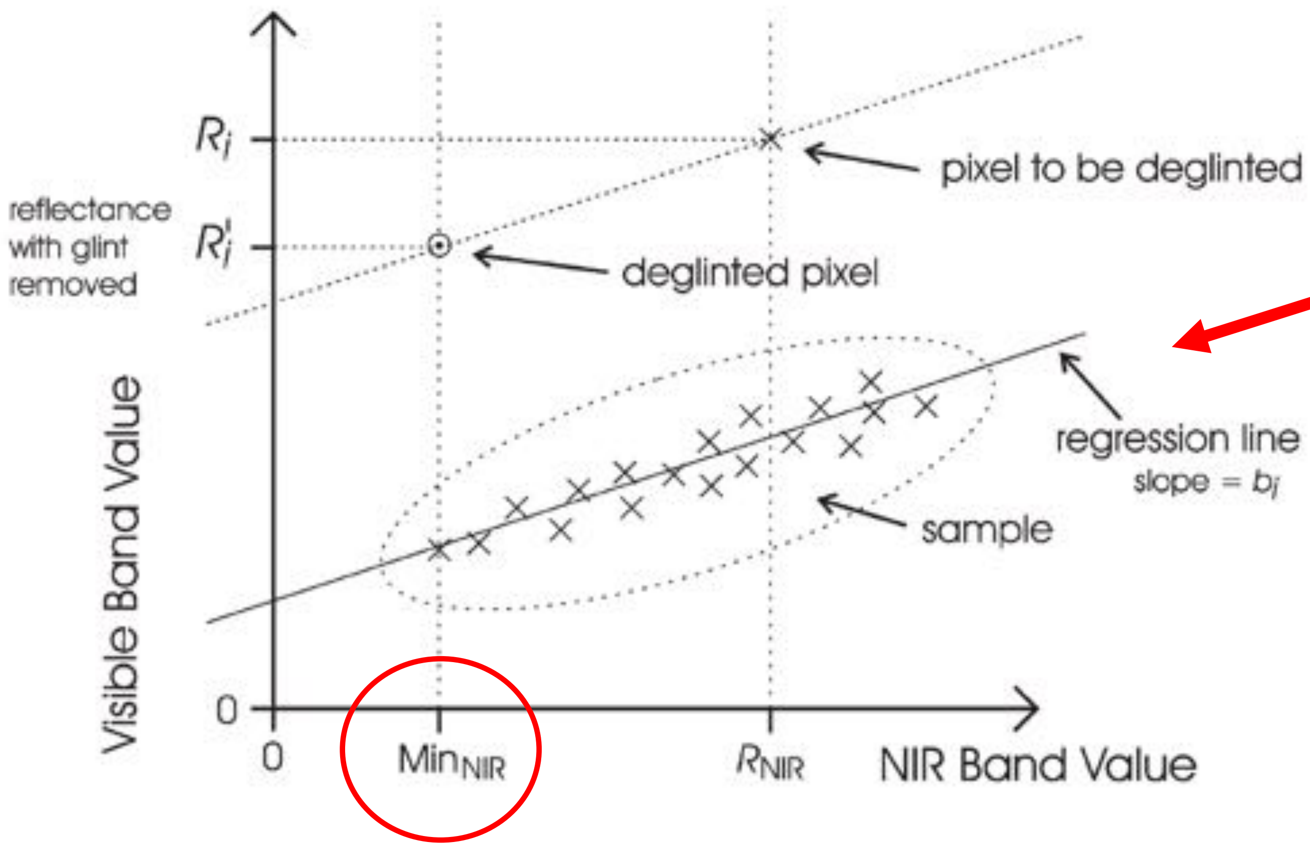
Sample over deep water



NIR reflectance
(or SWIR)

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

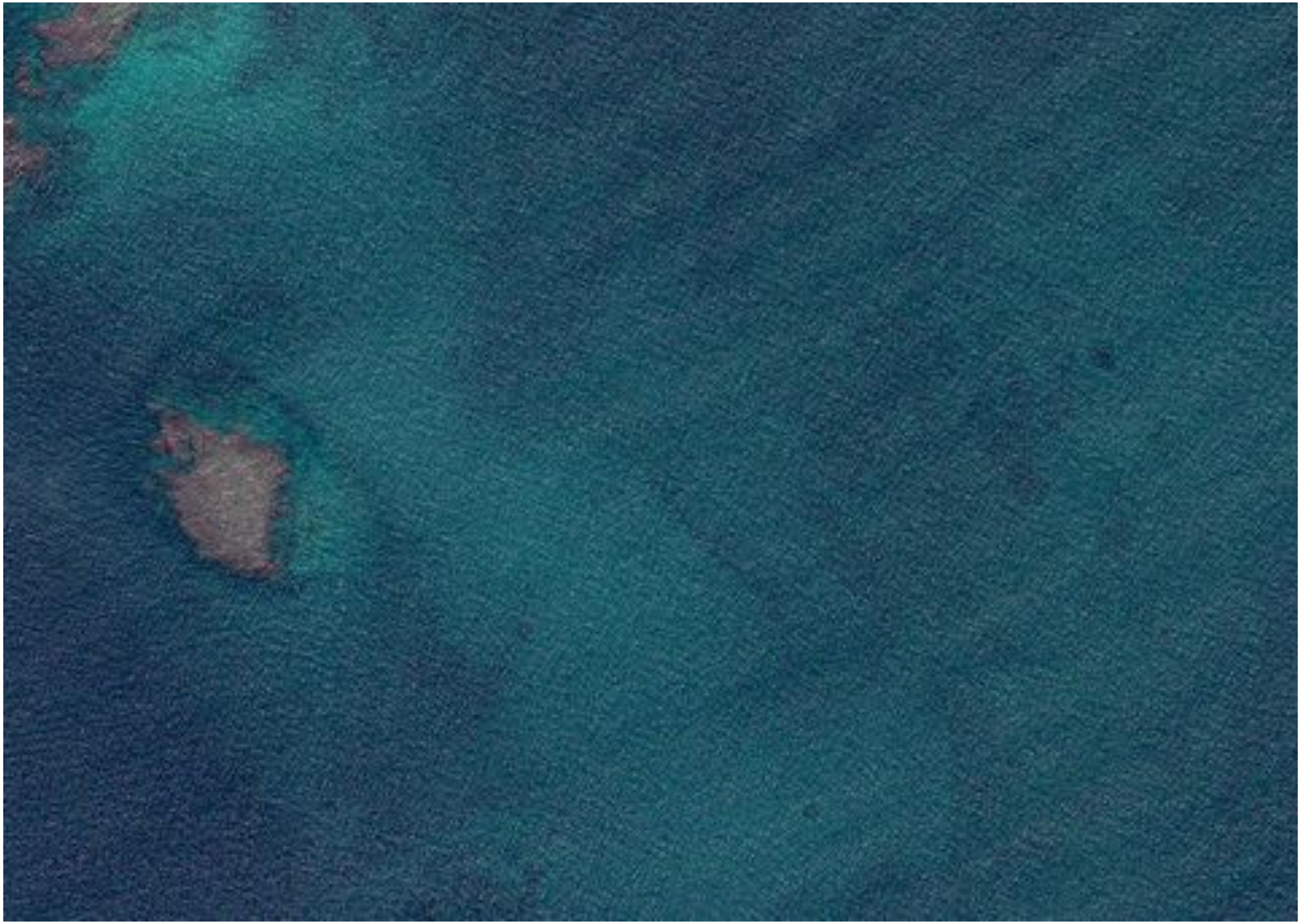


Sample over deep water

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

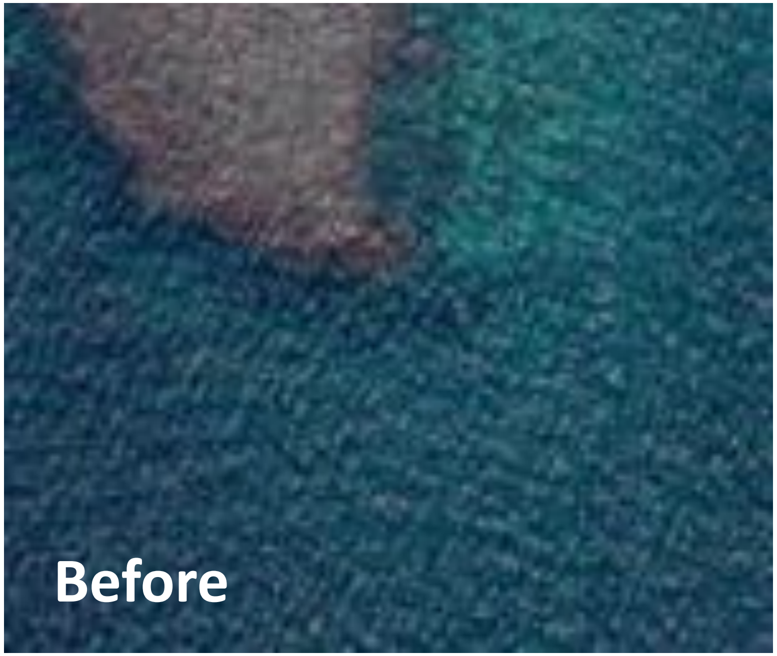
- Before or after atmospheric correction? – using minimum NIR reflectance means it probably doesn't matter, if you assume uniform atmospheric contribution

Before deglint



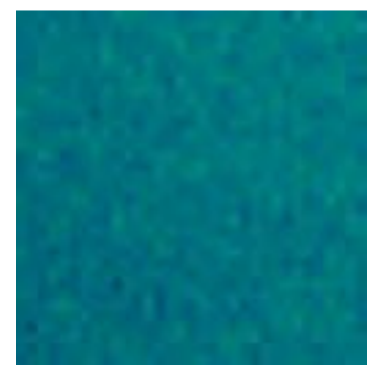
After deglint

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.

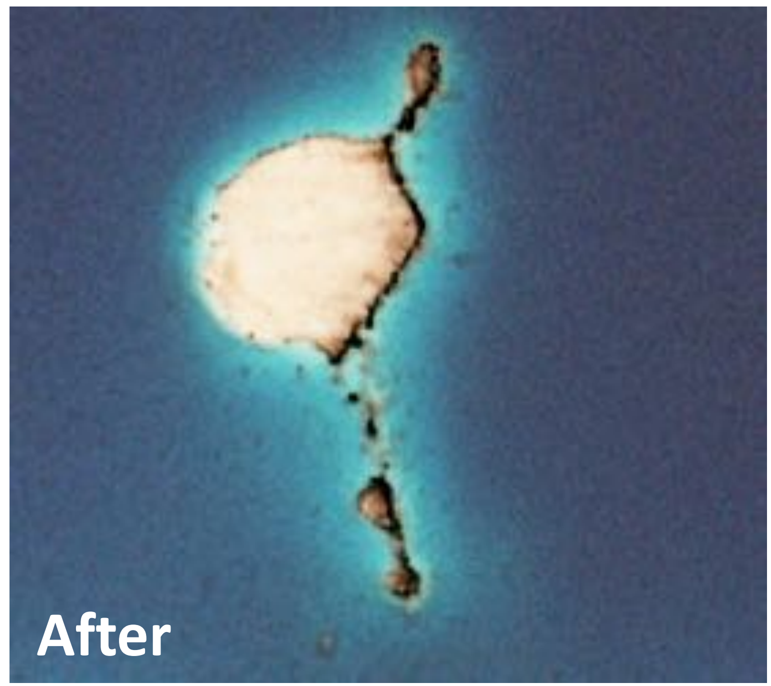
→ Spatial filtering (smoothing) may be useful



Pixel-to-pixel noise

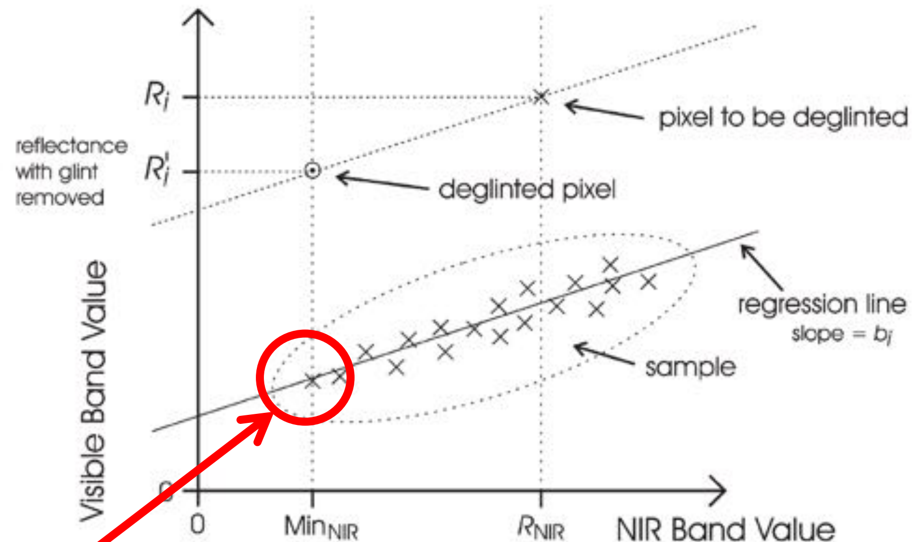
Over-correction when NIR below surface is not zero

- Assumption of zero NIR from below the water may not be valid in shallow water
- Corals and photosynthetic benthos can be bright in the NIR
- May or may not cause problems for subsequently applied algorithms



The challenge of getting a radiometrically correct output

Is the darkest pixel really a “no glint” reference?



The darkest pixels may contain some ‘sub-pixel’ glint, we have no way to know.

At TOA Min_{NIR} is sub-pixel glint plus aerosol backscatter.

Typically NIR is also important for aerosol estimation in atmospheric correction.

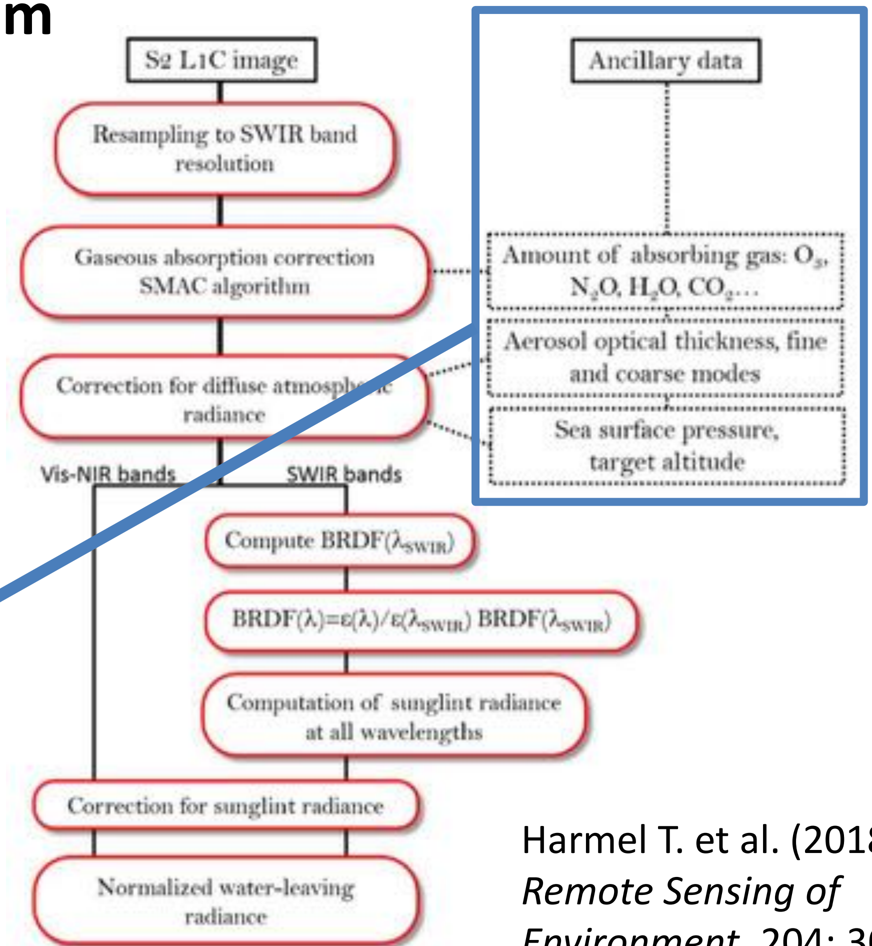
We are trying to use the NIR for two things!

Two routes to avoid this problem

1. Use ancillary data

- Harmel T. et al. (2018)
- Glint correction for Sentinel-2
- Uses SWIR to characterise glint
- Relies on a-priori separation of atmospheric reflectance from surface glint using data from AERONET station

Adds information to reduce uncertainty between aerosol and glint

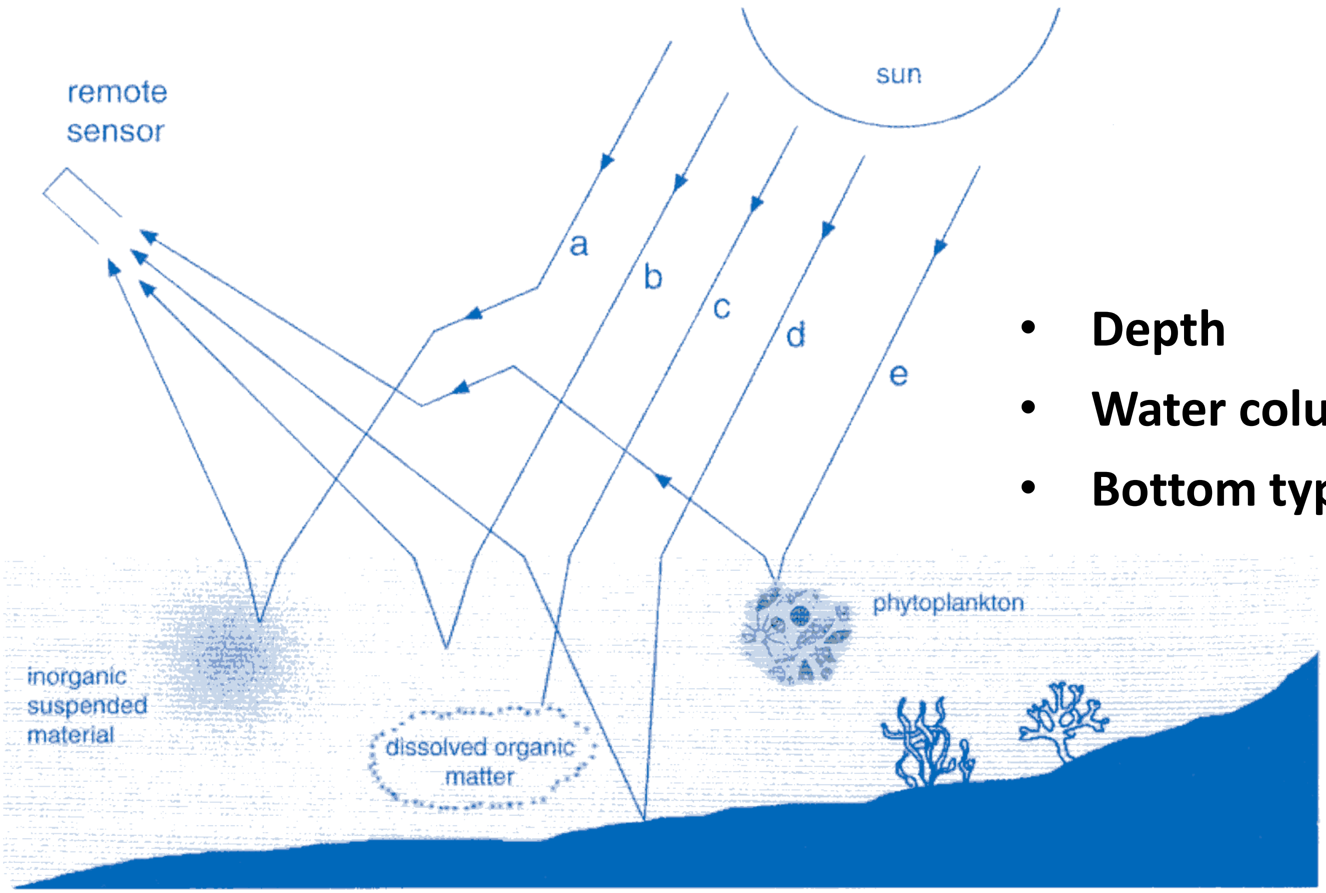


Harmel T. et al. (2018) *Remote Sensing of Environment*, 204: 308-321

2. Recognise we don’t really need to separate glint or aerosol

- Doesn’t matter if the glint and aerosol backscatter are confused as long their joint effect is removed, but, spectrally they may not be the same.

Inversion methods for shallow water applications



- **Depth**
- **Water column constituents**
- **Bottom type (sand, coral, etc.)**

Go from image $R_{rs}(\lambda)$ to model inputs = model inversion

Shallow water models for $R_{rs}(\lambda)$

1) HydroLight

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

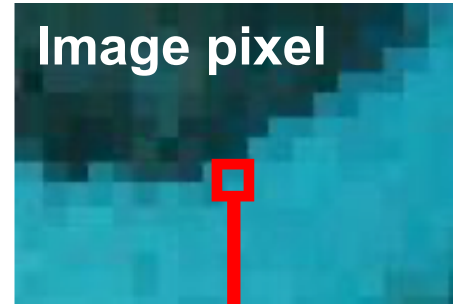
Results in a forward model that is faster to compute

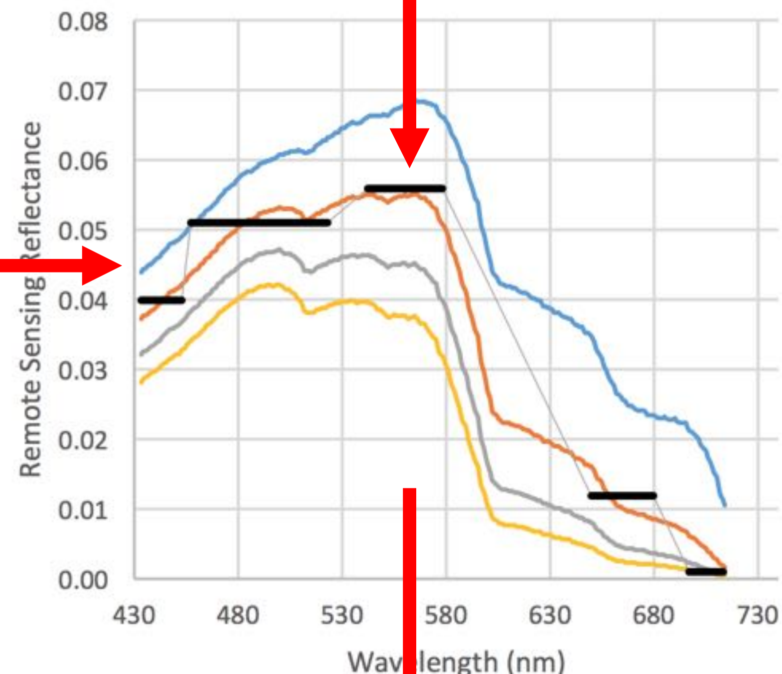
Lee et al. (1998) *Applied Optics* 37, 6329-6338

Spectral Matching (LUT)

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





- No in-situ training data required.

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

Lee et al's semianalytical model for shallow water reflectance

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

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

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

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

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

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

remote sensing reflectance

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

bottom reflectance

H = depth in metres

P = phytoplankton concentration (proxy)

G = dissolved organic matter concentration (proxy)

X = backscatter

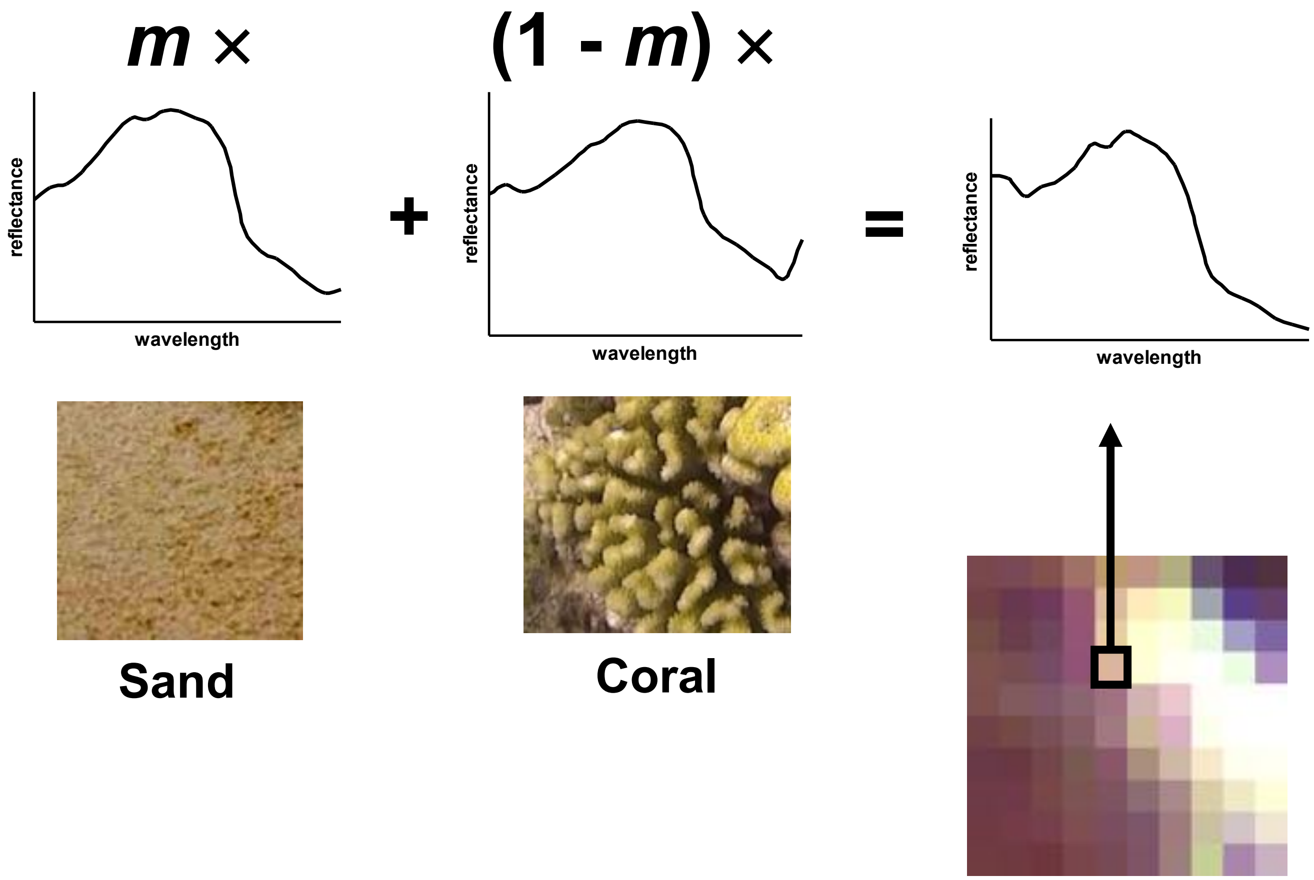
Y = (spectral slope of backscatter) is fixed at 1

Also incorporates sun and view zenith angles

Various factors derived from HydroLight

Bottom reflectance can be treated as a mix of types

- Use pairs selected from a small spectral library
- Then mixture is just one parameter, *m,* ranging 0 to 1
- Another parameter, *E*, specifies which particular pair are used.



Inversion of the model

This is a **<u>forward model</u>** 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

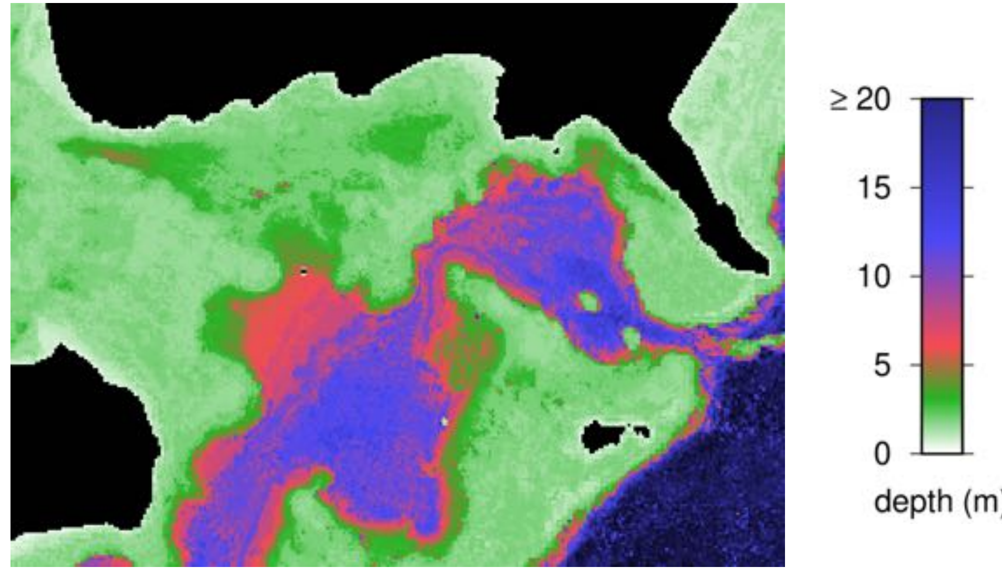
Successive approximation technique such as the Levenberg-Marquardt algorithm, keeps adjusting inputs to find the best match for the pixel $r_{rs}(\lambda)$

NOTE: You <u>can</u> get an estimate for more parameters than the number of bands, so you don't need 6 bands to do this.

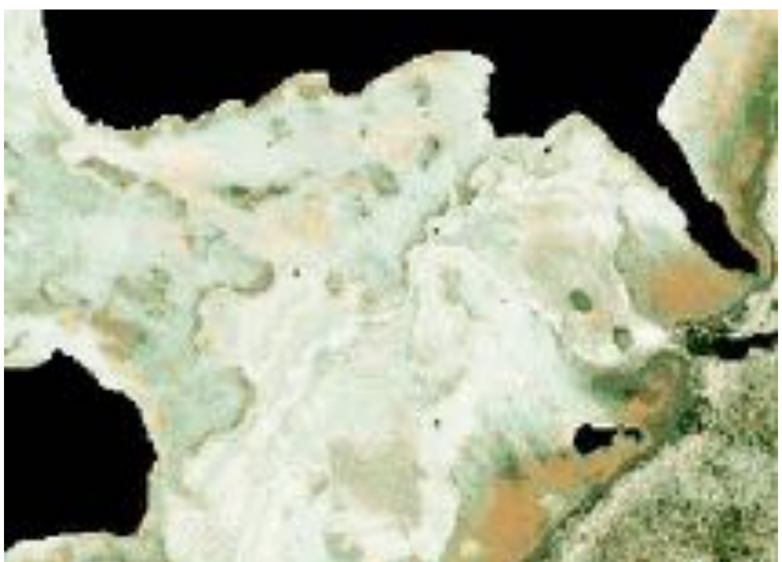
Examples of inversion products (Lizard Island, GBR)

Sentinel 2 image, RGB

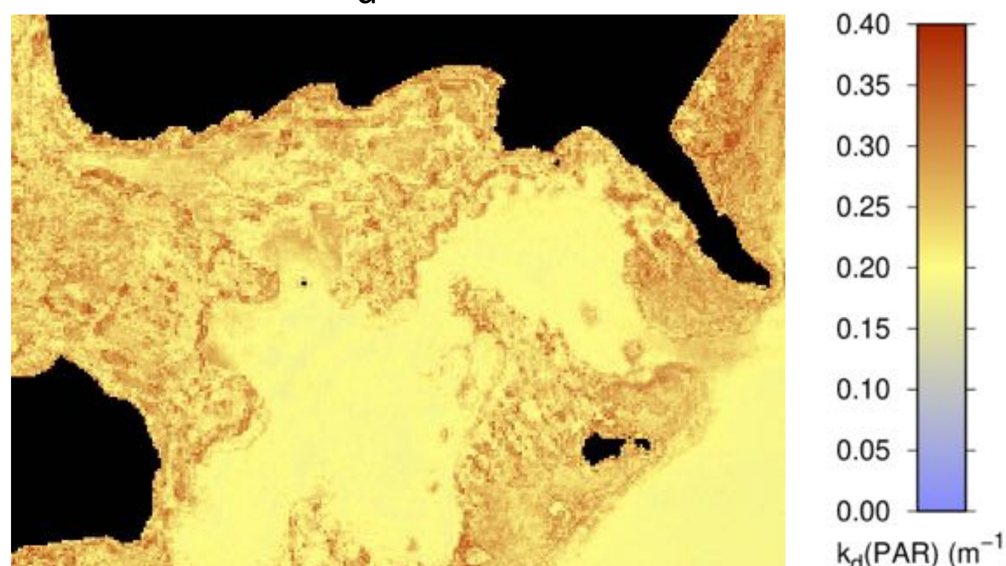
Bathymetry



Bottom reflectance, RGB



Water column k_d(PAR)



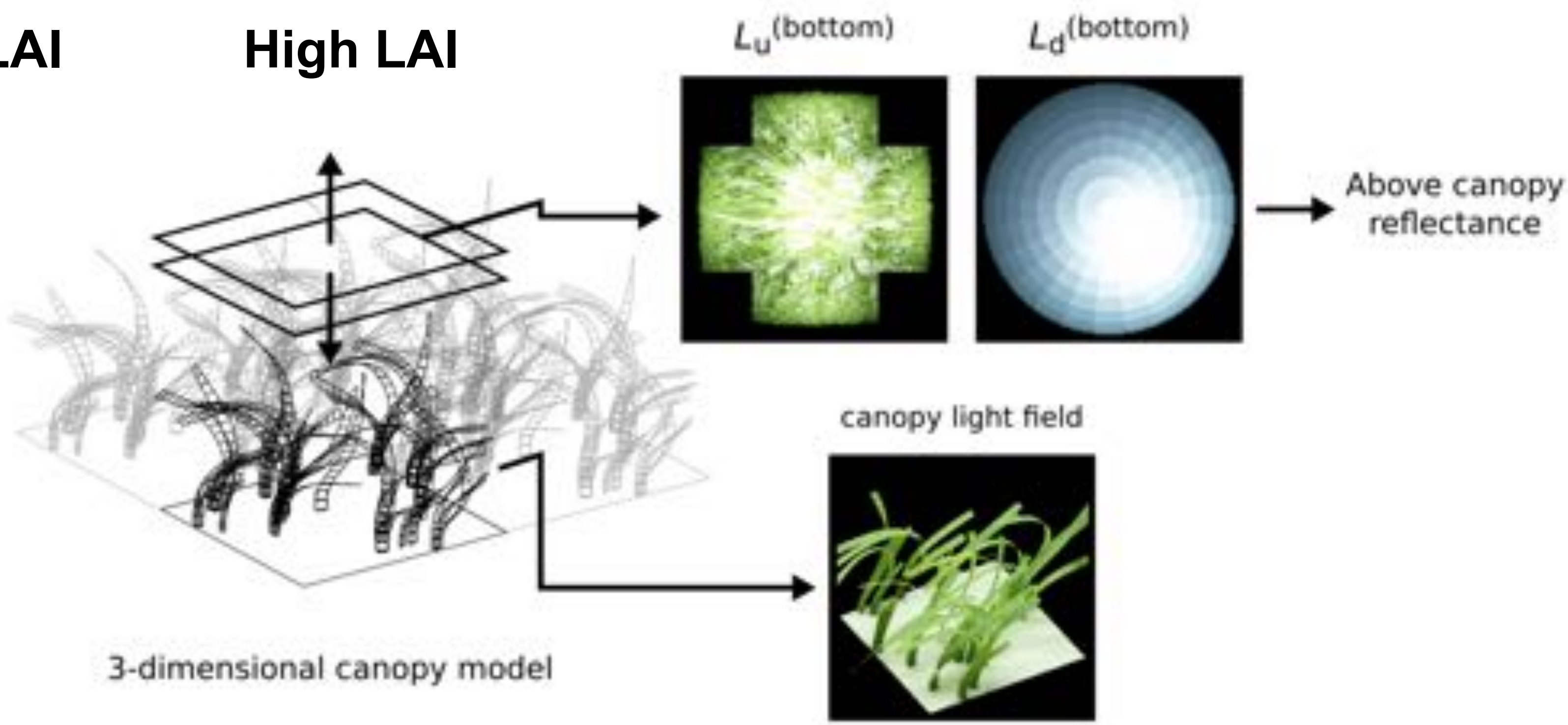
Canopy modelling, seagrass *Thalassia testudinium*

Low LAI

High LAI

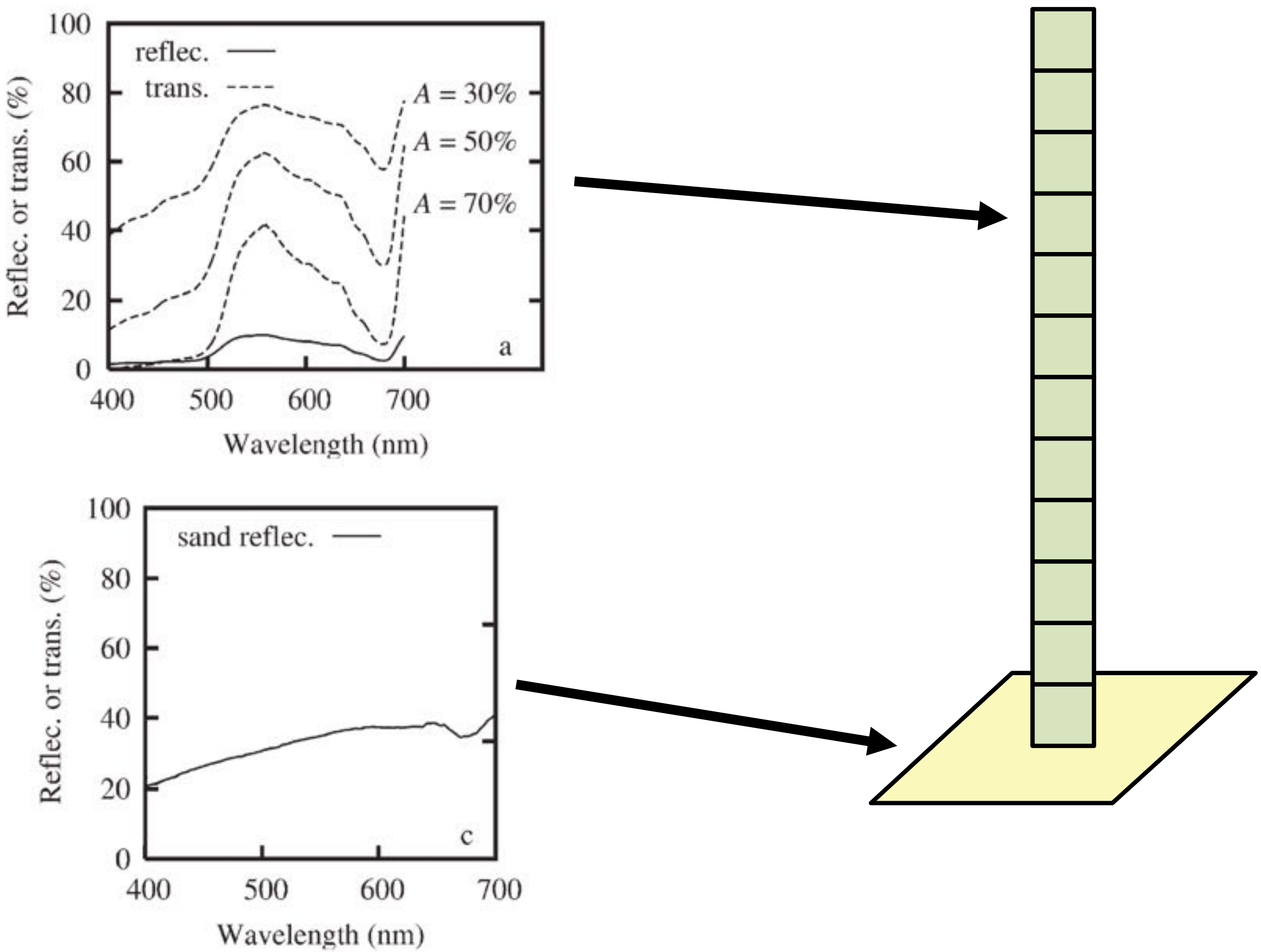
- 3-dimensional geometric optics model
- Hedley & Enríquez, L&O 2010
- Hedley, Russell, Randolph & Dierssen, RSE 2016

➢ Reflectance above the canopy as a function of leaf area index (LAI)



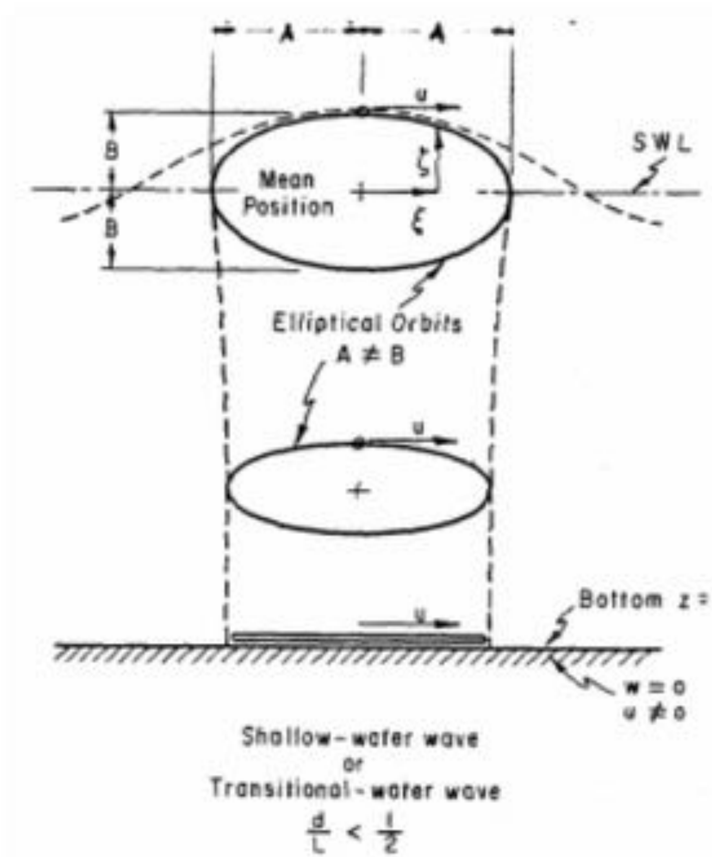
Leaf and sand optical properties

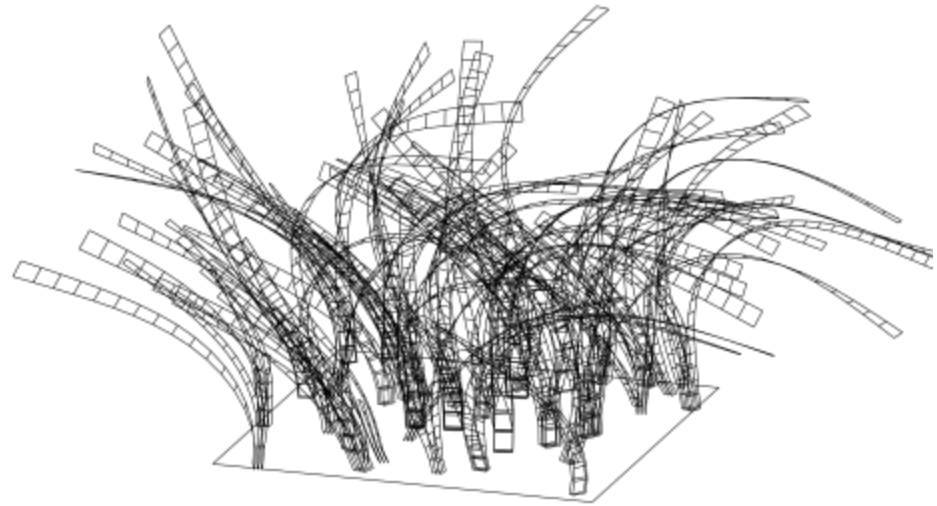
Reflectance and transmittance

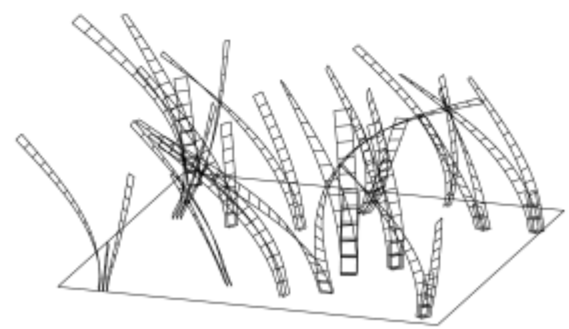


Canopy structure

- flexible strips in a simple wave motion model







Canopy structure

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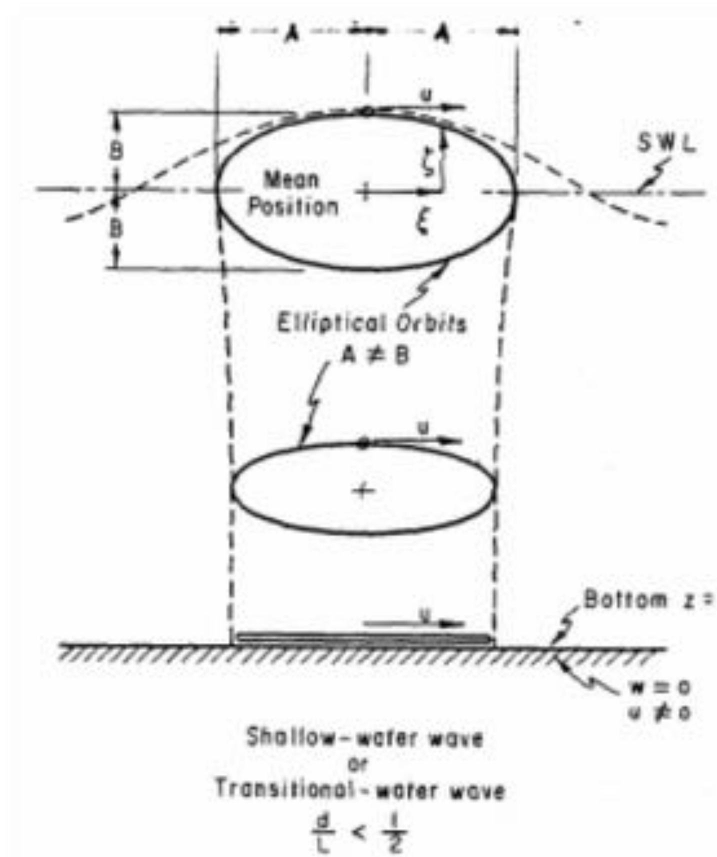


Model outputs (RGB from 17 bands)

LAI 4.5, depth 0.5 m

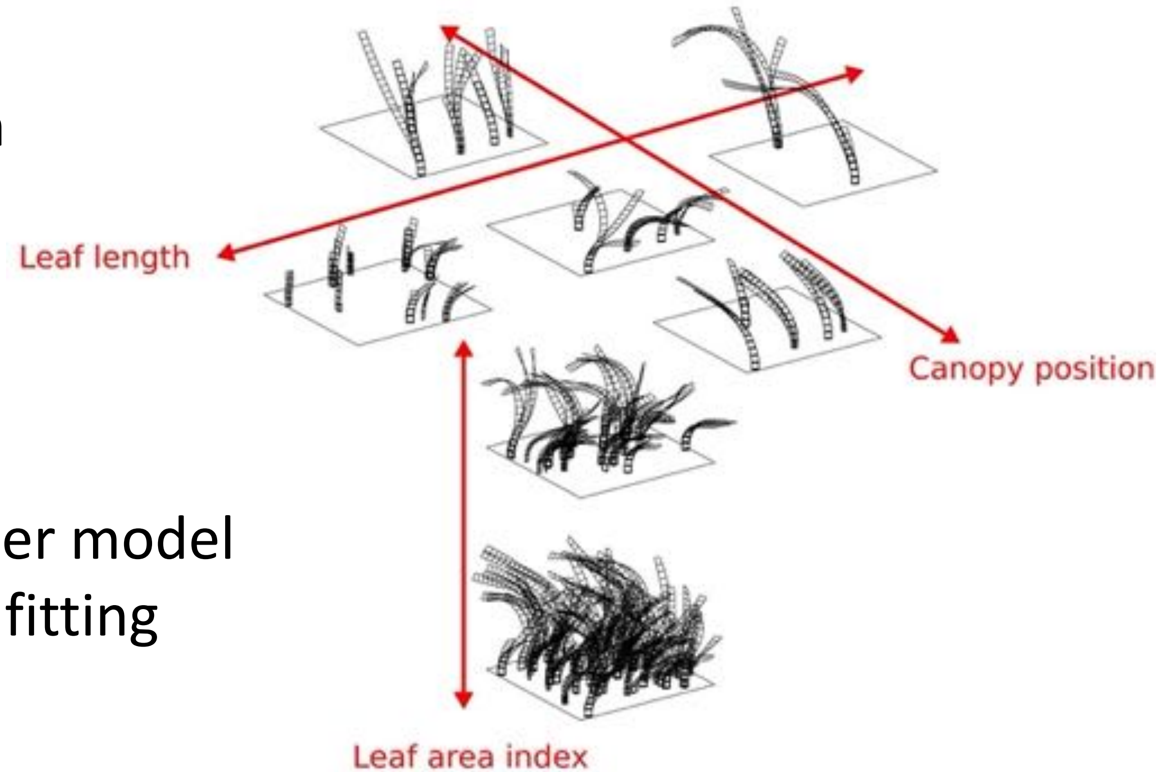
LAI 1.0, depth 1.5 m

Model outputs **(RGB from 17 bands)**

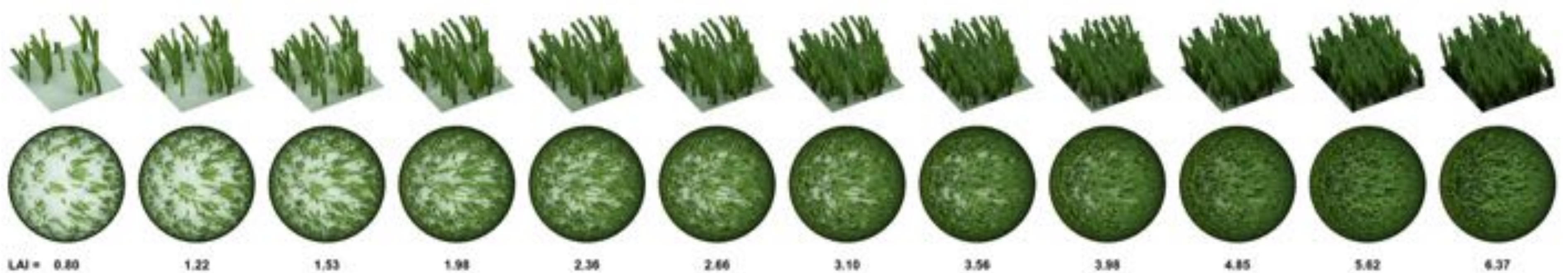
LAI 4.5, depth 0.5 m

LAI 1.0, depth 1.5 m

Model many canopies
with a multi-factor design



Reduce results to a simpler model
by regression & function fitting



$$\rho(\lambda) \approx R_{\text{canopy}}(\text{LAI}, e, \lambda)$$

e is a parameter that ranges from 0 to 1 and encompasses the variation for a specific LAI

Embed into Lee's model for shallow water reflectance

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

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

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

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

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

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

bottom reflectance

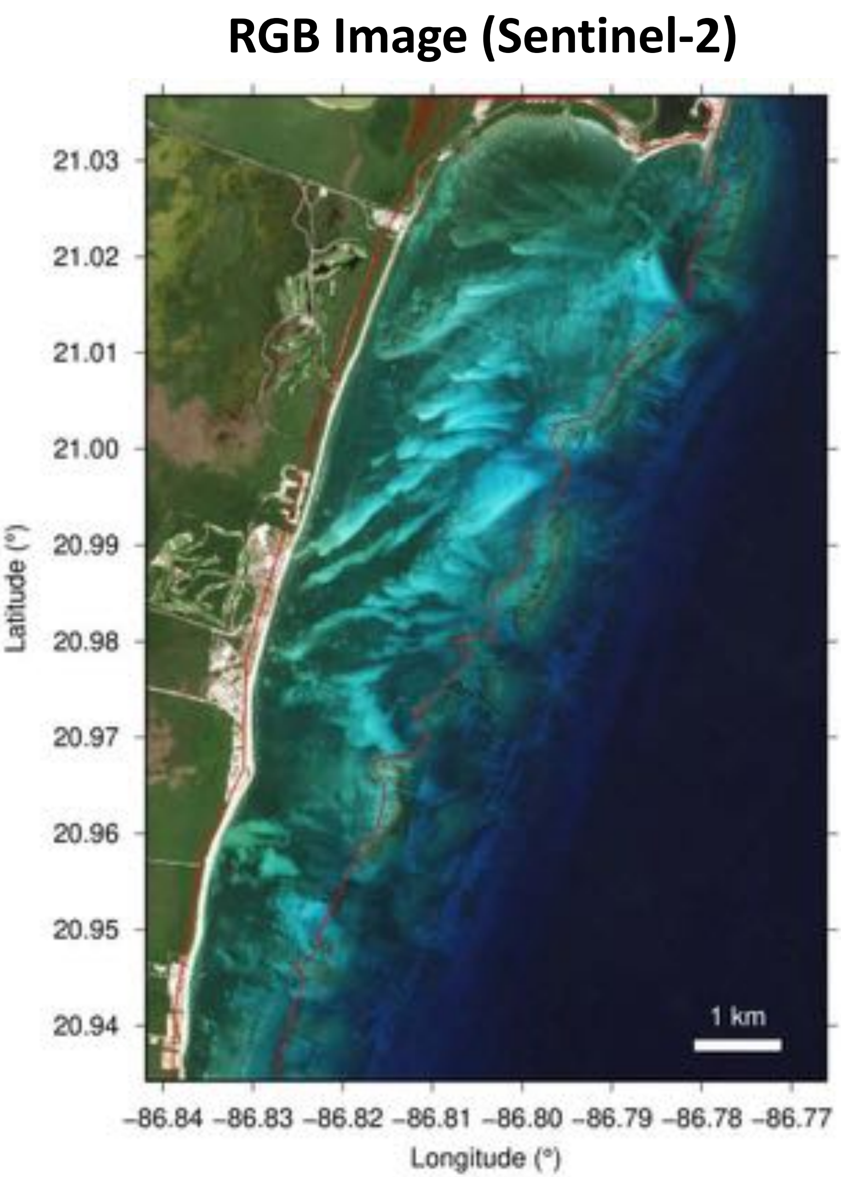
$$\rho(\lambda) \;\approx\; R_{\mathrm{canopy}}(\mathrm{LAI}, e, \lambda)$$

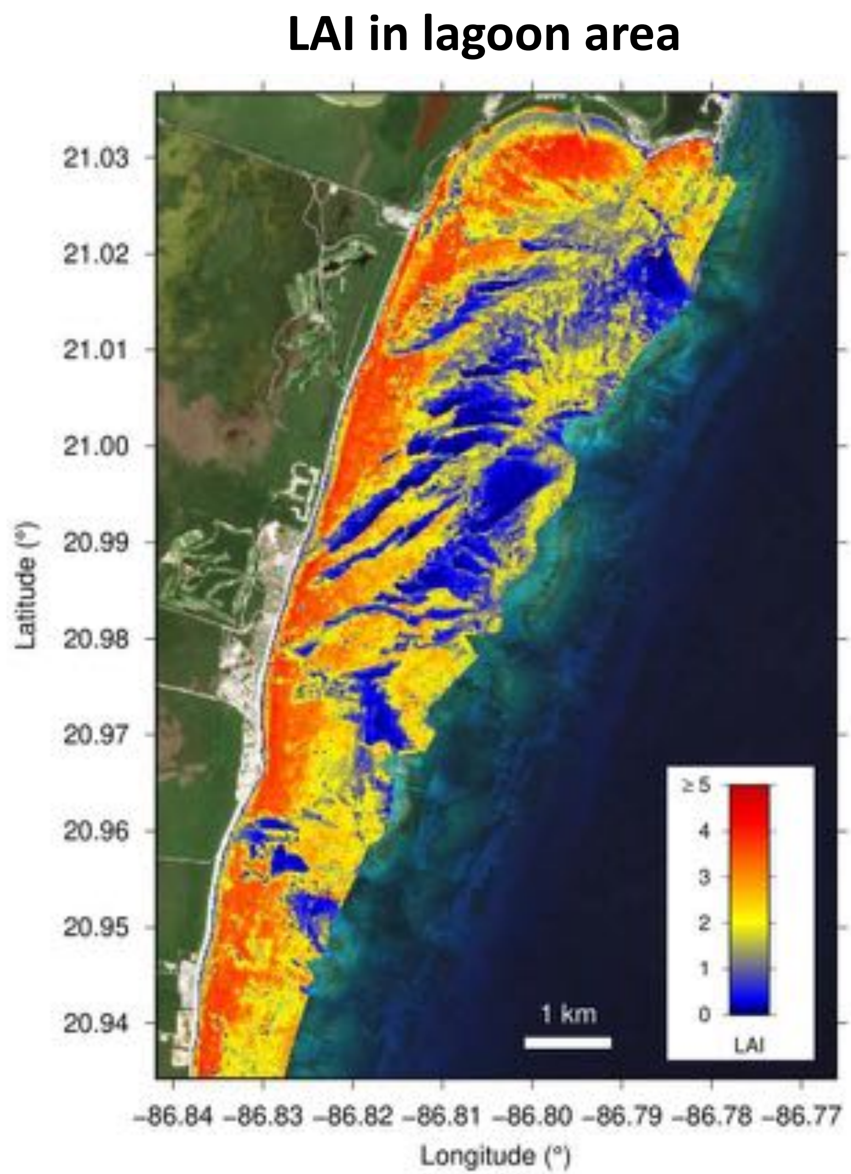
Substitute bottom reflectance for a model based on LAI and variation term *e*

Gives a model that can be inverted directly for LAI

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

Seagrass LAI mapping, Yucatán, Mexico

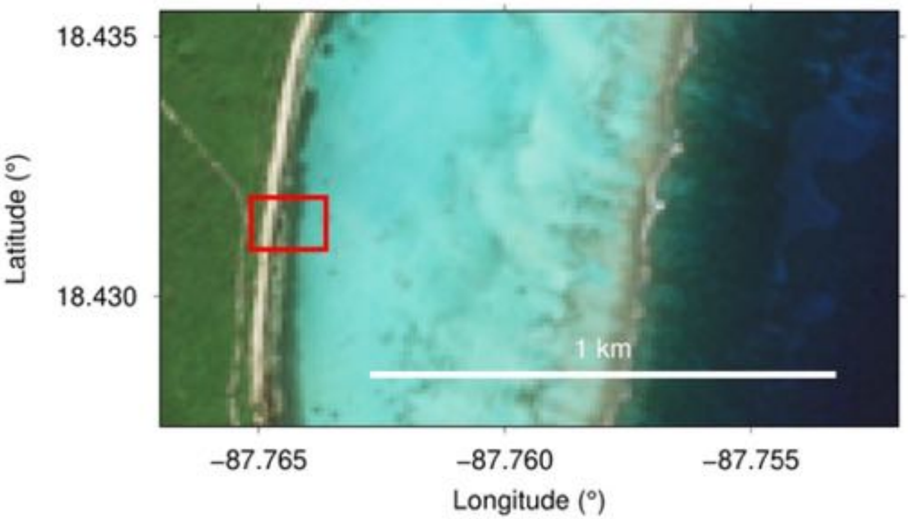


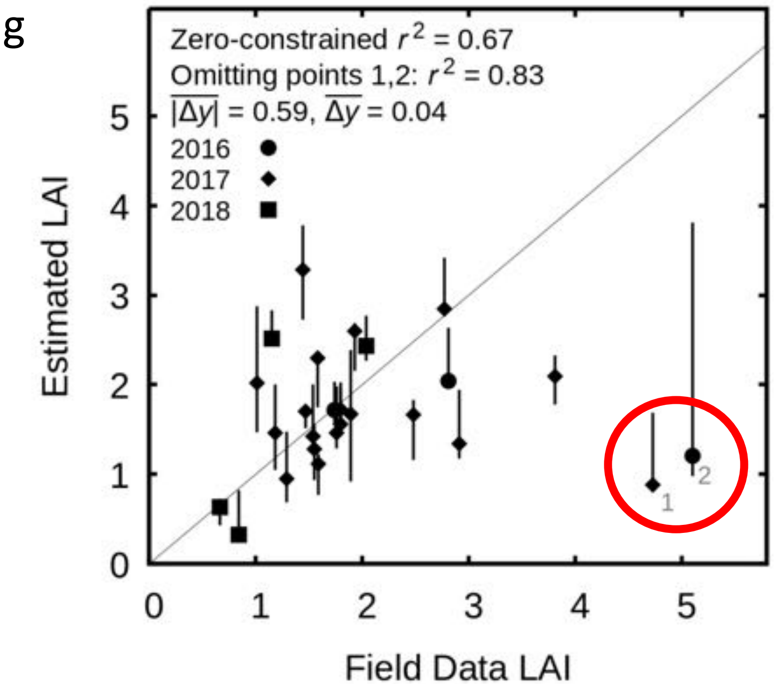


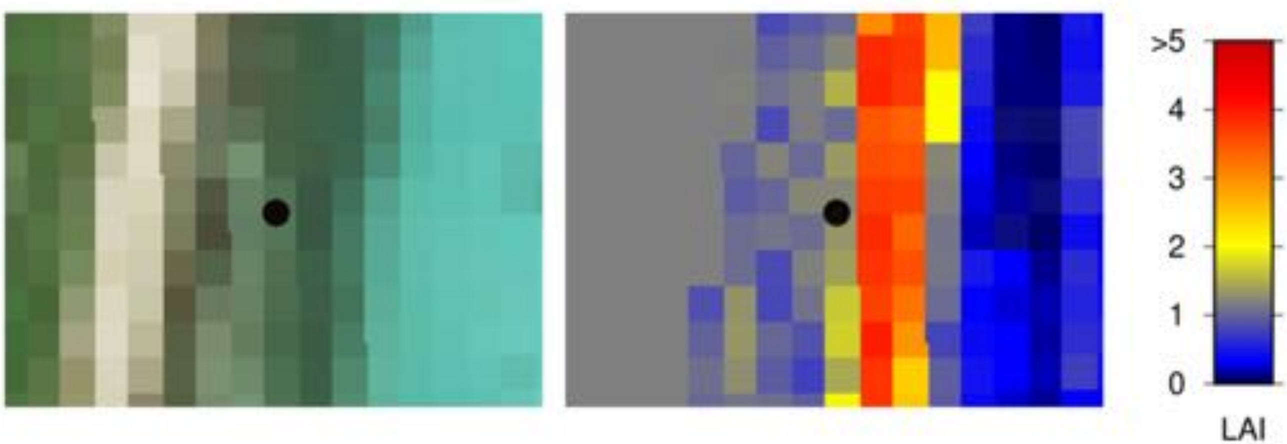
Hedley et al. 2021, *Frontiers in Marine Science*, 8, 733169 doi:10.3389/fmars.2021.733169

Difficulty in geo-locating ground truth data

Hard to survey at scales relevant to remote sensing







Hedley et al. 2021, *Frontiers in Marine Science*, 8, 733169 doi:10.3389/fmars.2021.733169

Benthic mapping – uncertainties and confidence

Typical objectives:

- say how much of something is there
- say if it has changed

How to be sure of conclusions?

- uncertainty estimates
- statistical tests

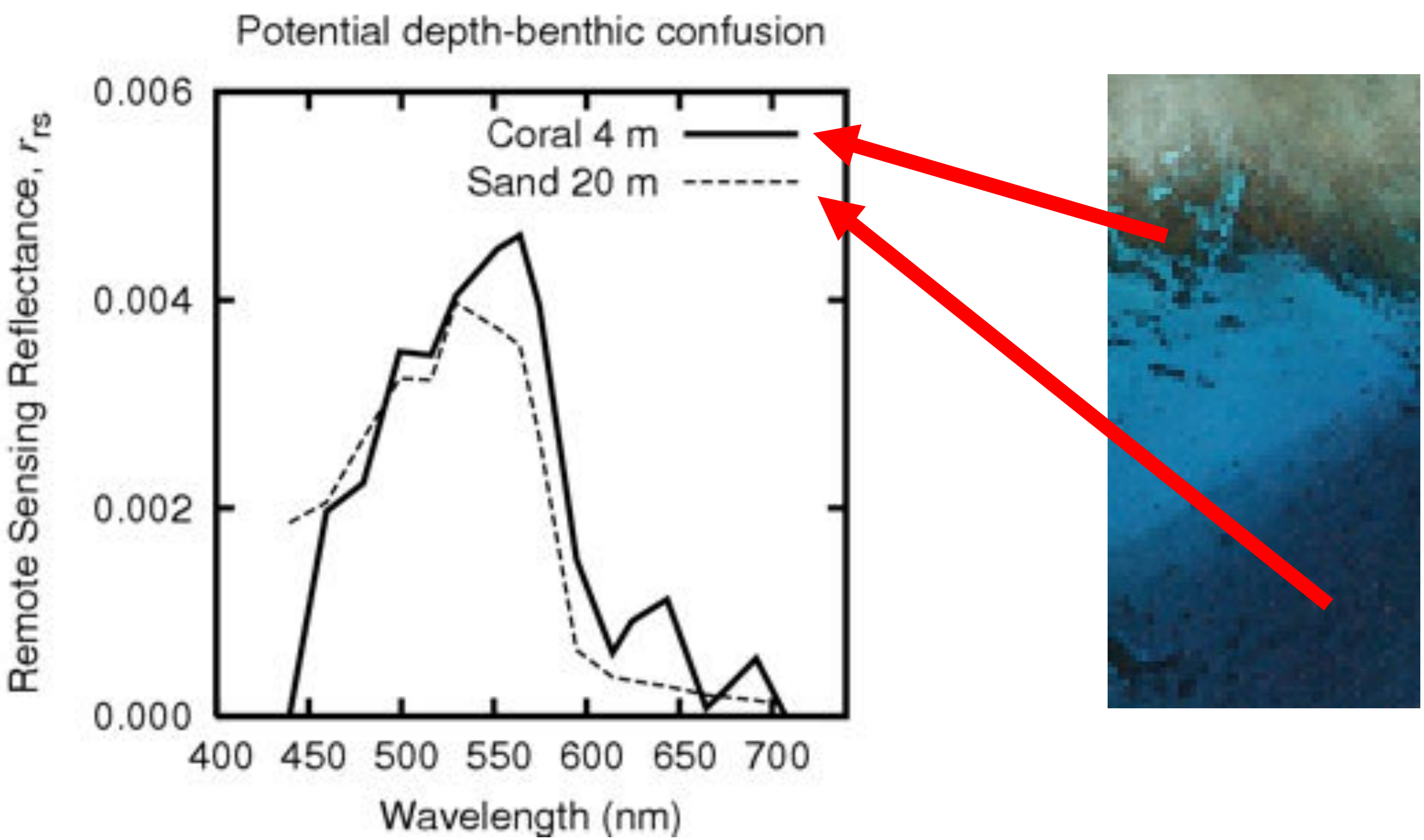
Two potential approaches

1) Image based uncertainty propagation
2) Multi image analysis and statistical tests

1. Uncertainty propagation through model inversion

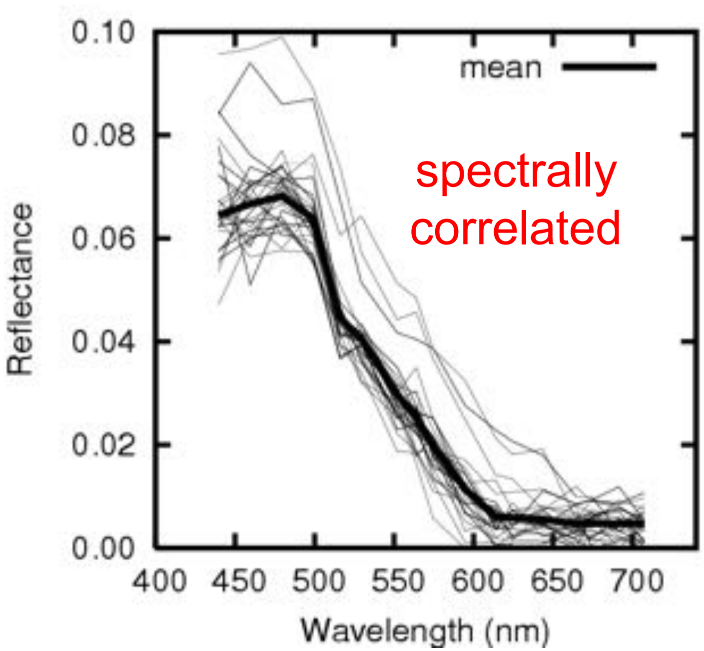
Fundamental uncertainty

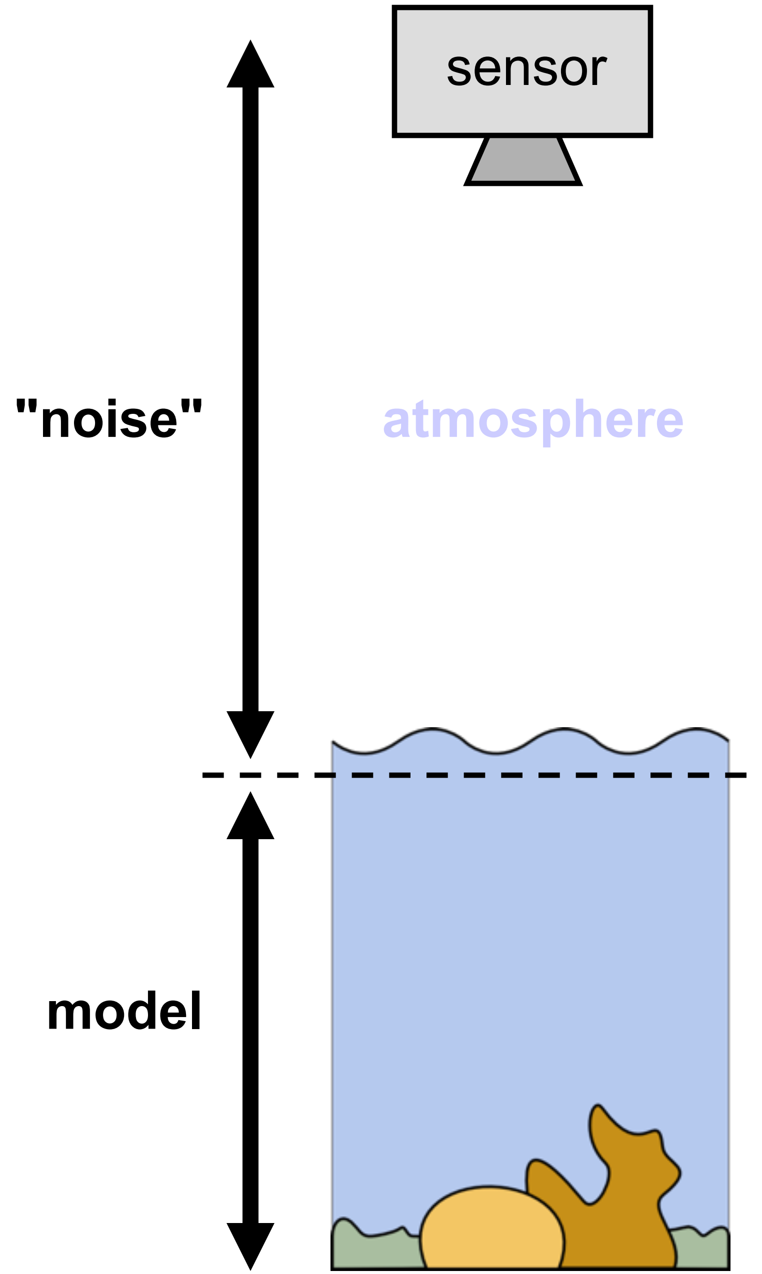
$\rightarrow$ similar spectra from differing parameters



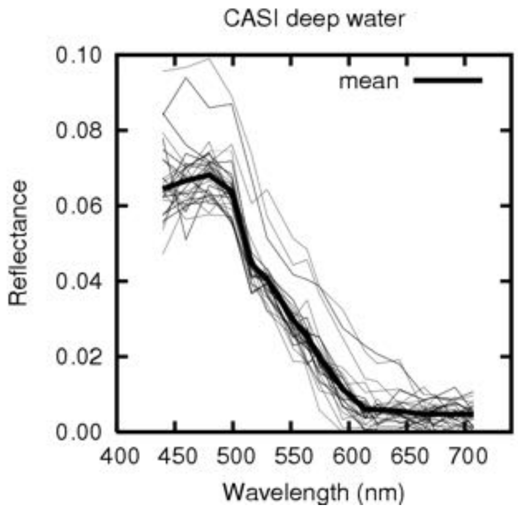
Sources of "noise" → uncertainty

Hyperspectral deep water pixels





Propagation through inversion



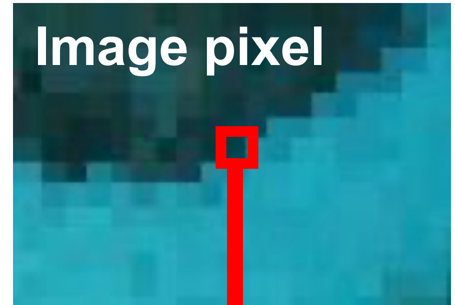


image noise

(multivariate normal)

subtract random noise term × 20 times

20 reflectance spectra

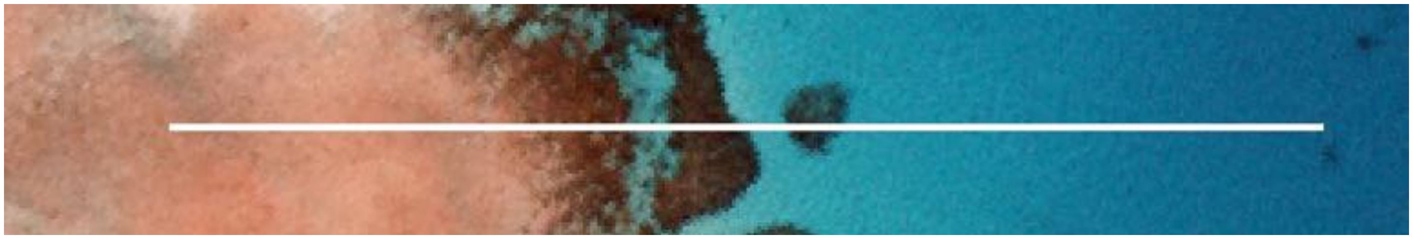
invert to retrieve parameter estimations

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

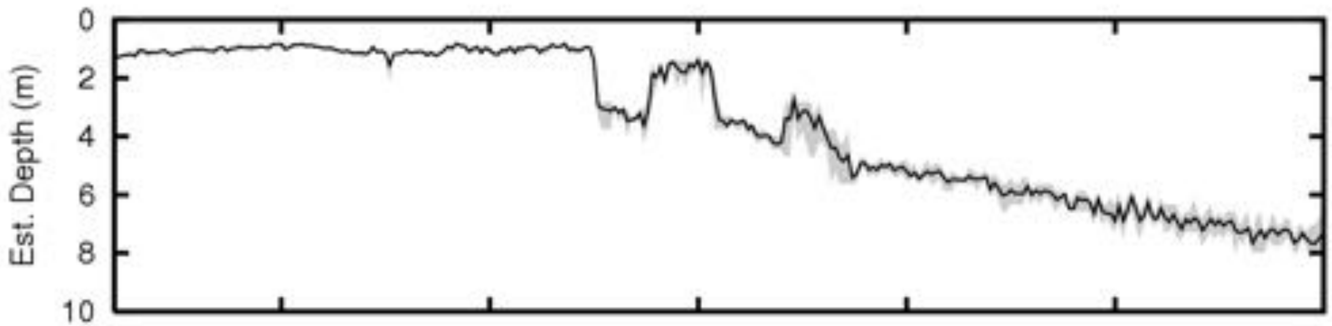
use mean for actual result

is actually better than direct single-inversion result

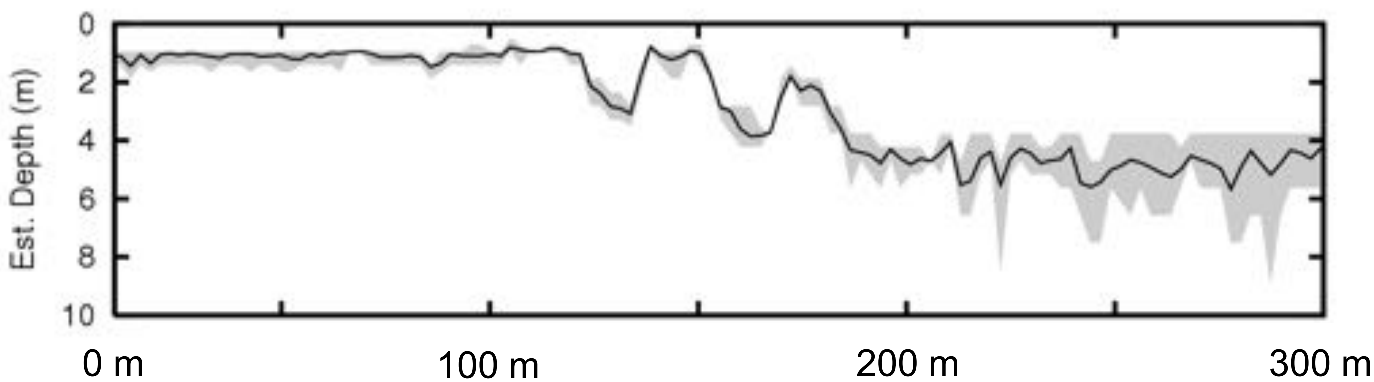
Bathymetry estimation with uncertainty



CASI



Quickbird

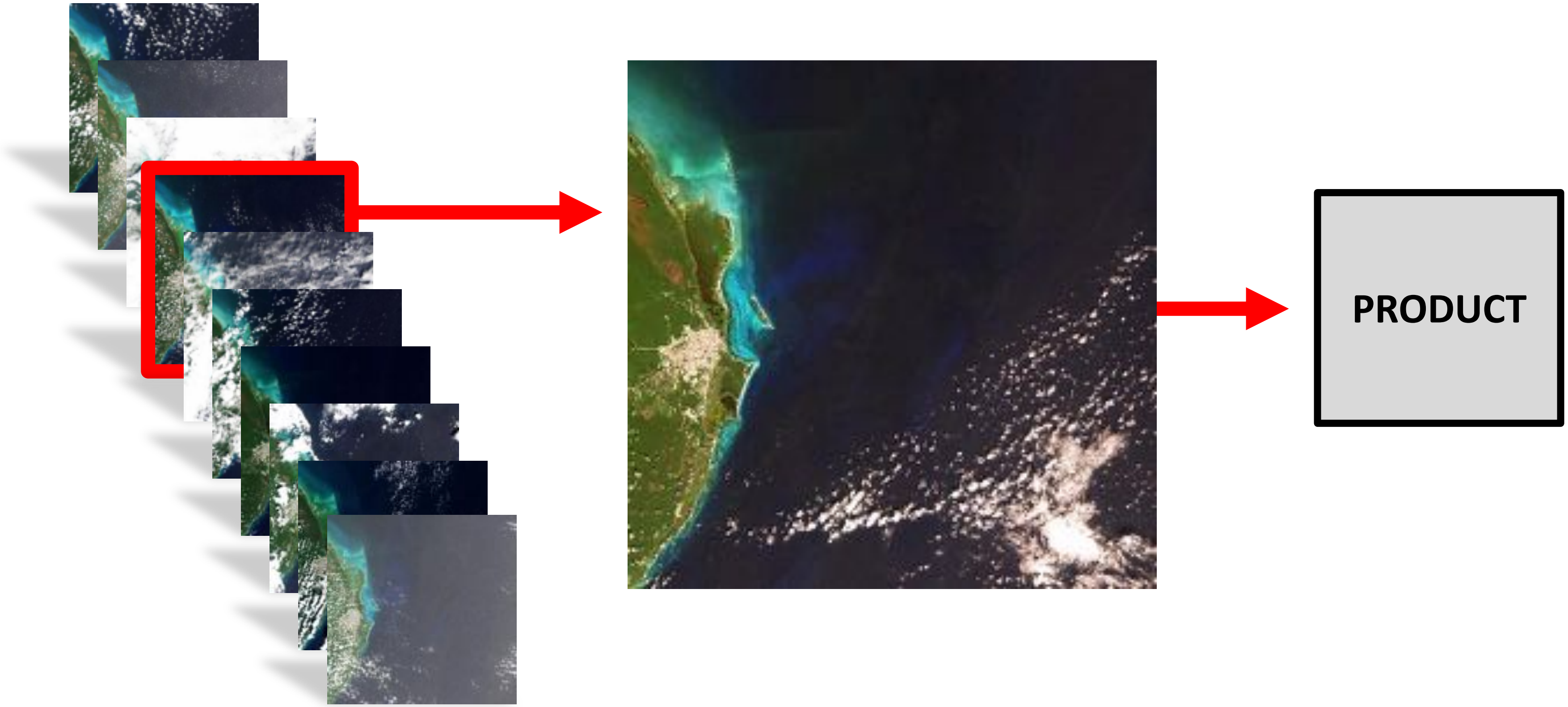


= 90% confidence interval

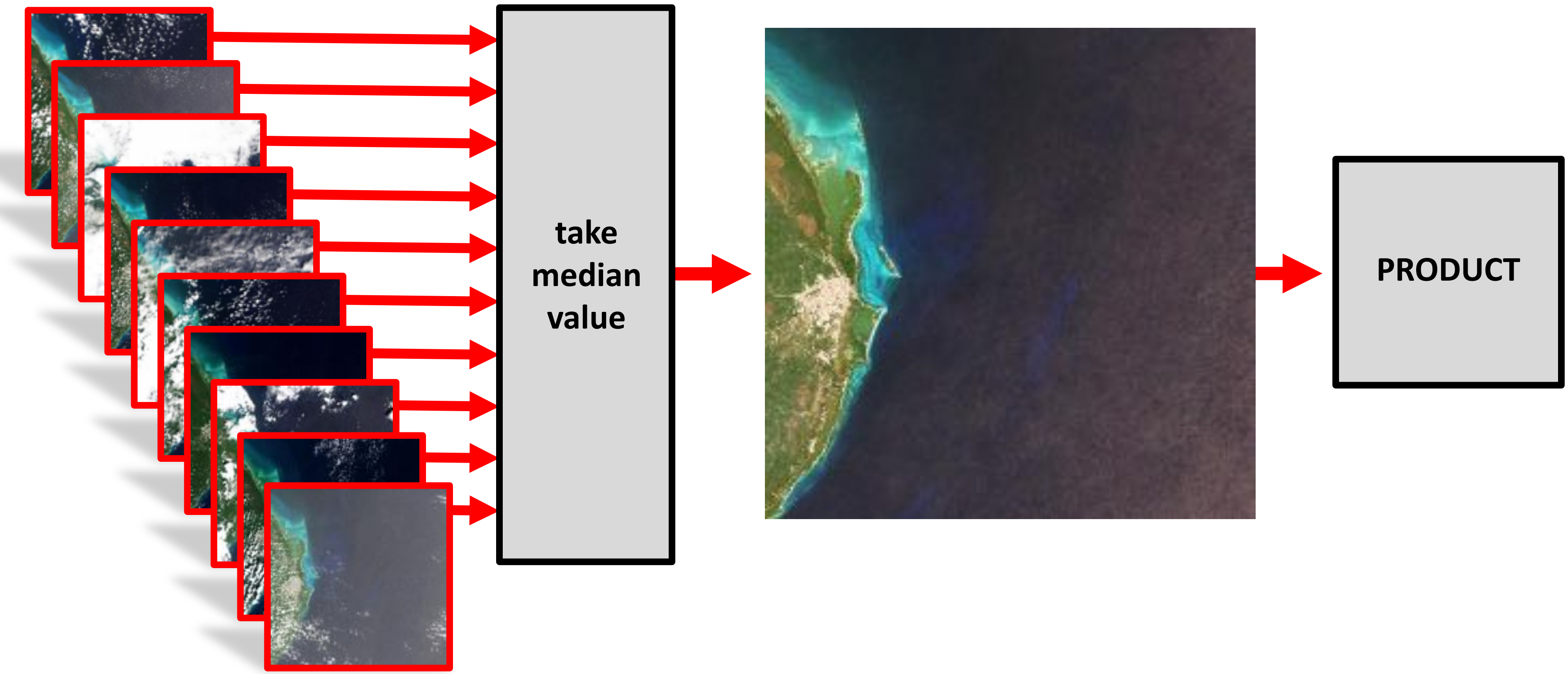
2. Multi-image analysis

- Slow changing features - e.g. benthic cover or bathymetry
- How to utilise the image archive?

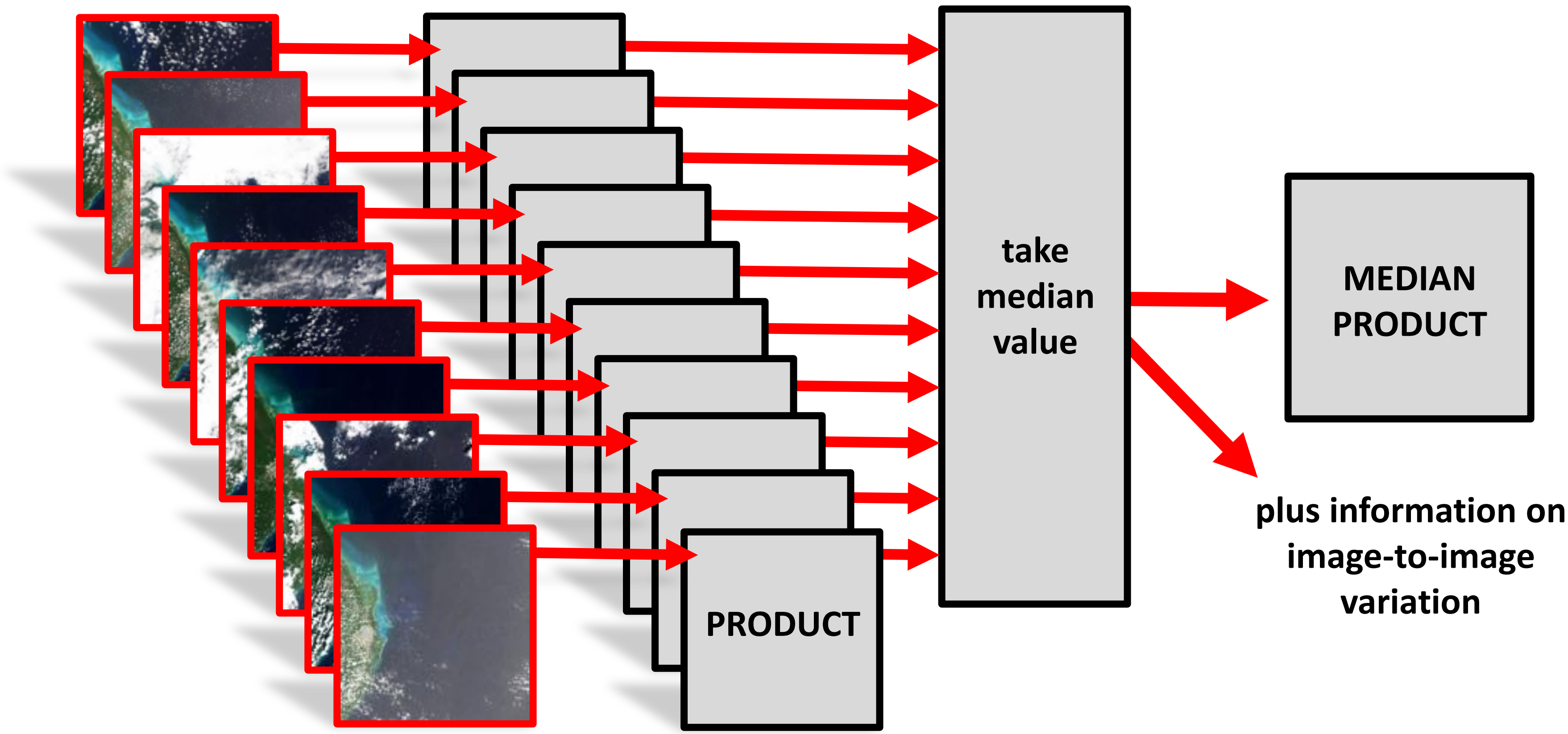
1. Pick a good image



2. Automated – make a median image



3. Automated – median product



(note processing does include cloud screening)

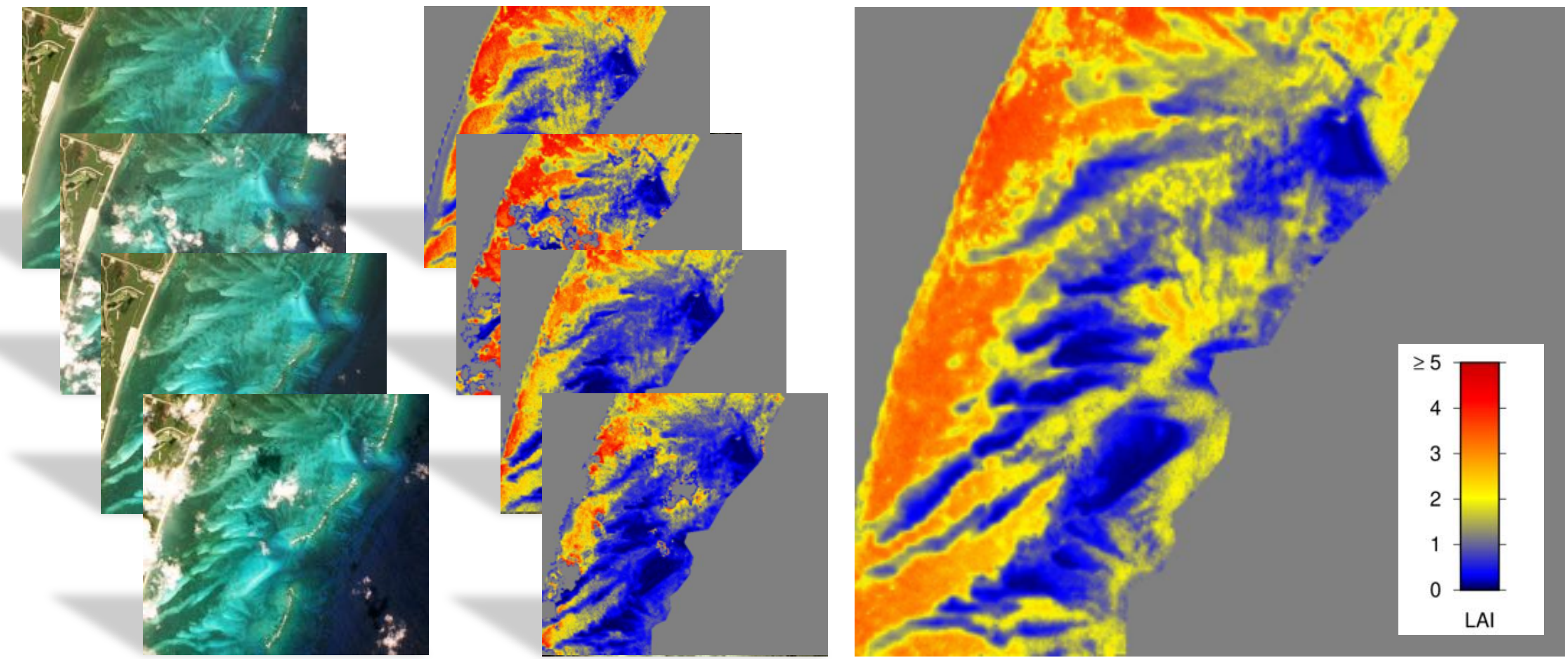
Annual median LAI (canopy density)

source images

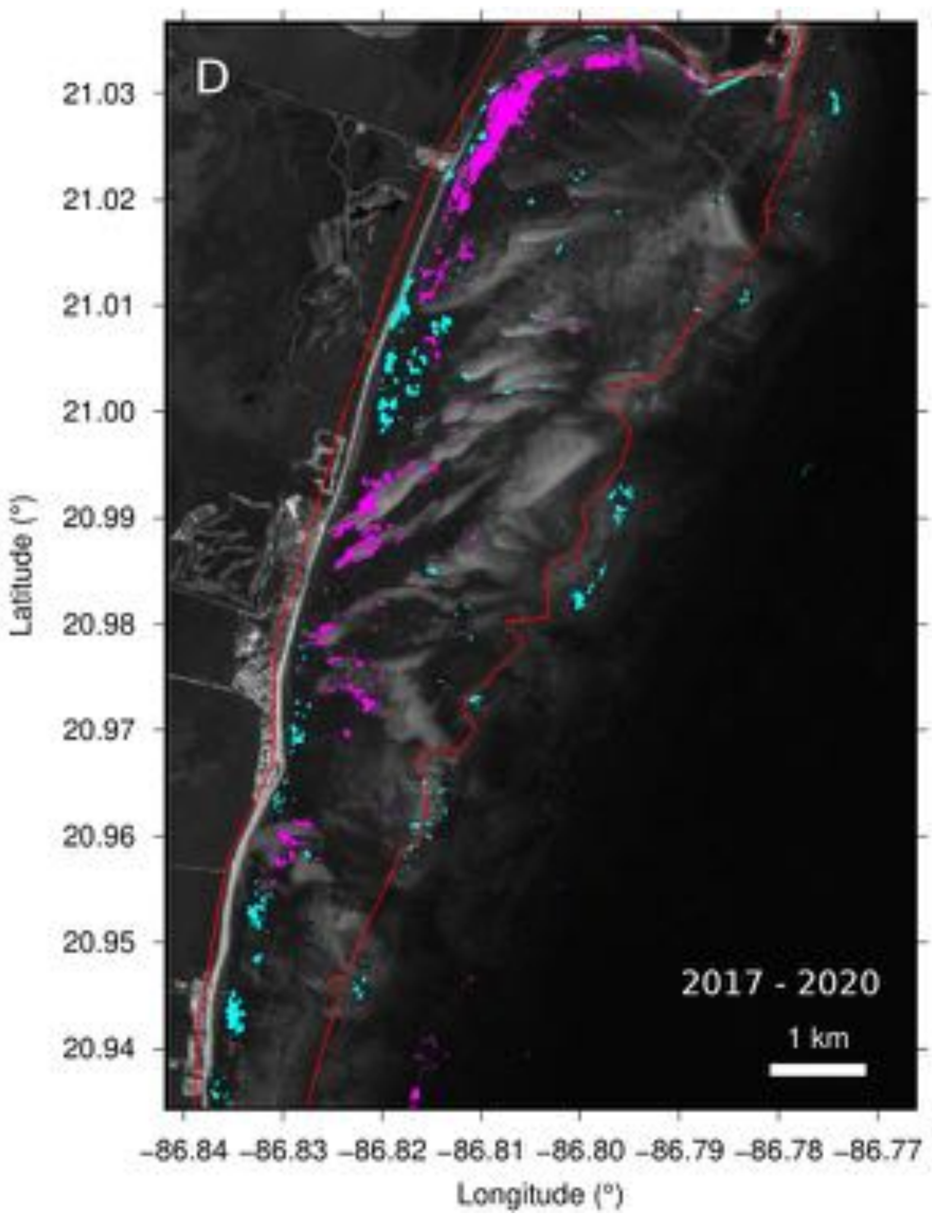
LAI

annual median LAI

(from 65 images)



Change detection in annual median LAI estimates - <u>with statistical test</u>



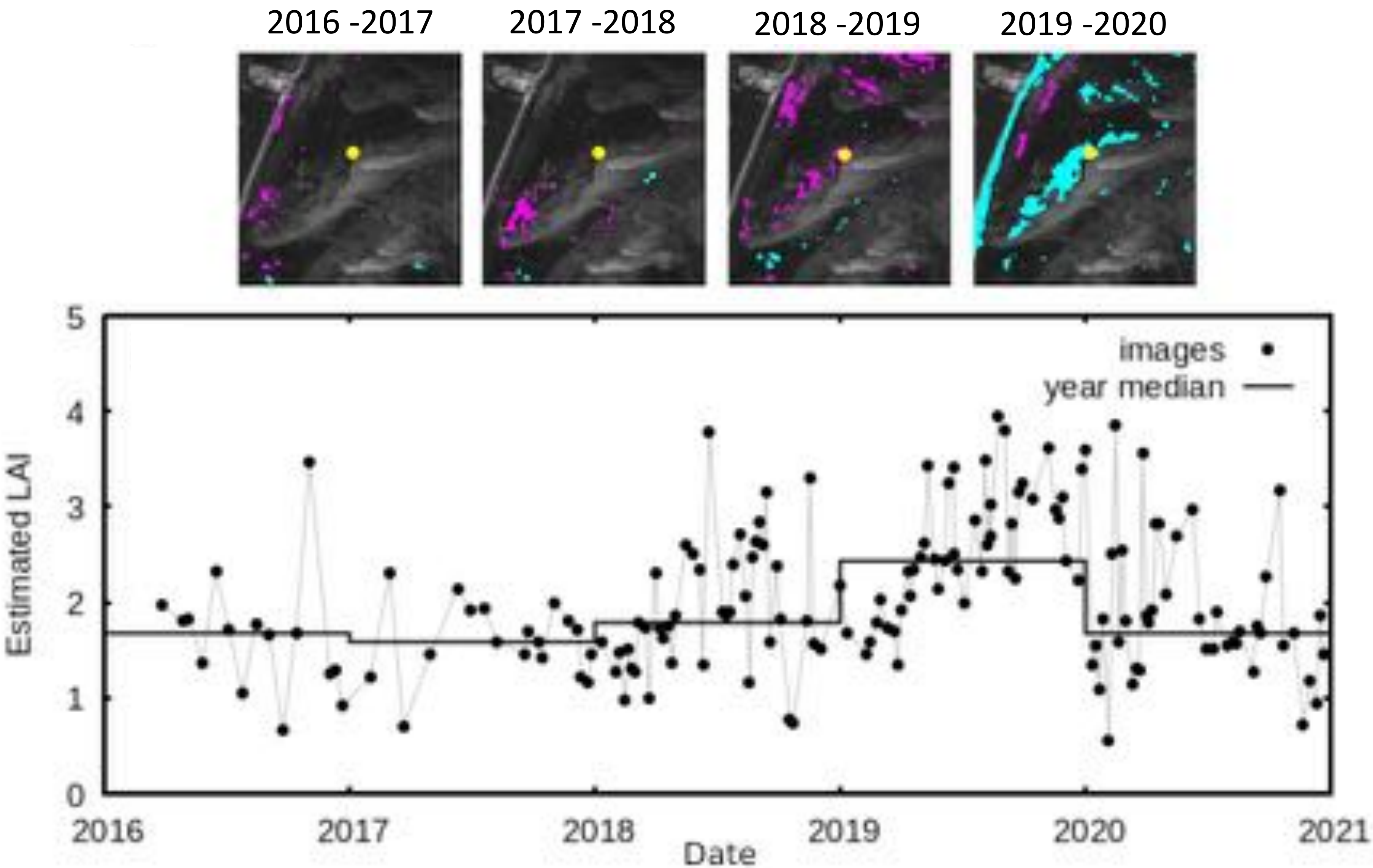
Increase

Decrease

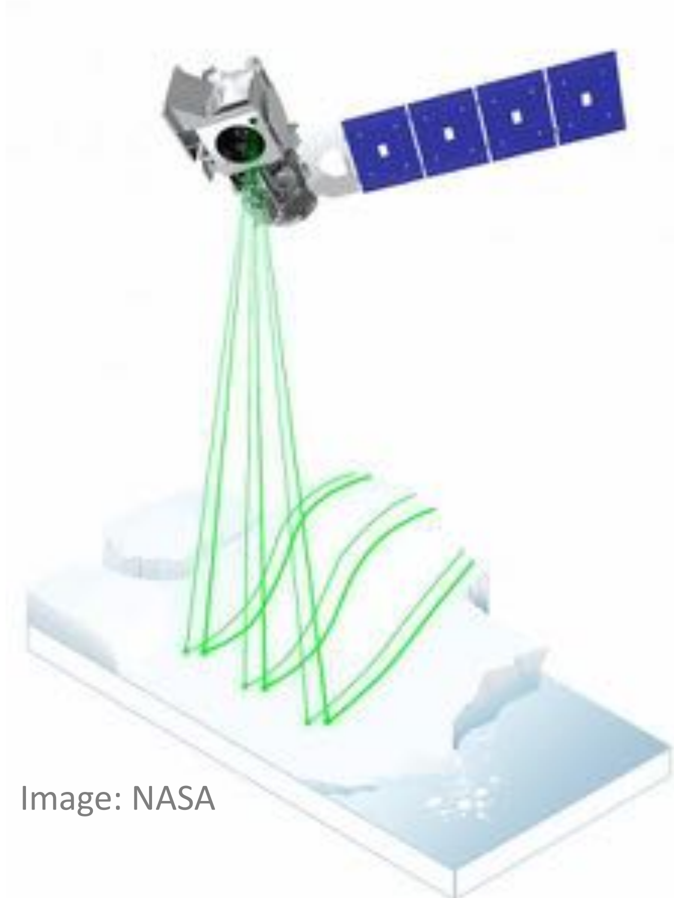
$p < 0.01$

Mood's median test

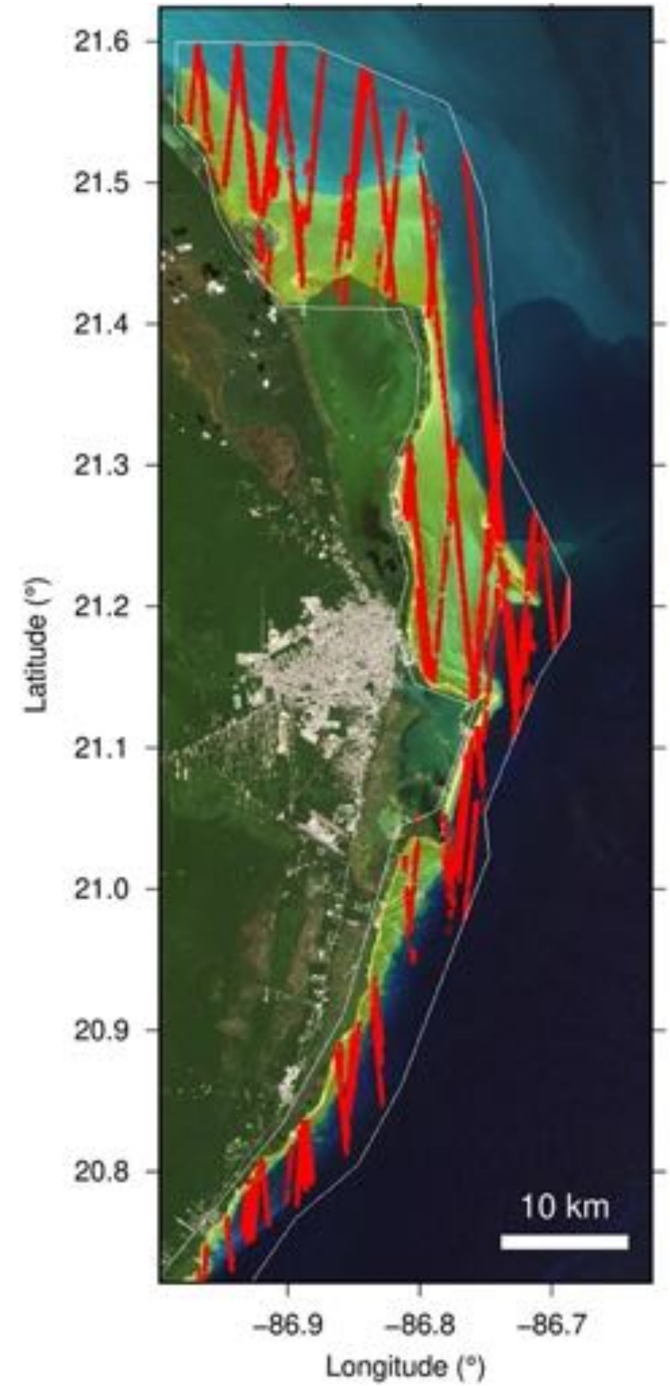
Detail of one location (yellow dot)



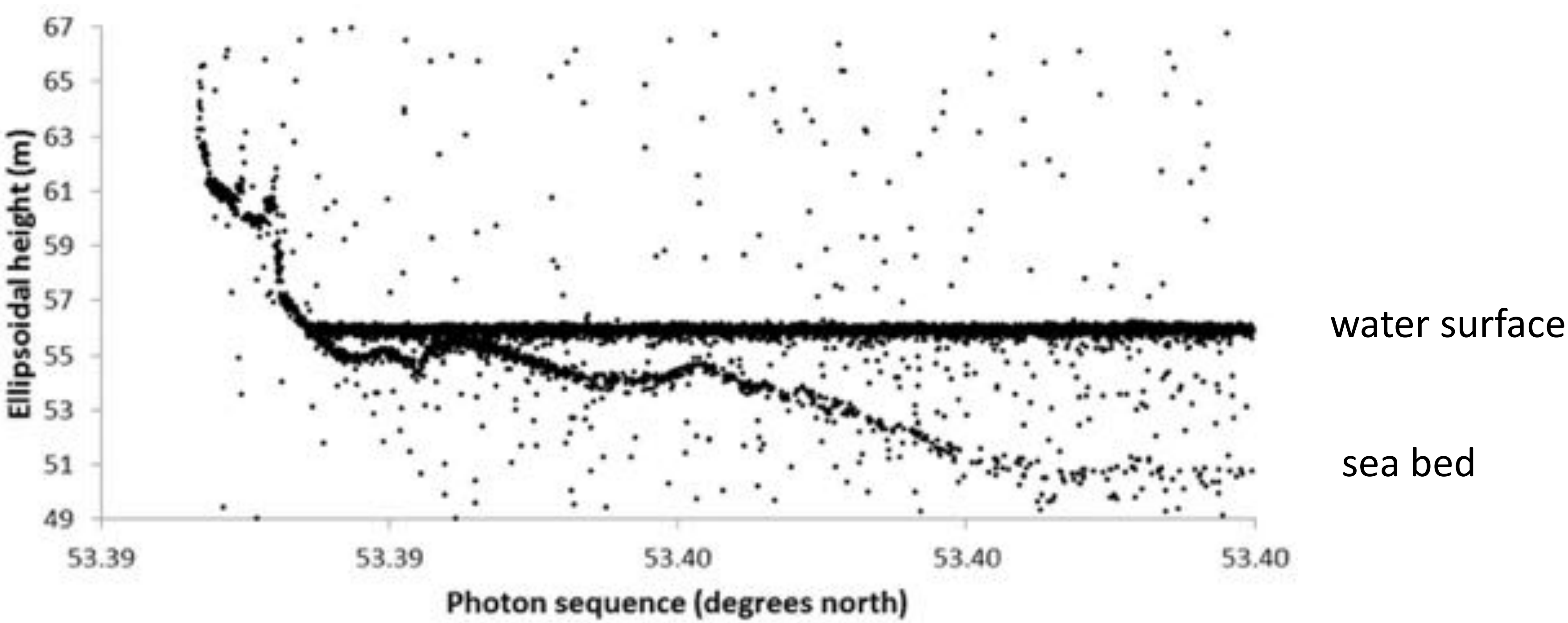
ICESat-2



- Space-bourne LIDAR
- Launched 15 Sept. 2018
- Global acquisition
- Data freely available on on the web
- Possible to extract bathymetry

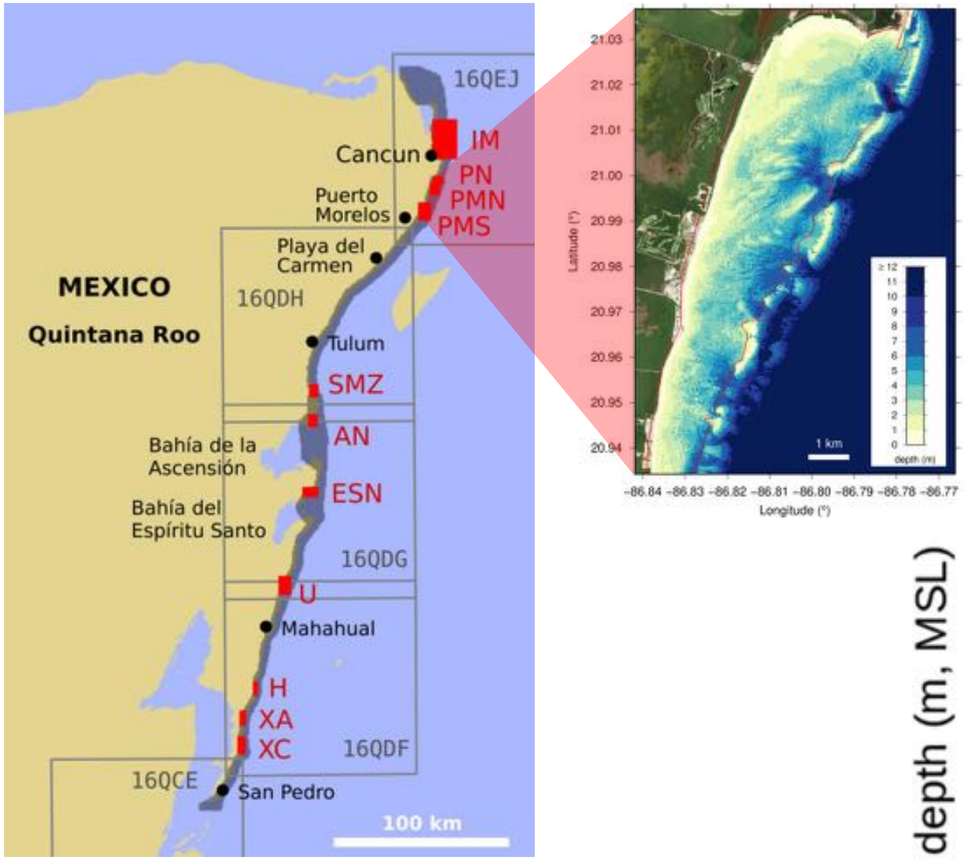


Typical ICESat-2 data

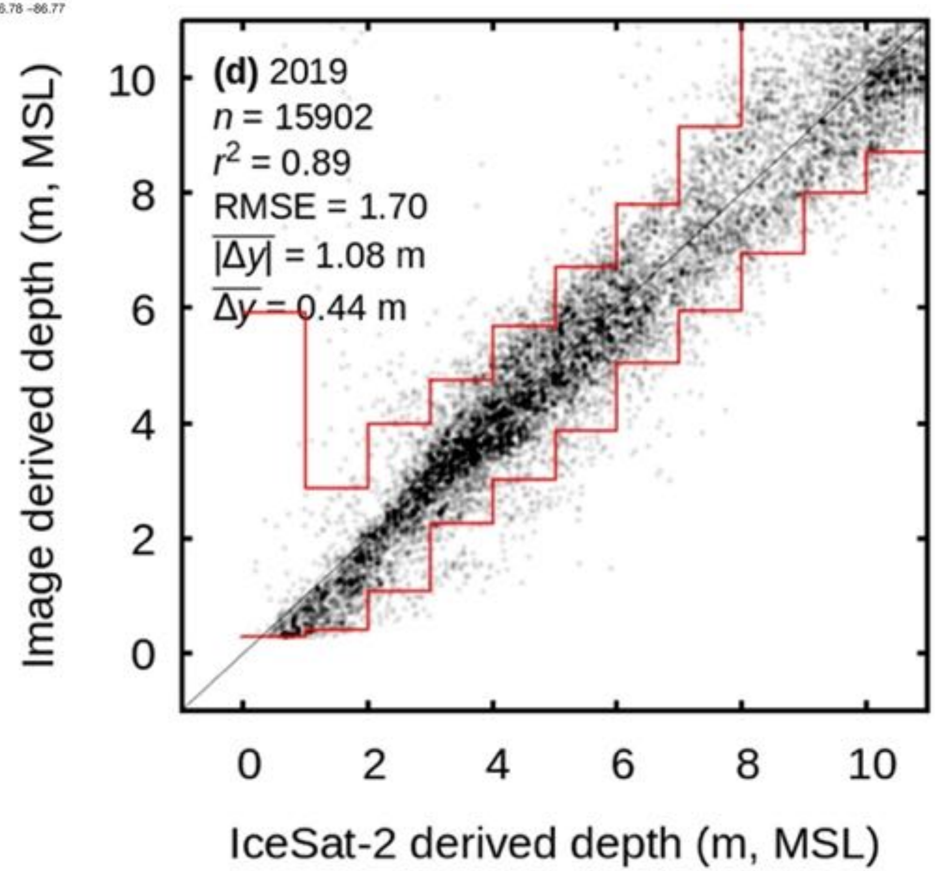


- Under favourable conditions depths to 20 m (or more) can be extracted
- Difficult to automate extraction
- Correct for refractive index, apparent depth is ~1.33 × depth

Coveney et al. 2021, *Remote Sensing*, 13, 4352; doi:10.3390/rs13214352



Comparison of model inversion bathymetry vs. ICESat-2 data for the entire Yucatan coast (~400 km)



- Scale is more appropriate to remote sensing than echo sound data
- Use data for calibration or validation

Hedley et al. 2021, *Frontiers in Marine Science*, 8, 733169
doi:10.3389/fmars.2021.733169

Questions…