

Shallow Water Remote Sensing

John Hedley, IOCCG Summer Class 2026

- 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

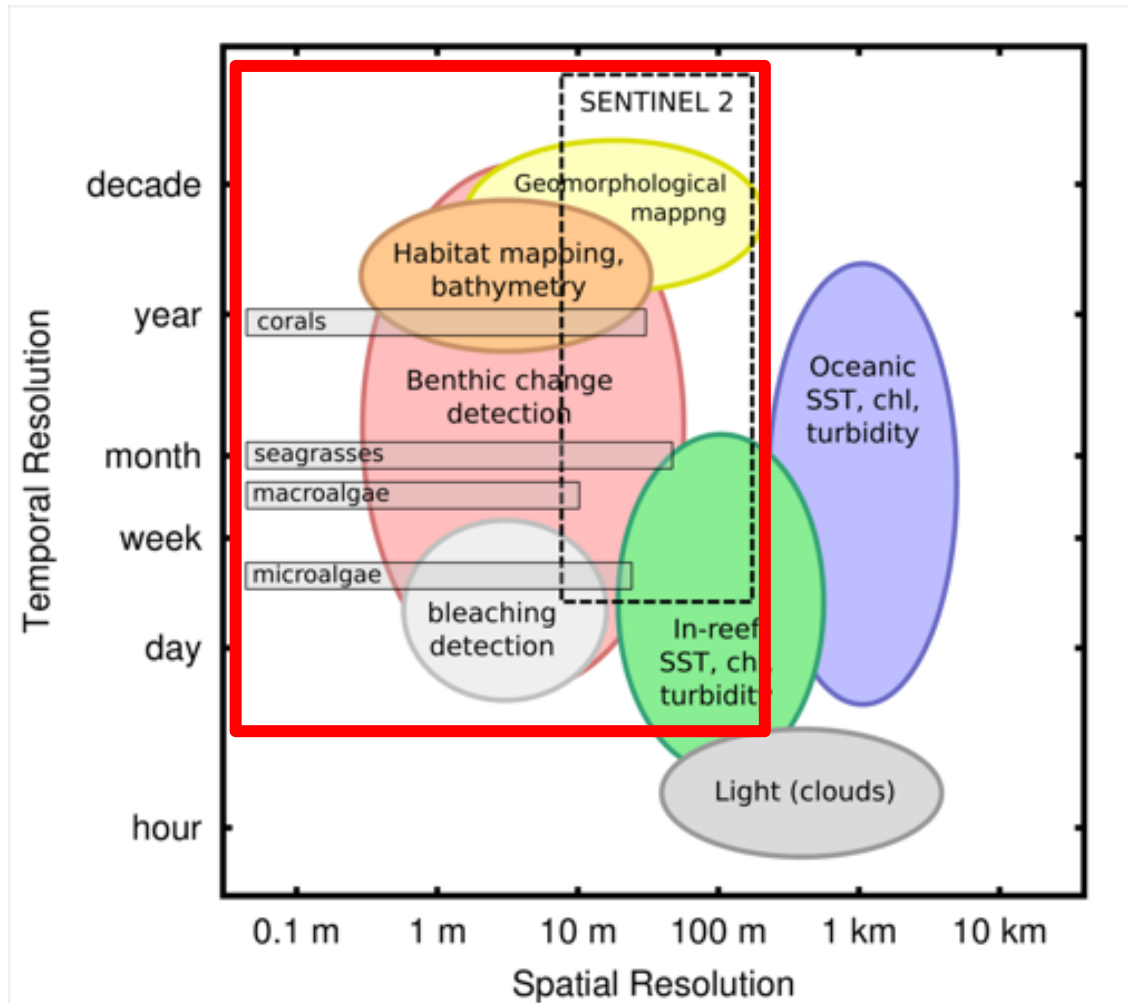
- Bottom mapping
 - seagrasses, macroalgae, coral
- Water optical properties
- Bathymetry (depth) – ‘SDB’

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

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 focused on aquatic applications

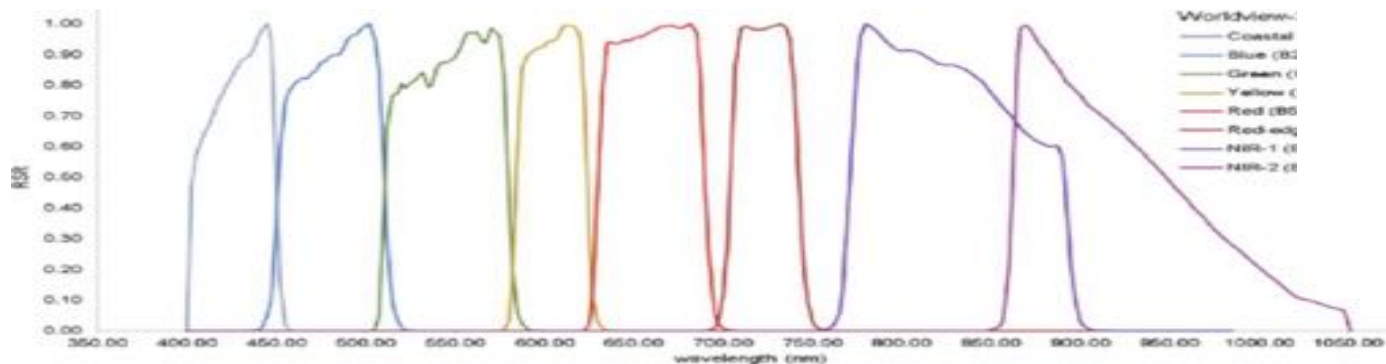
- Landsat 8, 9 (30 m)
- Sentinel 2 (10 m in four bands)

Note:

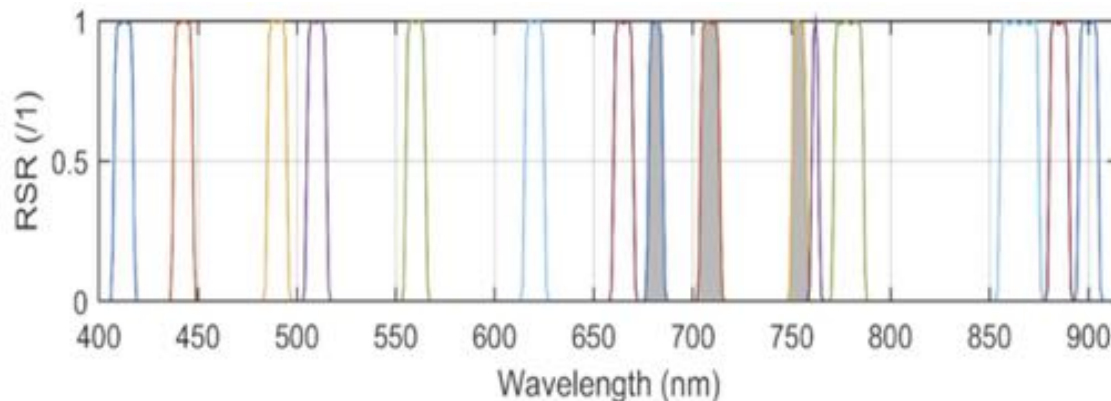
- Radiometric calibration and on-going quality assurance on commercial satellites is often not as good as on space agency satellites.

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

→ SNR still will be lower than for ocean colour

→ Better to do modelling at higher resolution and convolve with band response



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

(c) DigitalGlobe



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

ESA / Copernicus

Empirical image based methods (e.g. bathymetry)

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

Lyzenga 1978

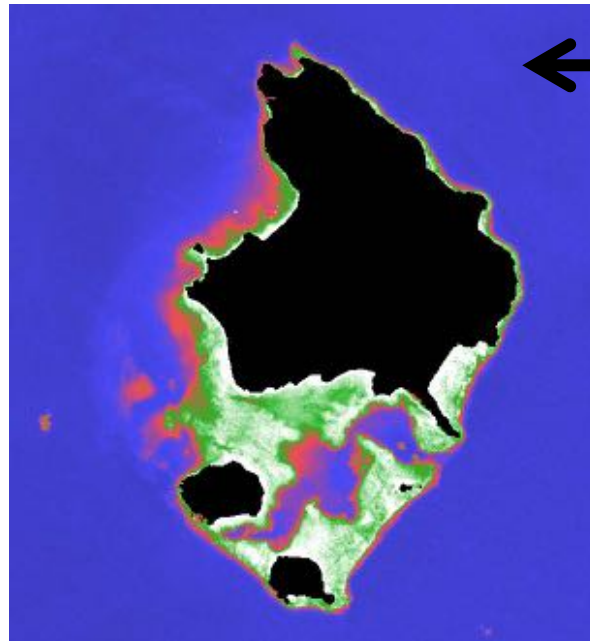
$$X_i = \ln(L_i - L_{si})$$
$$Z = a_0 + a_i X_i + a_j X_j$$

a_0, a_1, a_2 from regression

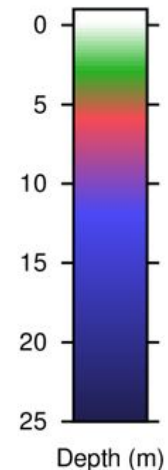
Stumpf et al. 2003

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

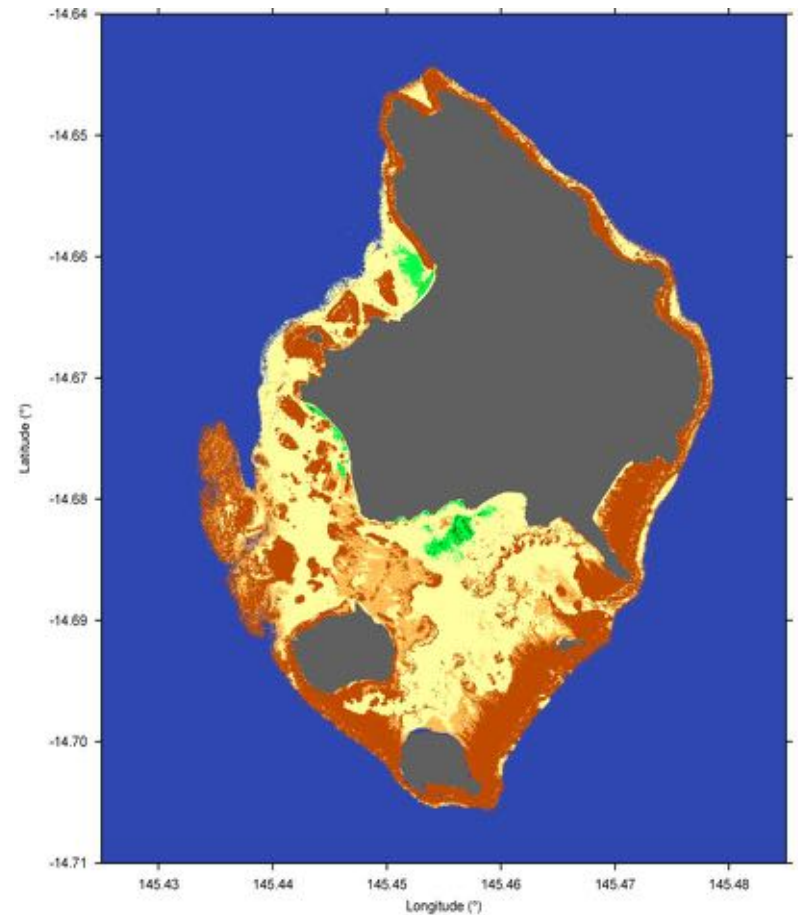
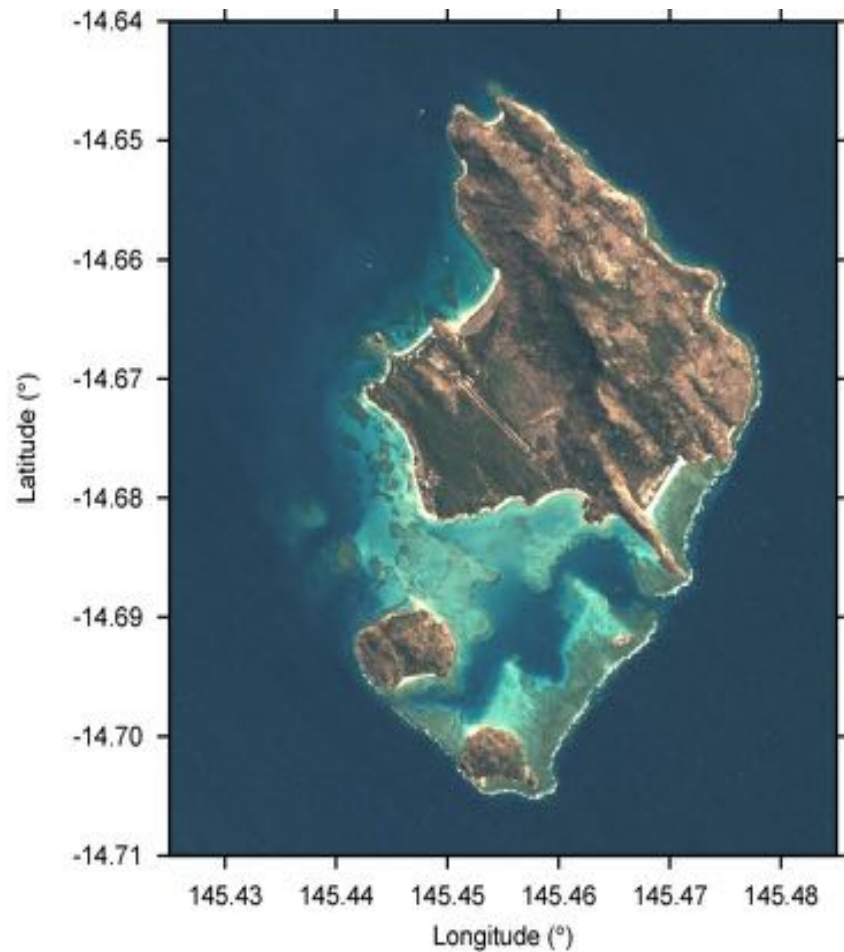
m_0, m_1 , from regression



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

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

Get one band from each pair of original bands

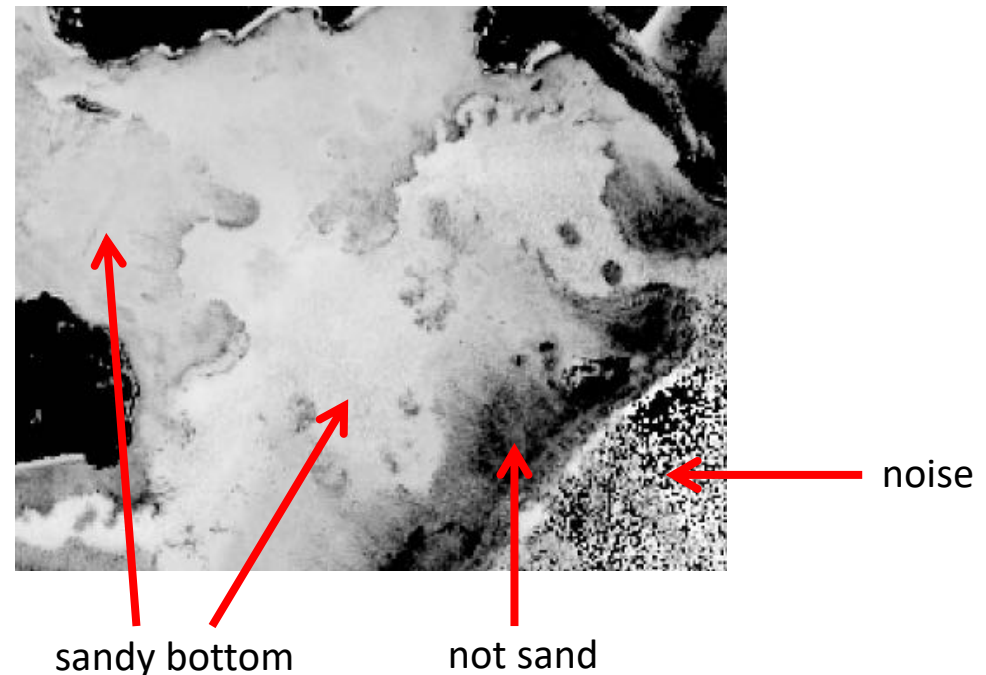
Need: 1) ratio of attenuation coefficients

2) deep water reflectance

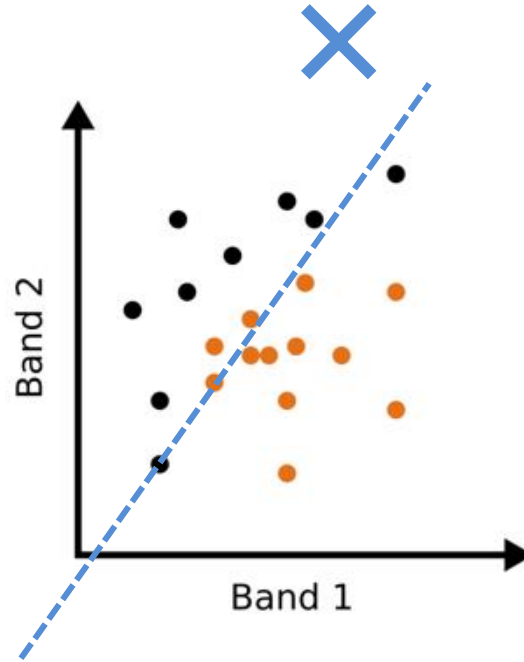
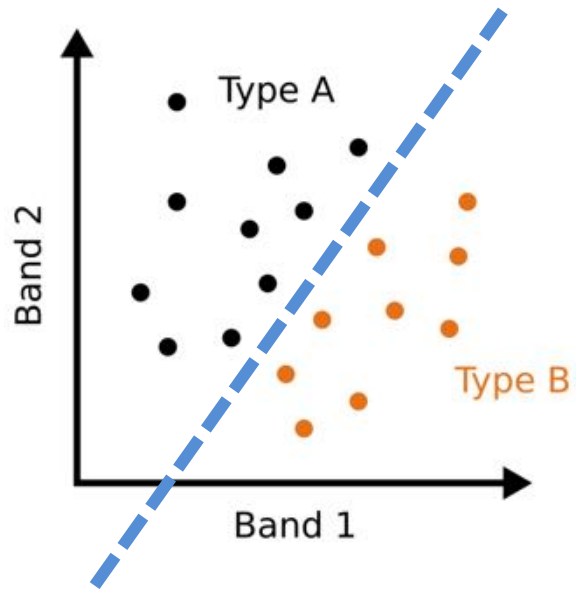
$$X_i = \ln(R_i - R_i^{\text{deep}})$$

➤ 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} ”

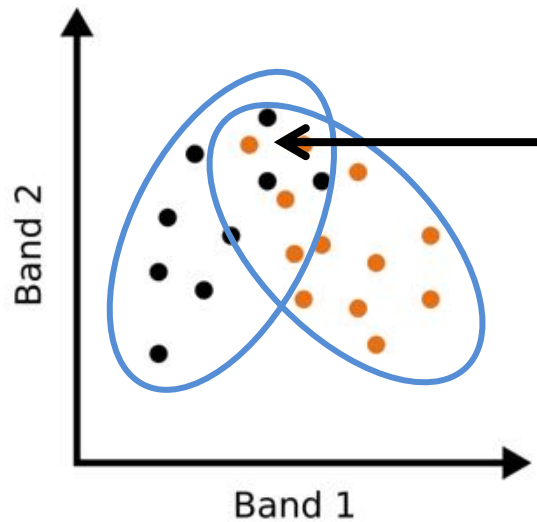
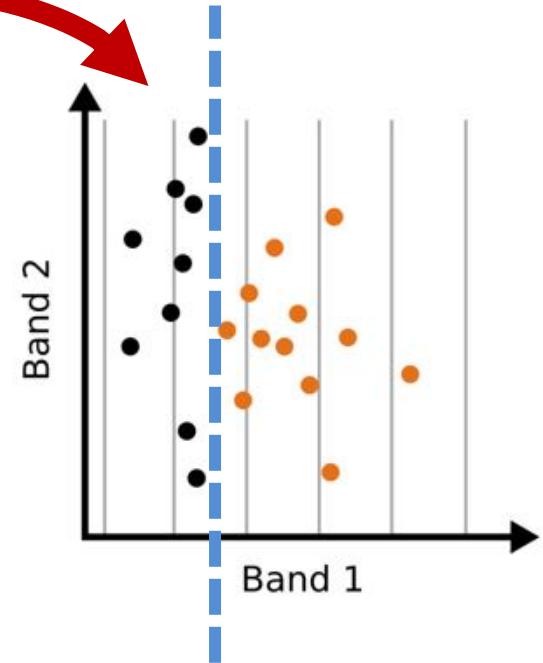
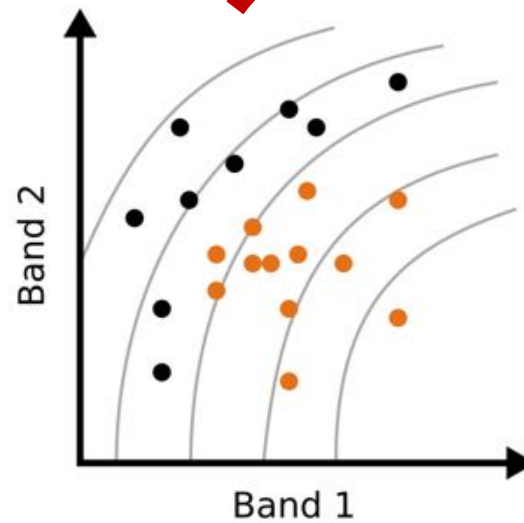
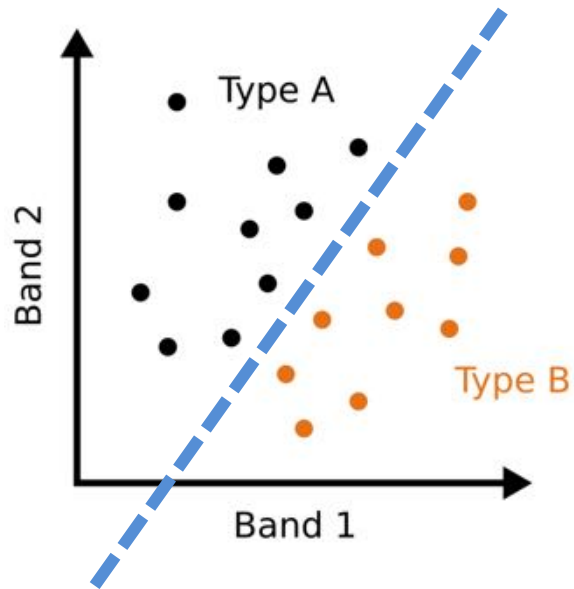


Machine learning



Machine learning

Mathematical transform



Fundamentally
inseparable

Machine learning - comparing techniques

Many different techniques

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

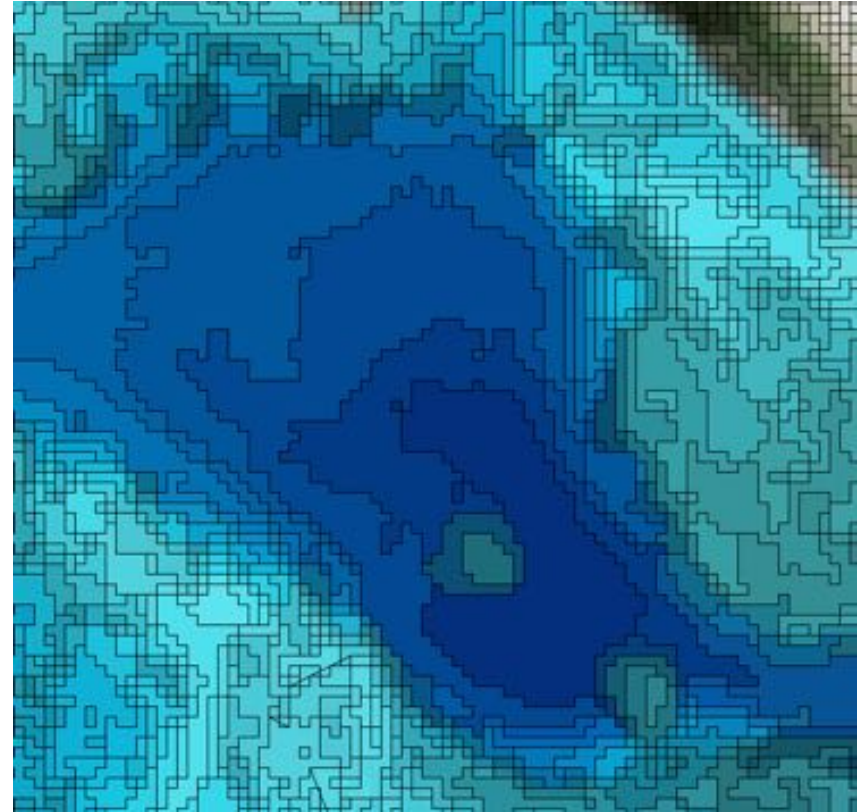
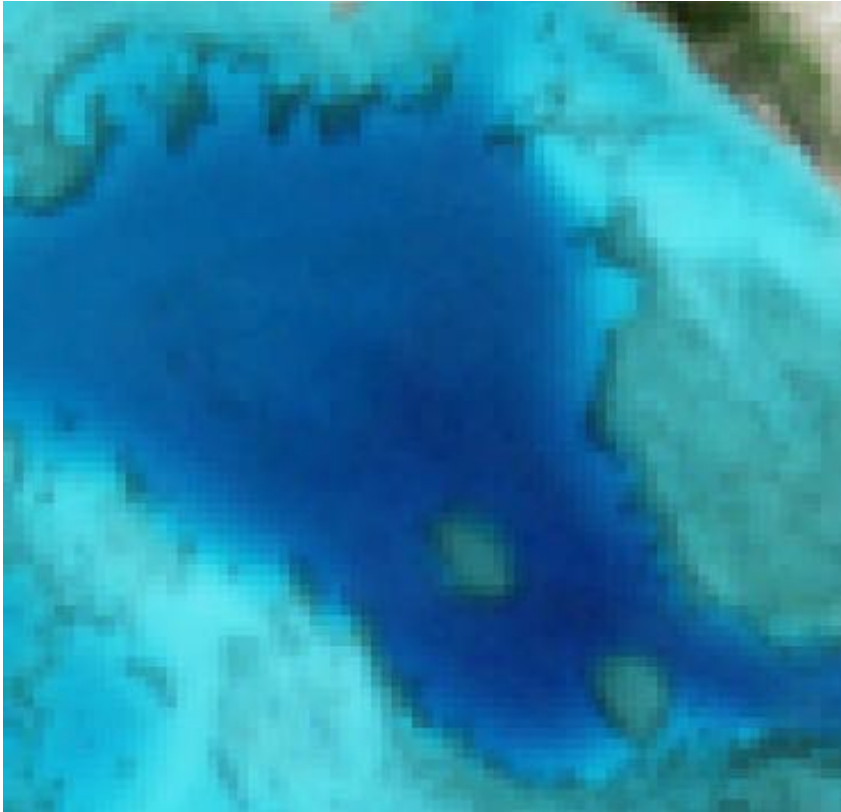
Why do they perform differently? (if they do)

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

* XAI - “Explainable AI”

see: papers by Jorge Garcia

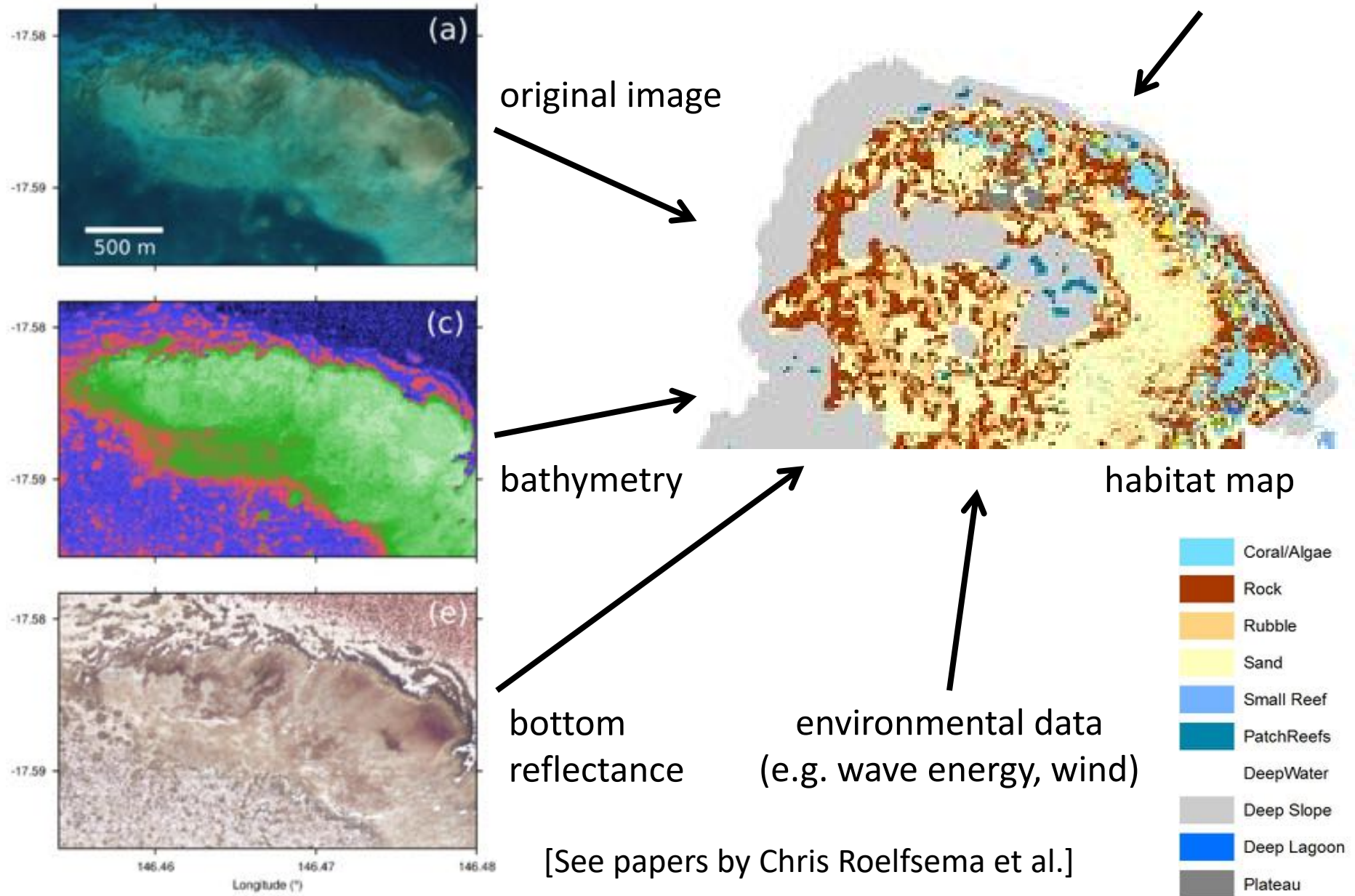
Going beyond single pixels - image segmentation



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

- Size, shape, orientation, etc.
- SNR of mean spectra also improved

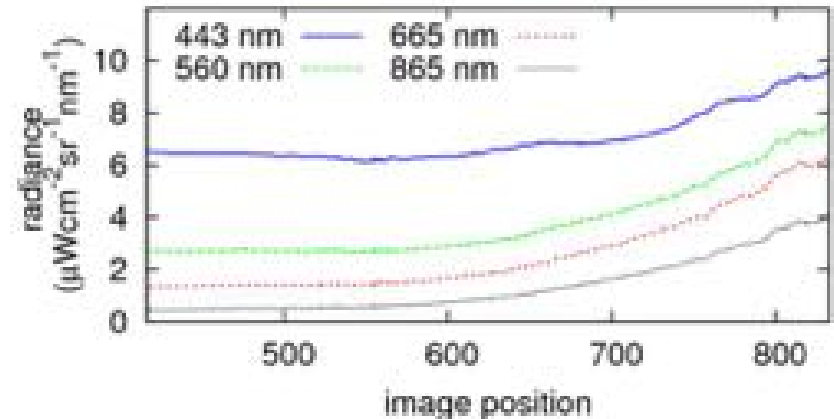
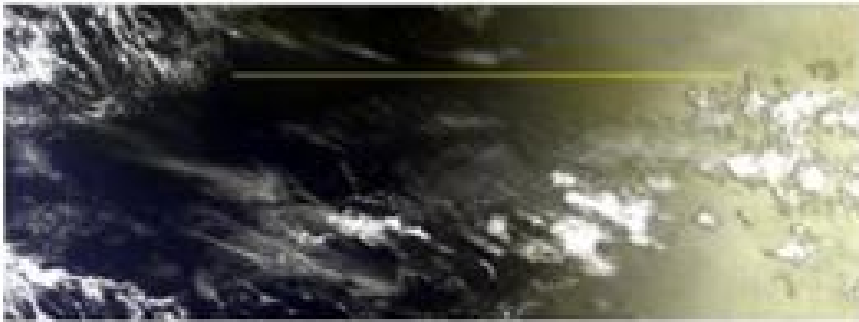
Object-orientated machine learning techniques



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

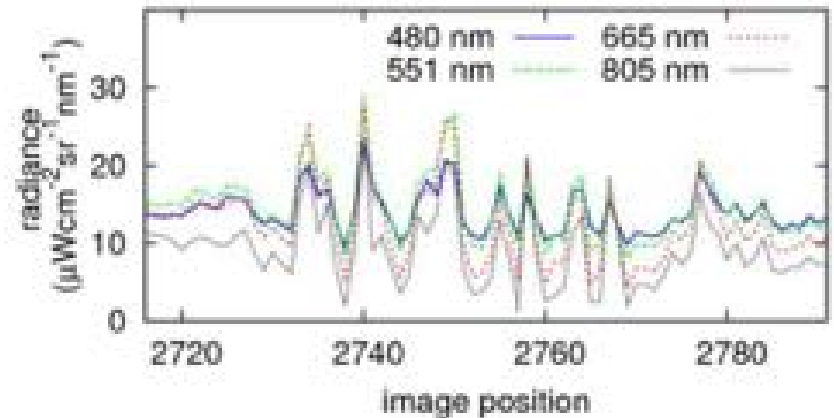
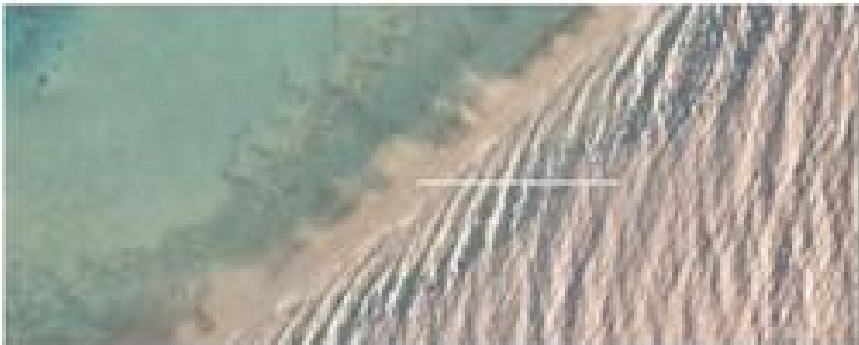
Large images e.g. MERIS, pixels > 100 m

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



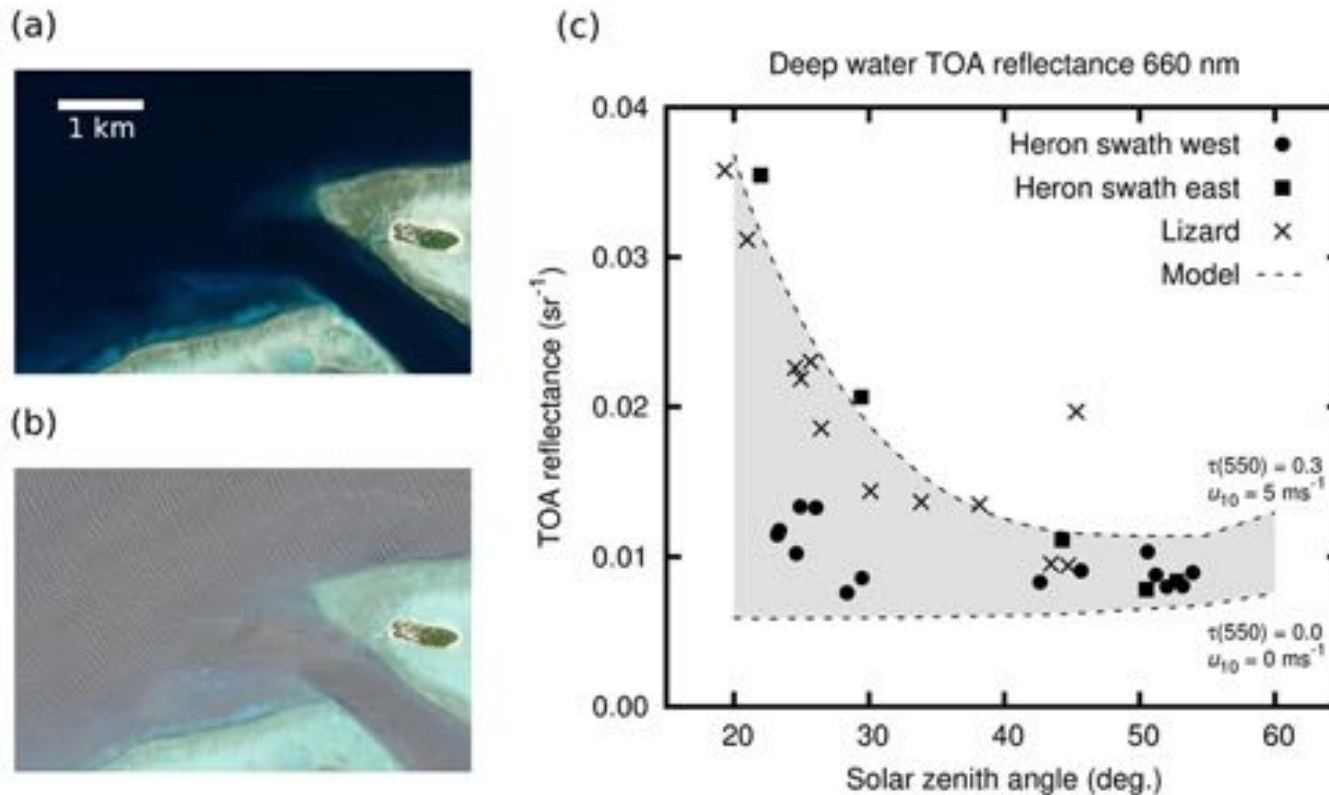
High spatial resolution, pixels < 10 m

→ individual waves



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. $\sim 12^\circ$)
- Some places are imaged in two orbits so occur at both east and west edges

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 constant (e.g. zero)



WorldView-2 Image
(c) DigitalGlobe

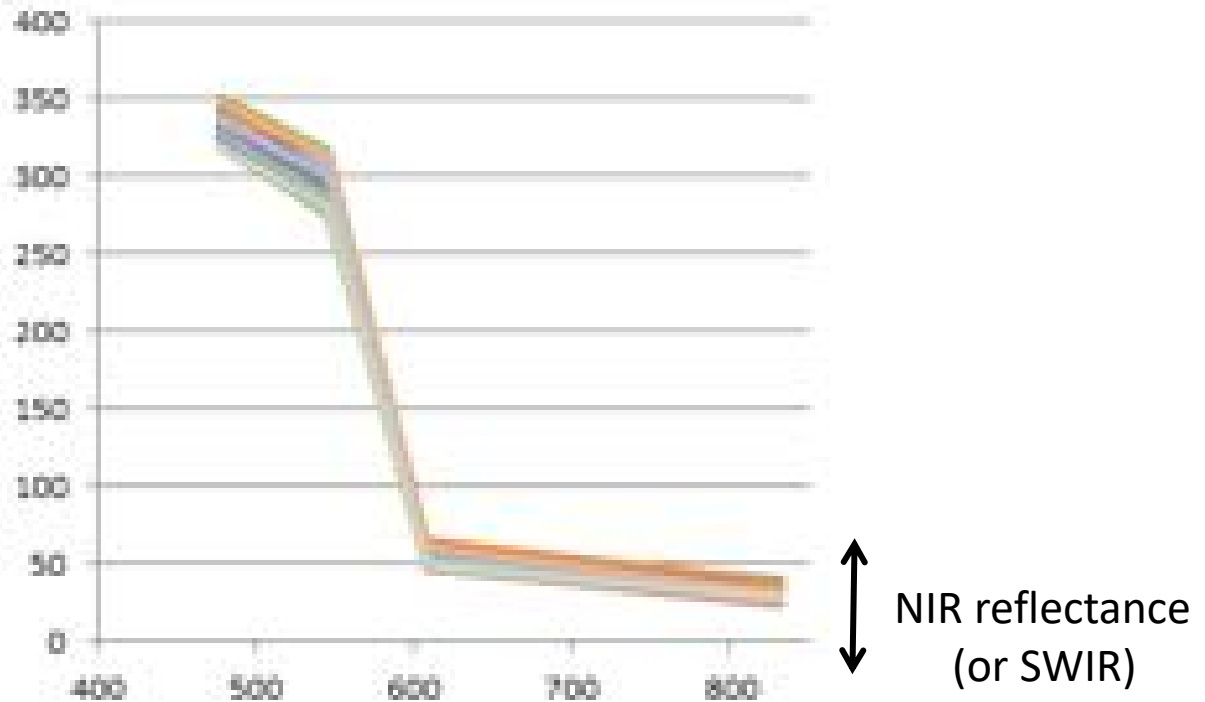
pixels ~2 m

- 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

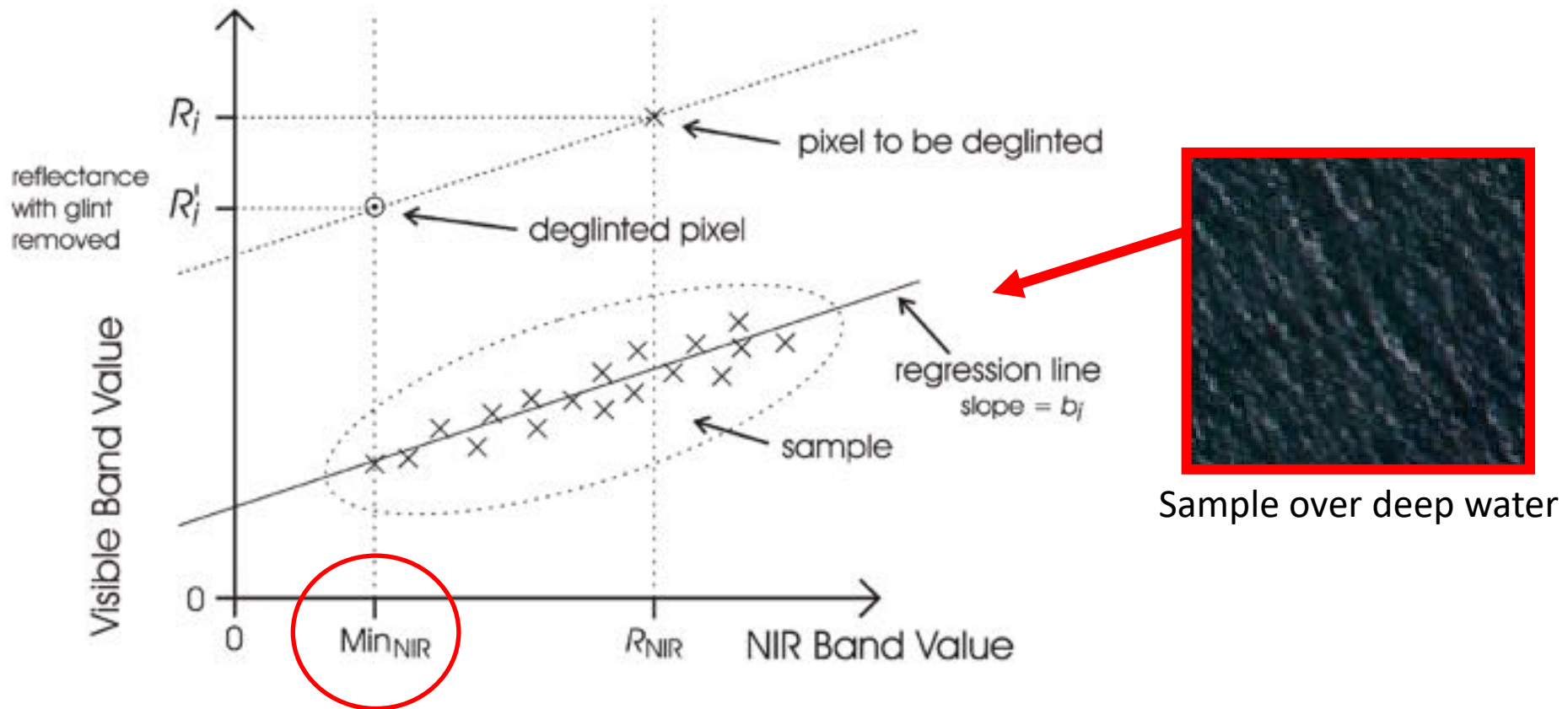


Sample over deep water



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



$$R'_i = R_i - b_i(R_{NIR} - Min_{NIR})$$

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

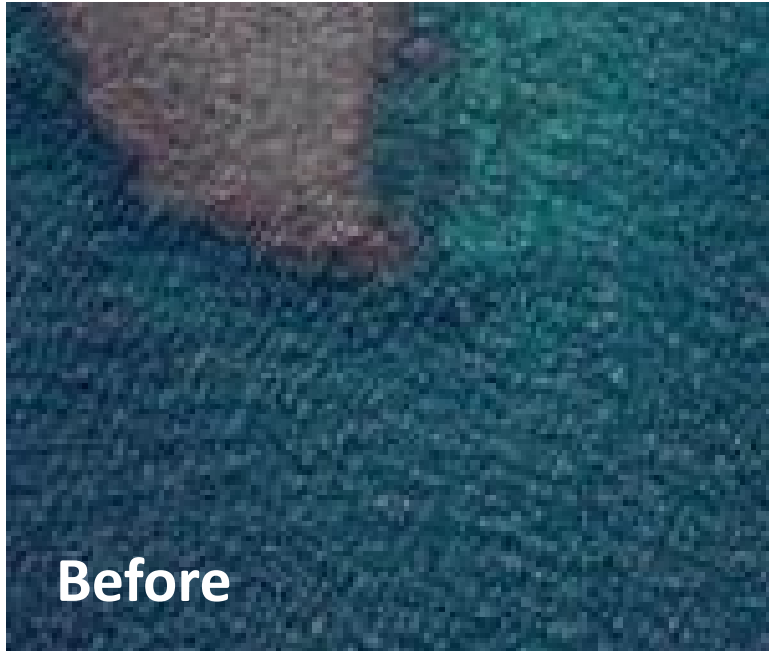
Before deglint



After deglint

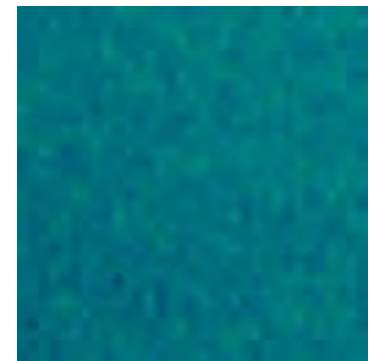


Glint corrected images are quite noisy



- 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.

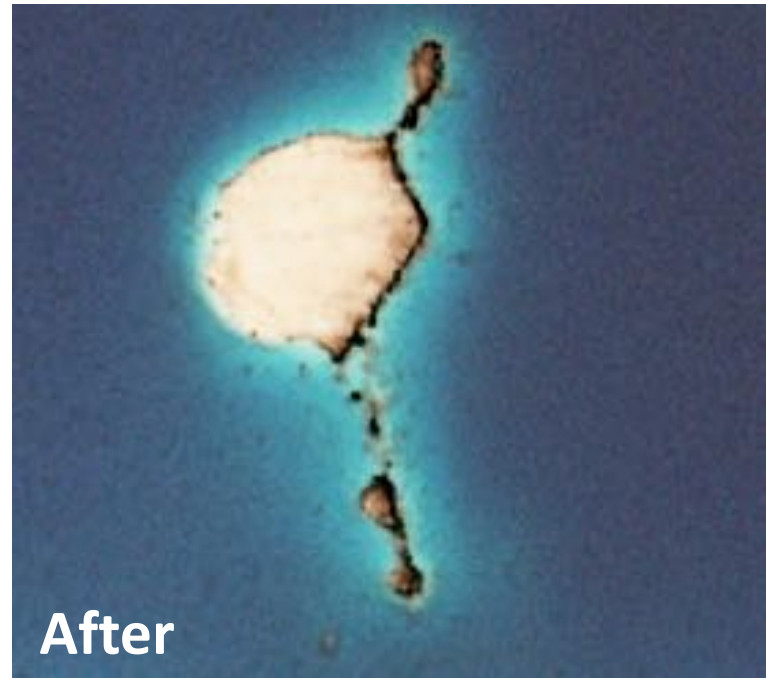
→ Spatial filtering (smoothing) may be useful



Pixel-to-pixel noise

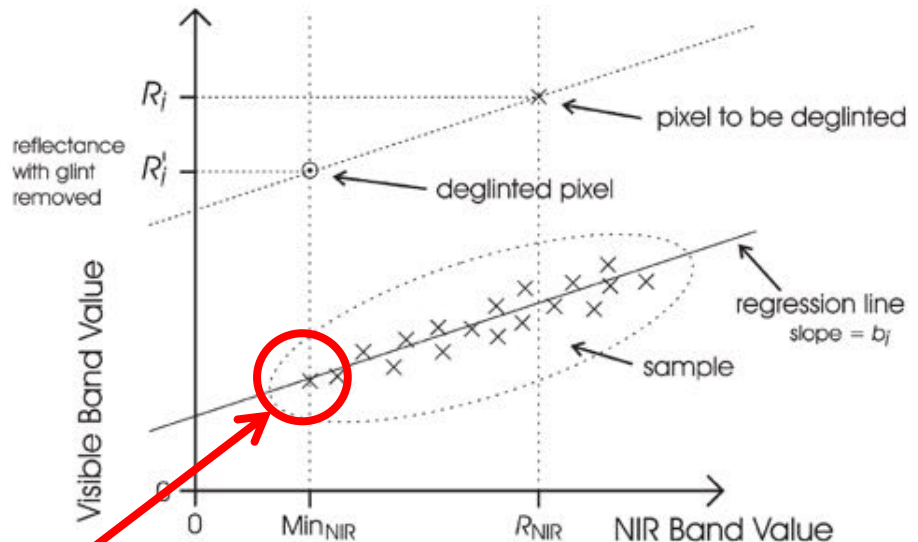
Over-correction when NIR below surface is not zero

- 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?



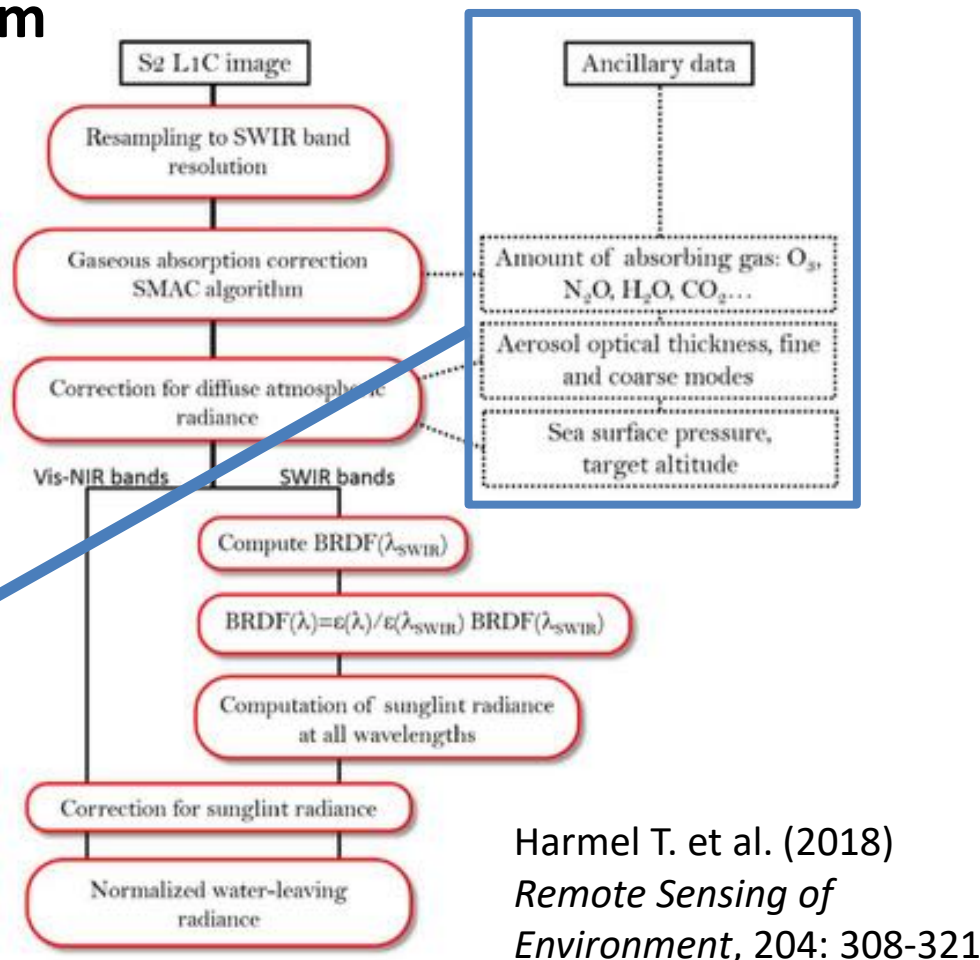
The darkest pixels may contain some ‘sub-pixel’ glint, we have no way to know.
At TOA Min_{NIR} is sub-pixel glint plus aerosol backscatter.
Typically NIR is also important for aerosol estimation in atmospheric correction.
We are trying to use the NIR for two things!

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

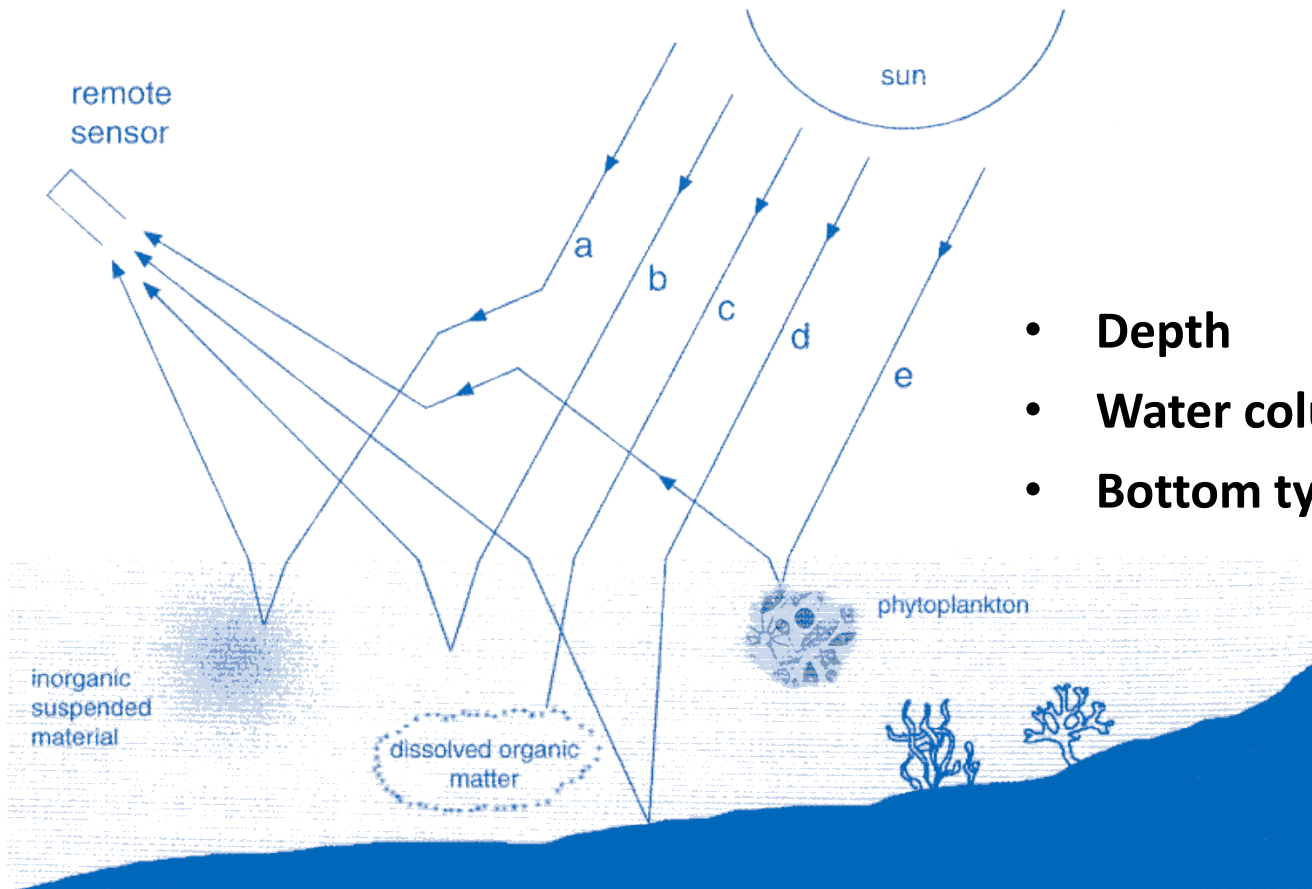
Adds information to reduce uncertainty between aerosol and glint



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.)

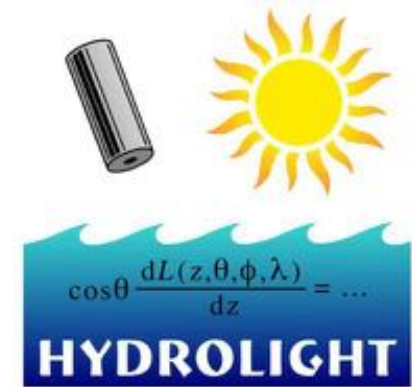
Go from image $R_{rs}(\lambda)$ to model inputs = model inversion

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 radiative transfer 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

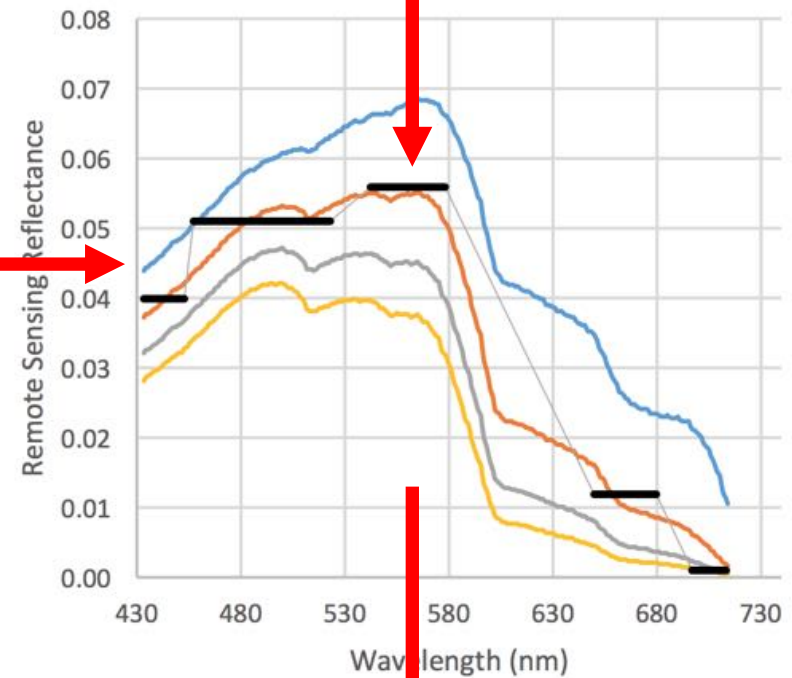
2 m 0.4 mg m⁻³

3 m 0.4 mg m⁻³

4 m 0.4 mg m⁻³

MODEL

Image pixel



- No in-situ training data required.

Estimate:

Depth = 2 m

Phytoplankton = 0.2 mg m⁻³

... etc

Lee et al's semianalytical model for shallow water reflectance

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

$$a(\lambda) = a_w(\lambda) + [a_0(\lambda) + a_1(\lambda) \ln P] P + G \exp[-0.015(\lambda - 440)]$$

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

$$u(\lambda) = b_b(\lambda) / [a(\lambda) + b_b(\lambda)], \quad \kappa(\lambda) = a(\lambda) + b_b(\lambda)$$

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

$$D_u^C(\lambda) \approx 1.03\sqrt{1 + 2.4u(\lambda)} \quad D_u^B(\lambda) \approx 1.04\sqrt{1 + 5.4u(\lambda)}$$

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

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

Lee et al's semianalytical model for shallow water reflectance

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

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remote
sensing
reflectance

$$r_{rs}(\lambda) \approx r_{rs}^{dp}(\lambda) \left(1 - \exp \left\{ - \left[\frac{1}{\cos \theta_w} + \frac{D_u^C(\lambda)}{\cos \theta} \right] \kappa(\lambda) H \right\} \right) + \frac{1}{n} \rho(\lambda) \exp \left\{ - \left[\frac{1}{\cos \theta_w} + \frac{D_u^B(\lambda)}{\cos \theta} \right] \kappa(\lambda) H \right\}$$

bottom reflectance

H = depth in metres

P = phytoplankton concentration (proxy)

G = dissolved organic matter concentration (proxy)

X = backscatter

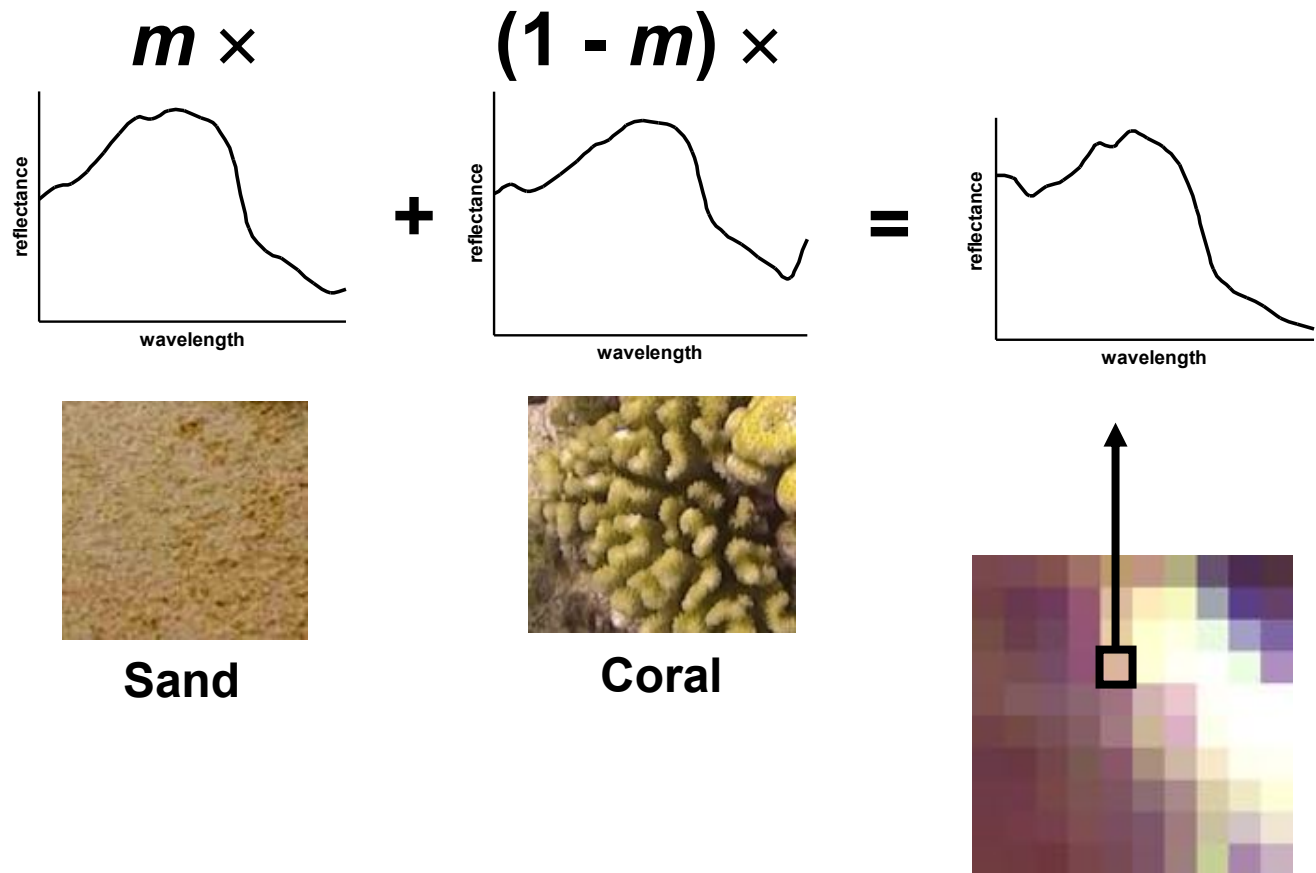
Y = (spectral slope of backscatter) is fixed at 1

Also incorporates sun
and view zenith angles

Various factors derived
from HydroLight

Bottom reflectance can be treated as a mix of types

- Use pairs selected from a small spectral library, 'endmembers'
- 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 **forward model** it describes what can occur in every individual pixel based on what is in the pixel

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

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 $r_{rs}(\lambda)$

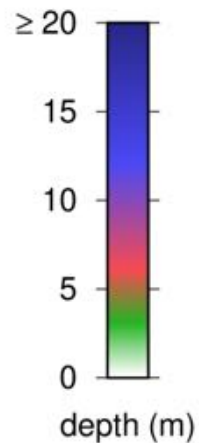
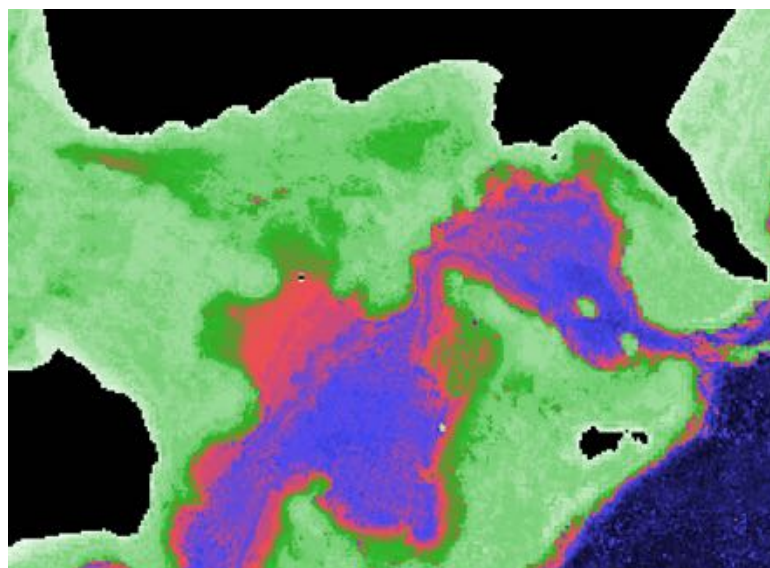
NOTE: You can get an estimate for more parameters than the number of bands, so you don't need 6 bands to do this.

Examples of inversion products (Lizard Island, GBR)

Sentinel 2 image, RGB



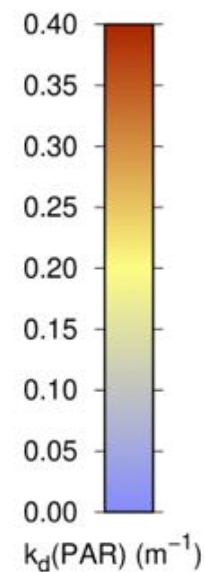
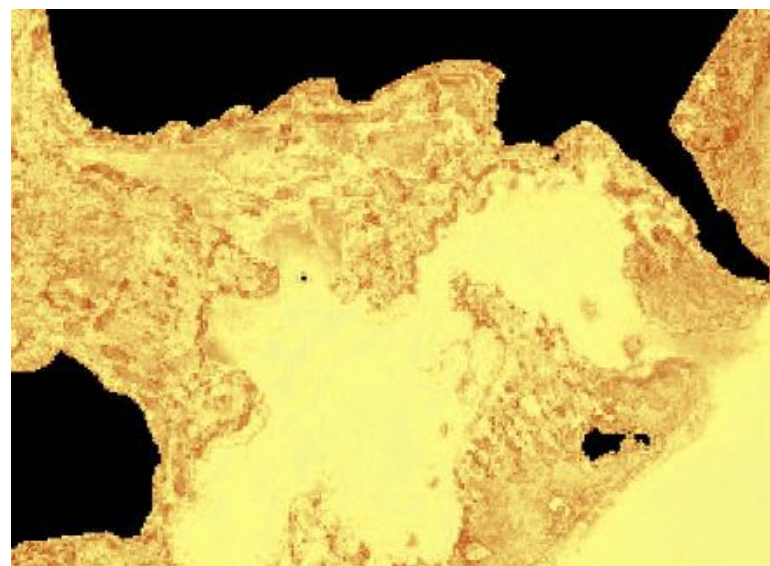
Bathymetry



Bottom reflectance, RGB



Water column $k_d(\text{PAR})$



Canopy modelling, seagrass *Thalassia testudinum*

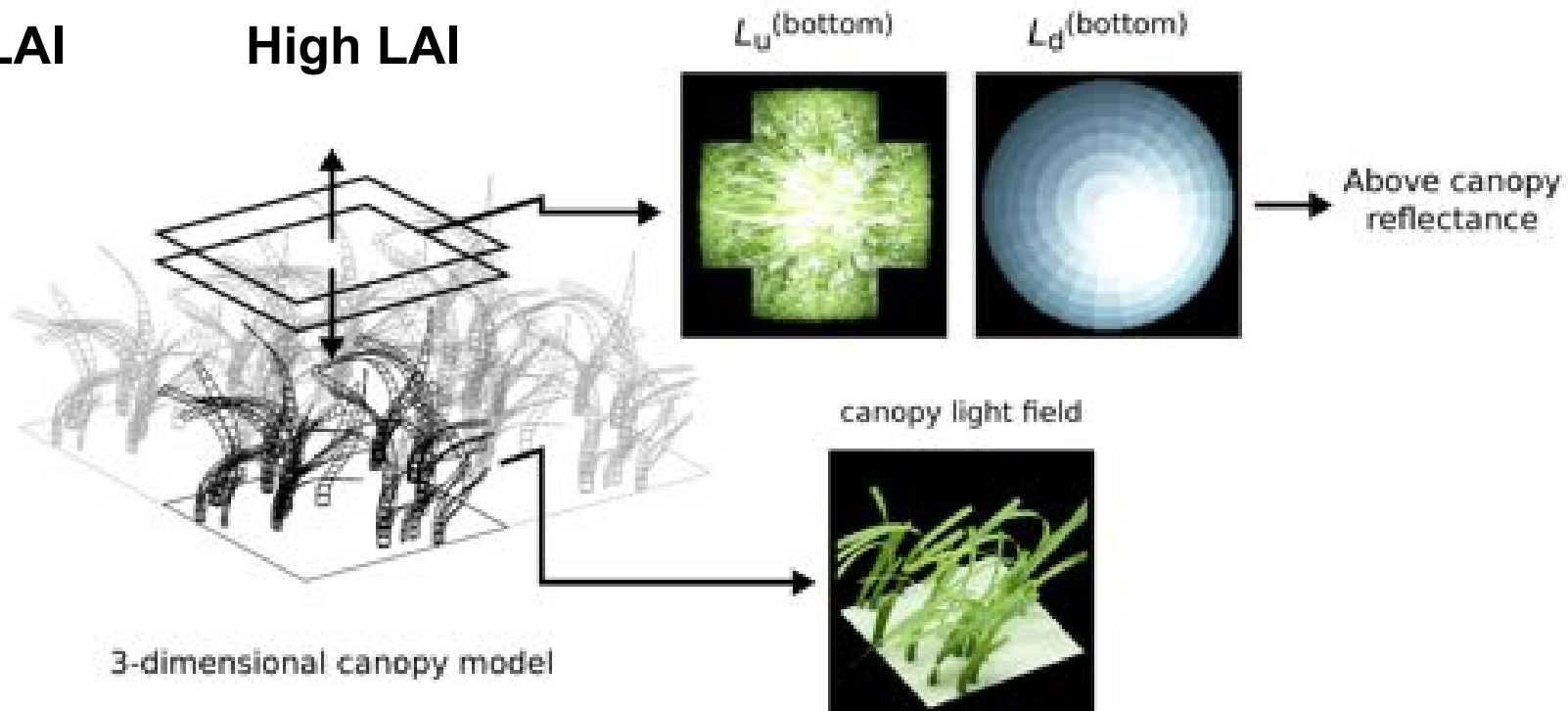


Low LAI



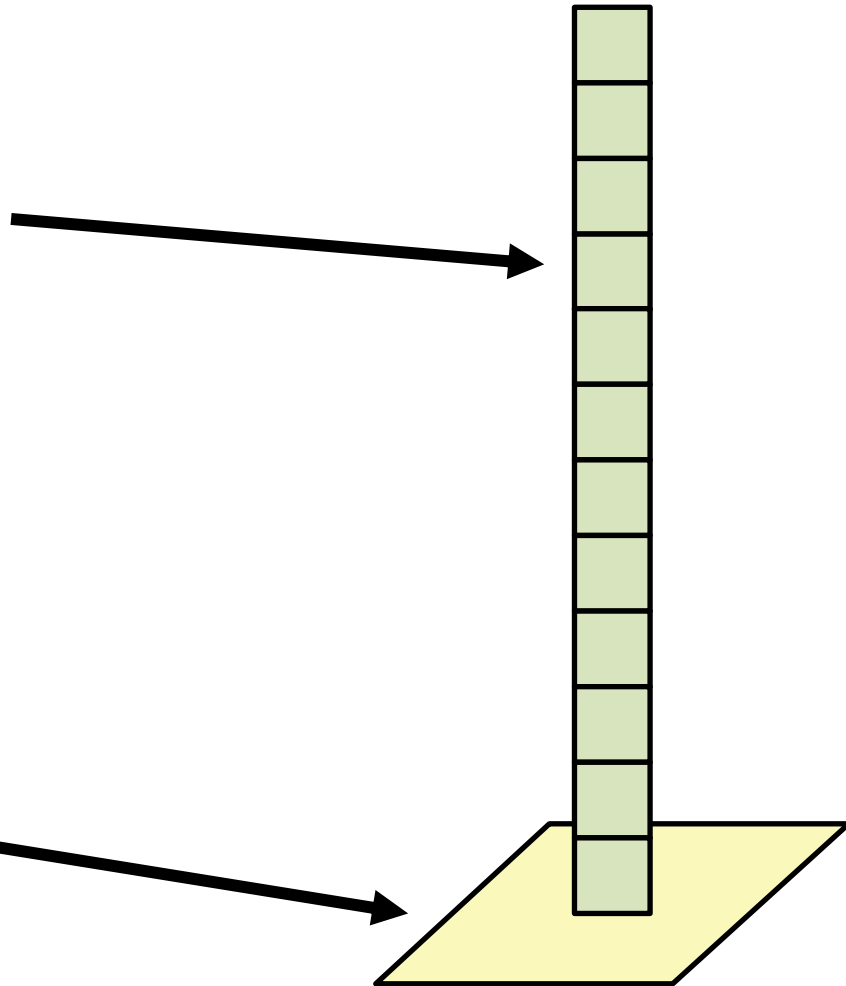
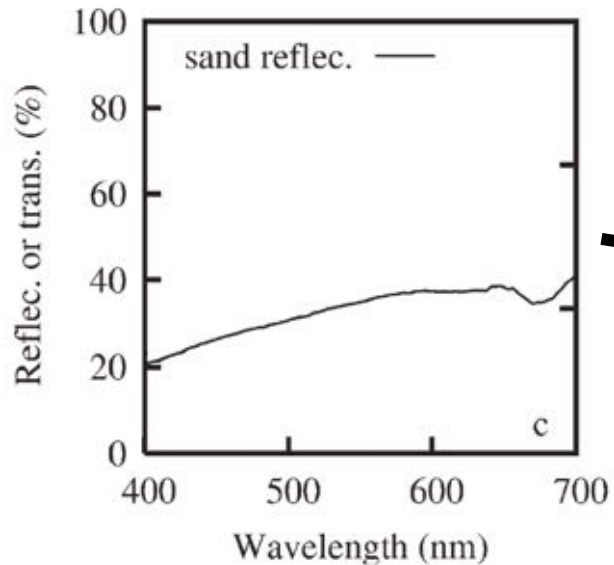
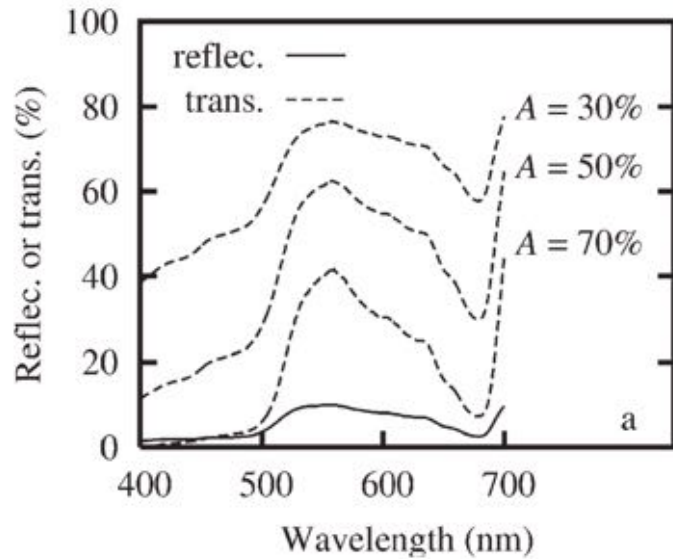
High LAI

- 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)



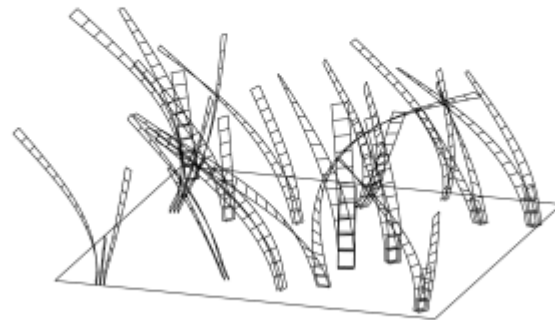
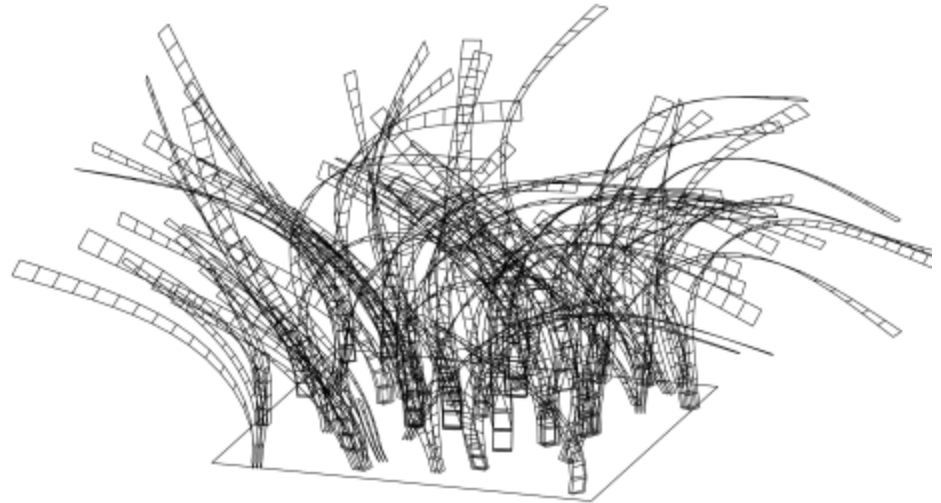
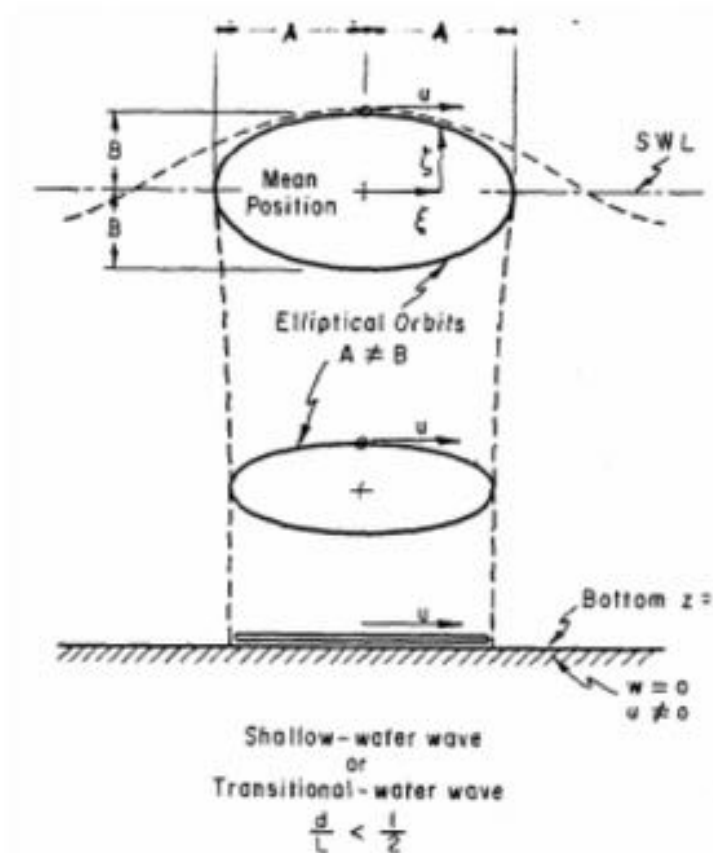
Leaf and sand optical properties

Reflectance and transmittance



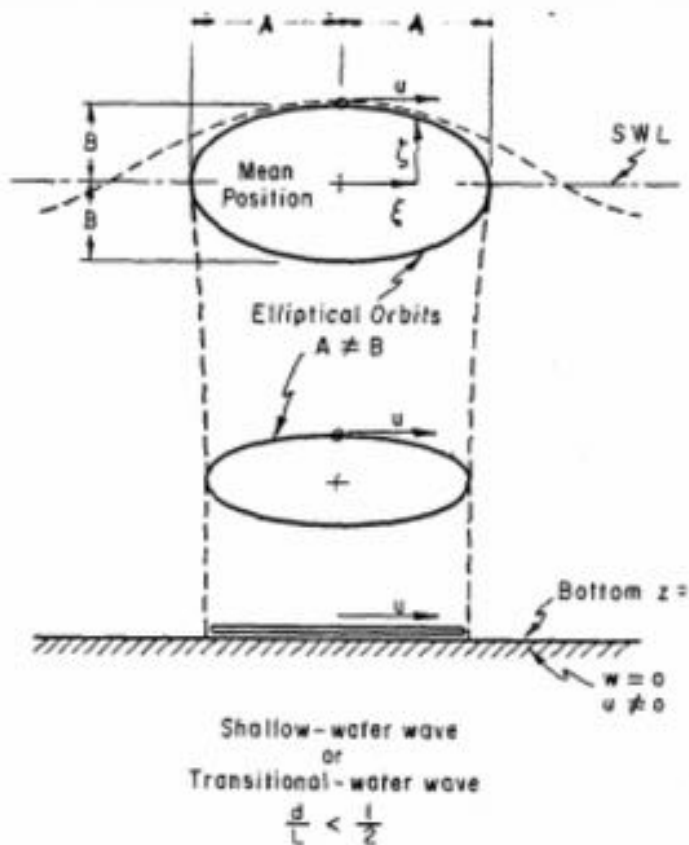
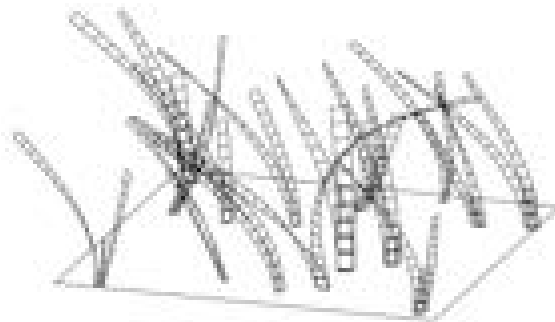
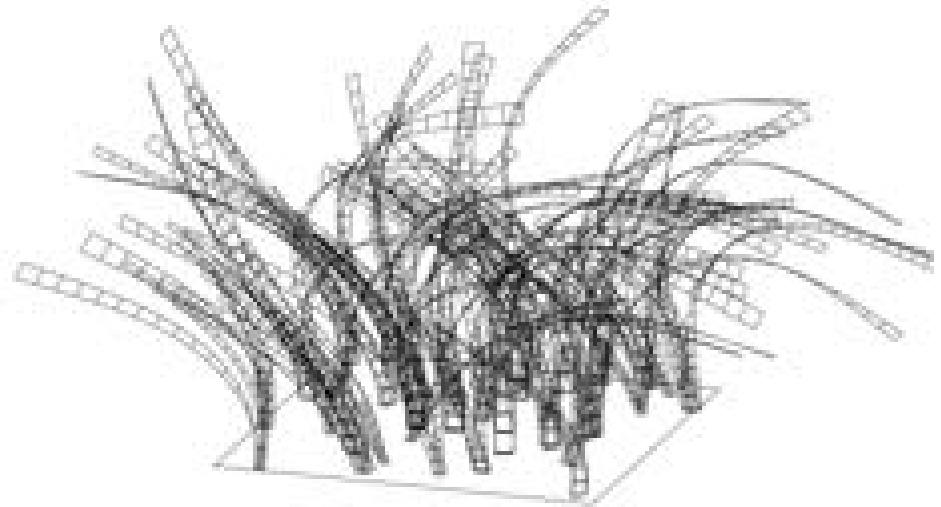
Canopy structure

- flexible strips in a simple wave motion model



Canopy structure

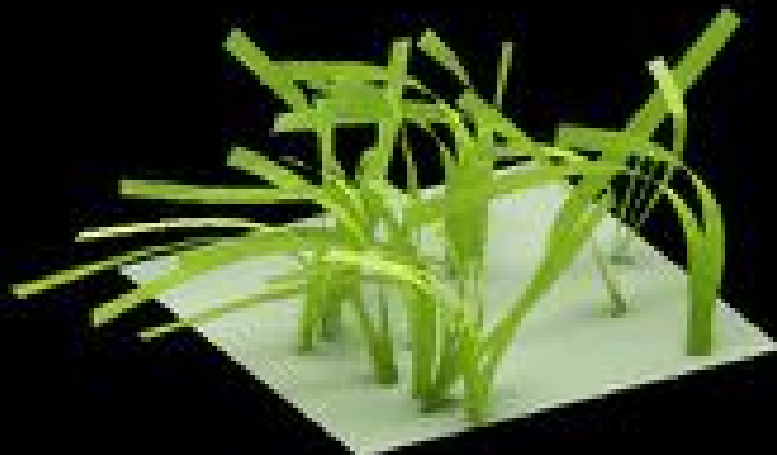
- flexible strips in a simple wave motion model



Model outputs (RGB from 17 bands)



LAI 4.5, depth 0.5 m

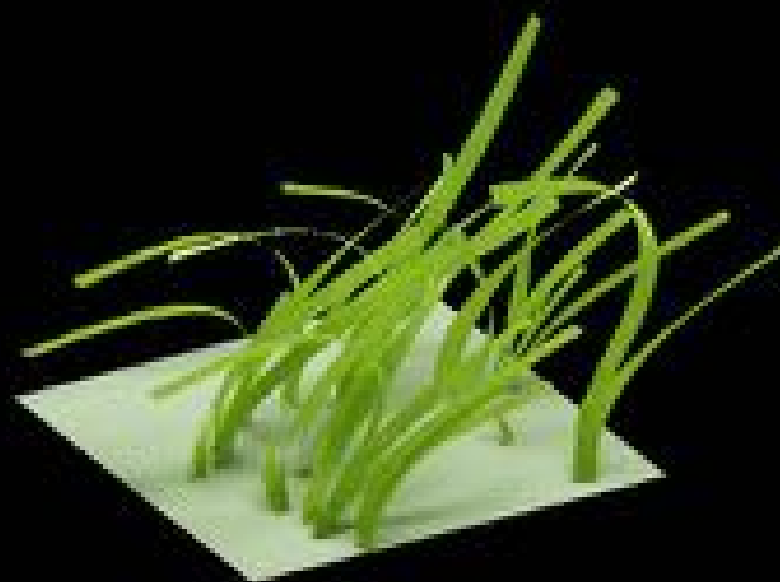


LAI 1.0, depth 1.5 m

Model outputs (RGB from 17 bands)



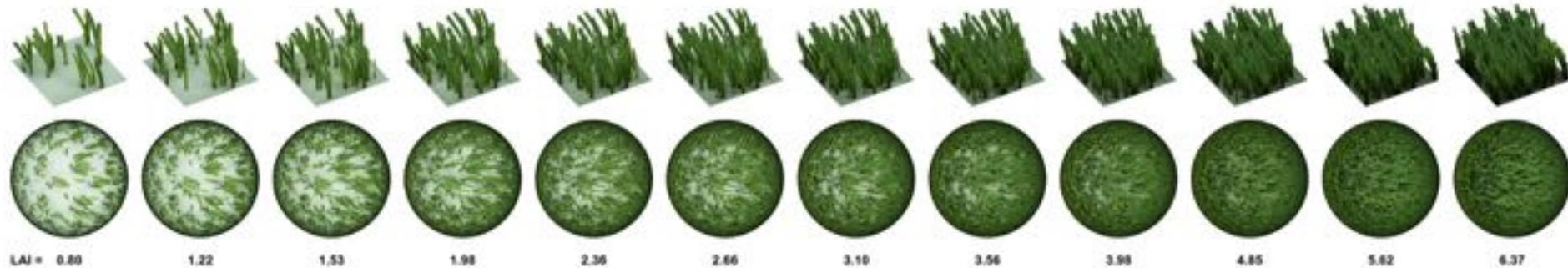
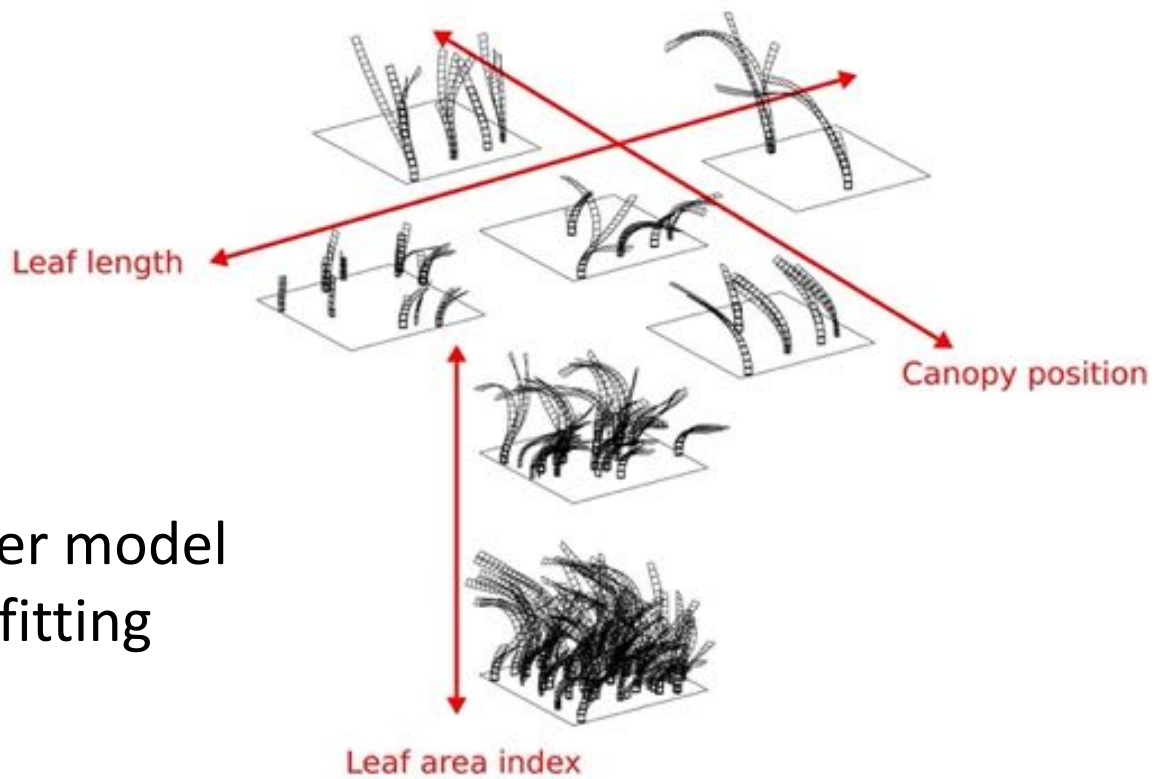
LAI 4.5, depth 0.5 m



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

$$a(\lambda) = a_w(\lambda) + [a_0(\lambda) + a_1(\lambda) \ln P] P + G \exp [-0.015 (\lambda - 440)]$$

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

$$u(\lambda) = b_b(\lambda) / [a(\lambda) + b_b(\lambda)], \quad \kappa(\lambda) = a(\lambda) + b_b(\lambda)$$

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

$$D_u^C(\lambda) \approx 1.03\sqrt{1 + 2.4u(\lambda)} \quad D_u^B(\lambda) \approx 1.04\sqrt{1 + 5.4u(\lambda)}$$

$$r_{rs}(\lambda) \approx r_{rs}^{dp}(\lambda) \left(1 - \exp \left\{ - \left[\frac{1}{\cos \theta_w} + \frac{D_u^C(\lambda)}{\cos \theta} \right] \kappa(\lambda) H \right\} \right) \\ + \frac{1}{2} \rho(\lambda) \exp \left\{ - \left[\frac{1}{\cos \theta_w} + \frac{D_u^B(\lambda)}{\cos \theta} \right] \kappa(\lambda) H \right\}$$

bottom reflectance



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

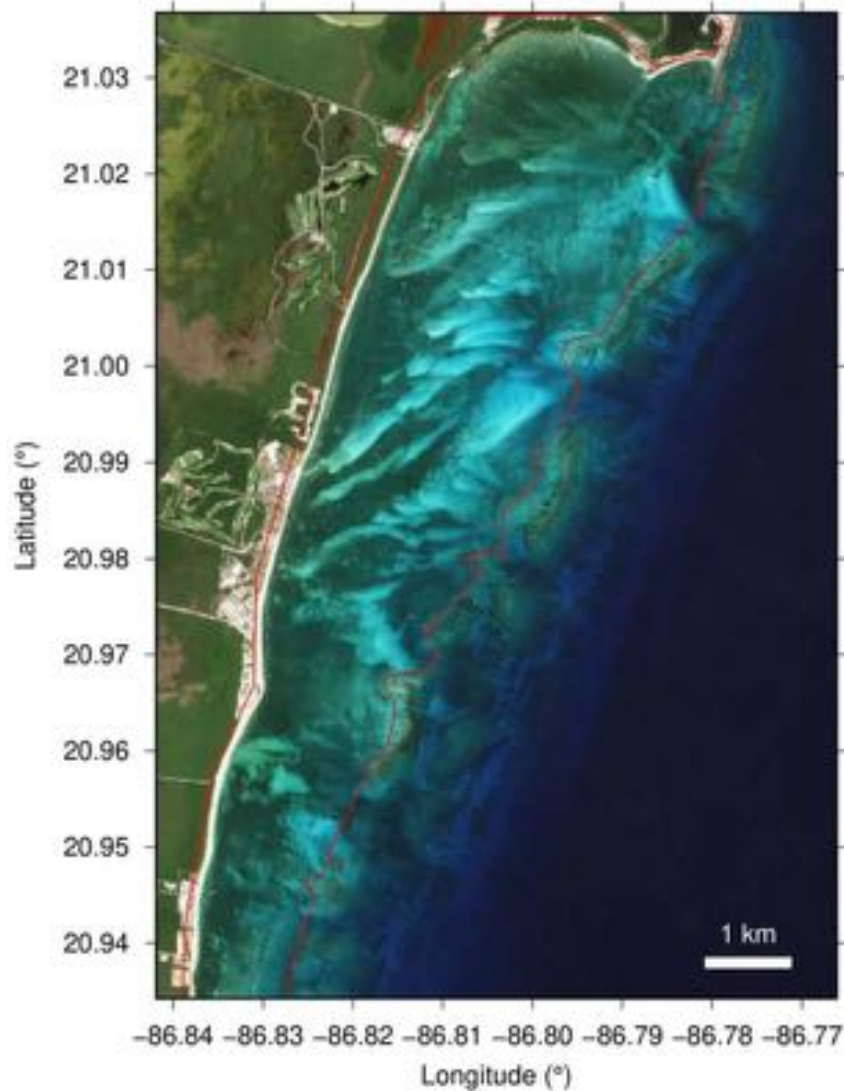
Substitute bottom reflectance for a model based on LAI and variation term e

Gives a model that can be inverted directly for LAI

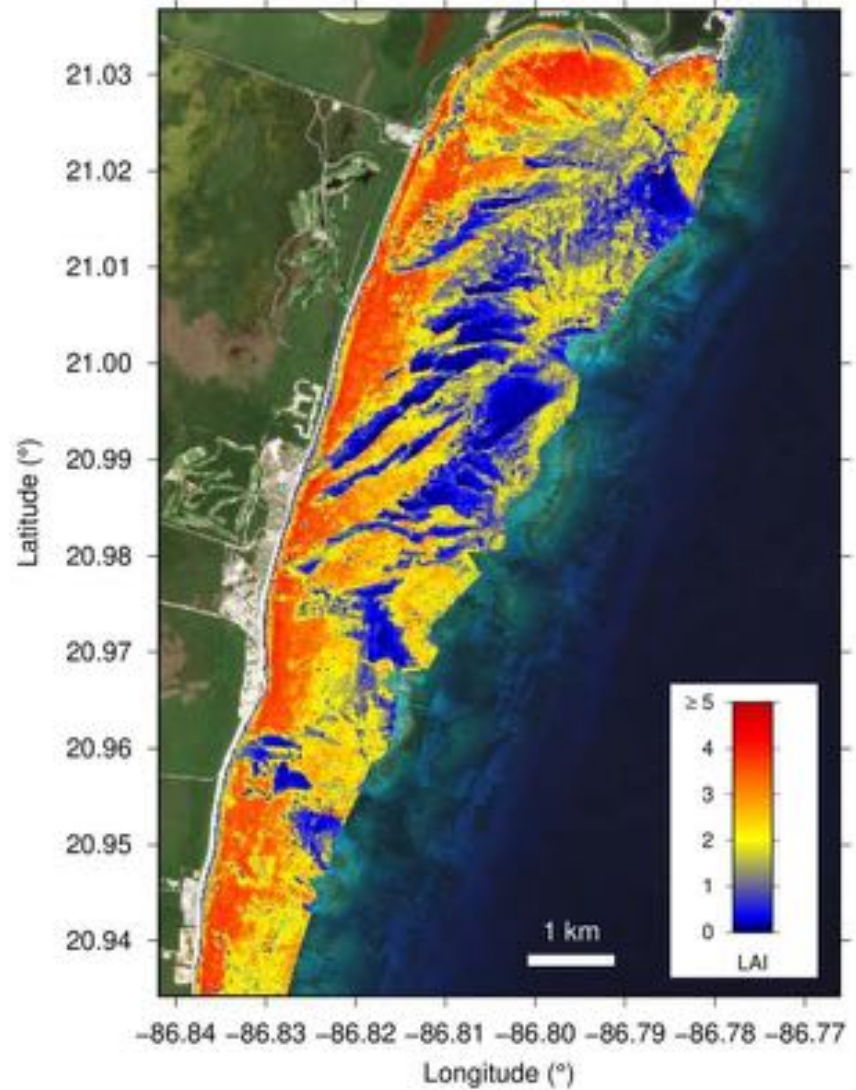
$$r_{rs}(\lambda) \approx f(P, G, X, H, \text{LAI}, e, \lambda)$$

Seagrass LAI mapping, Yucatán, Mexico

RGB Image (Sentinel-2)

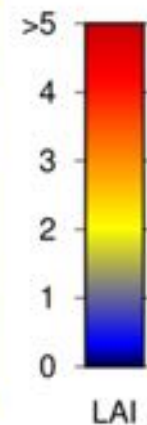
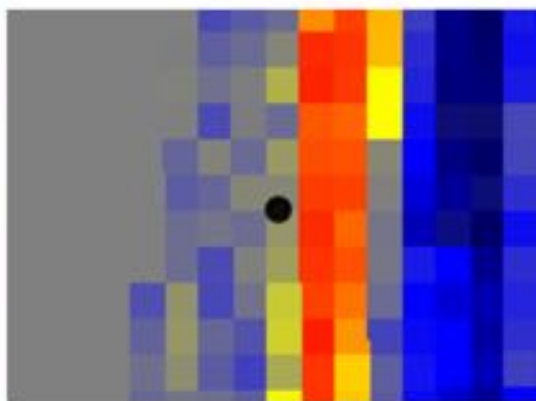
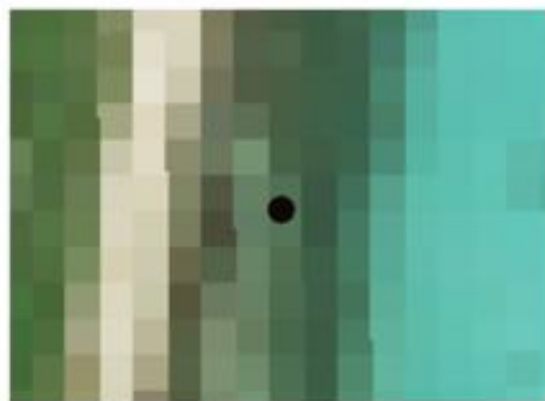
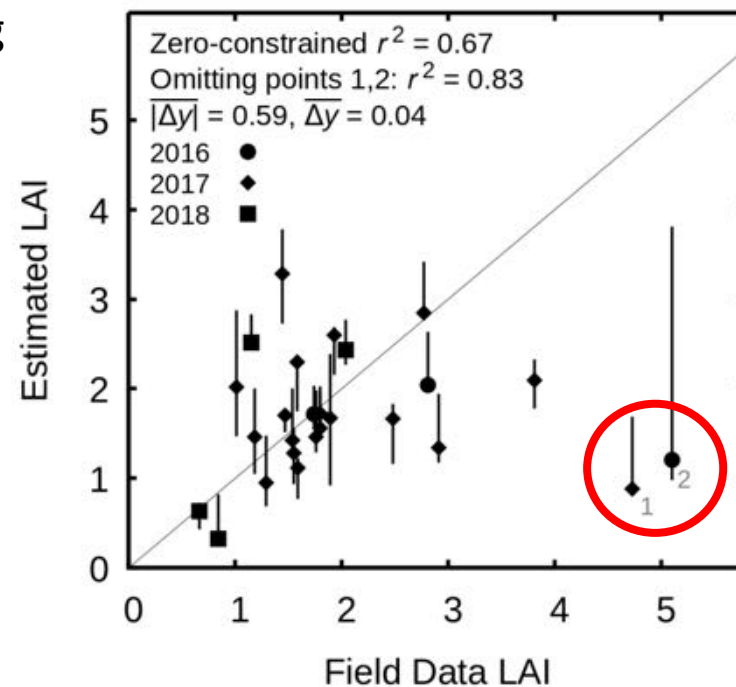


LAI in lagoon area



Difficulty in geo-locating ground truth data

Hard to survey at scales relevant to remote sensing



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

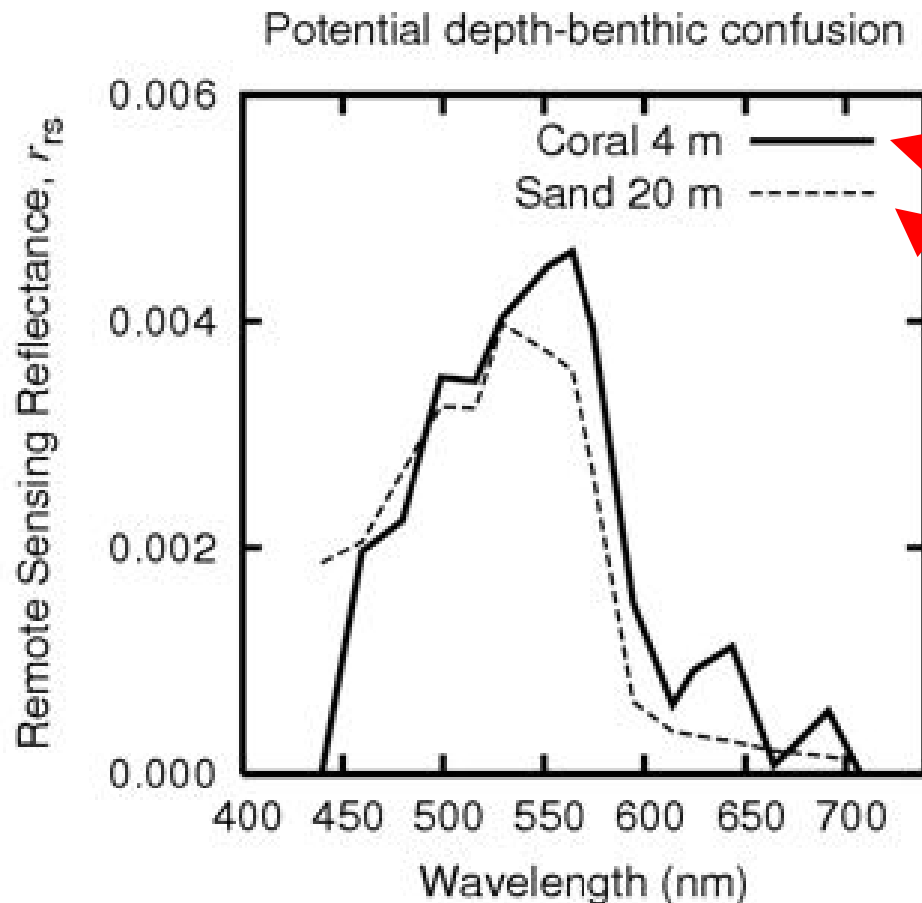
Two potential approaches

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

1. Uncertainty propagation through model inversion

Fundamental uncertainty

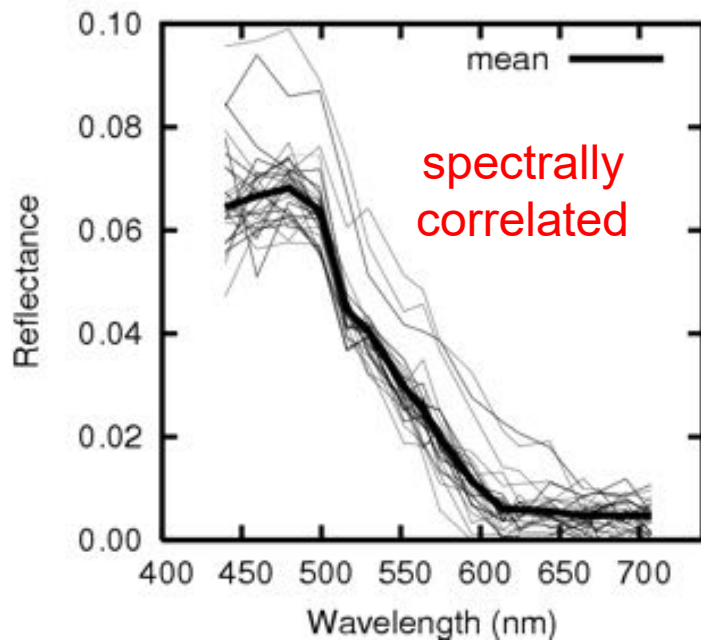
→ similar spectra from differing parameters



Sources of "noise" → uncertainty



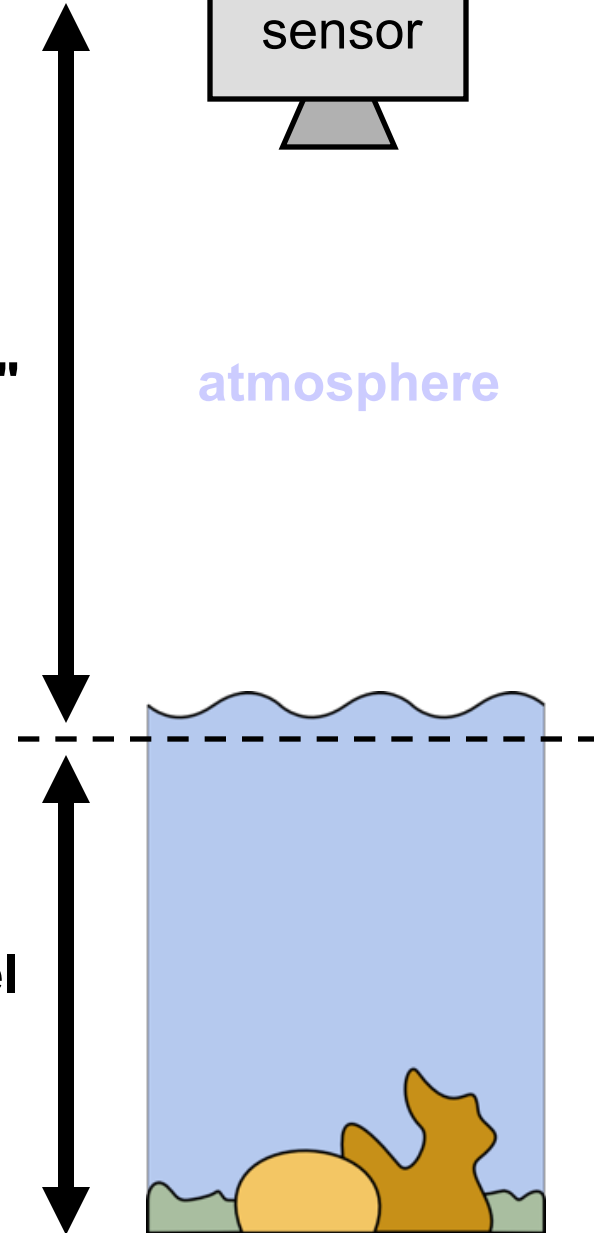
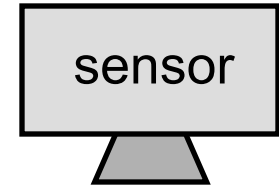
Hyperspectral deep water pixels



"noise"

atmosphere

model



Propagation through inversion

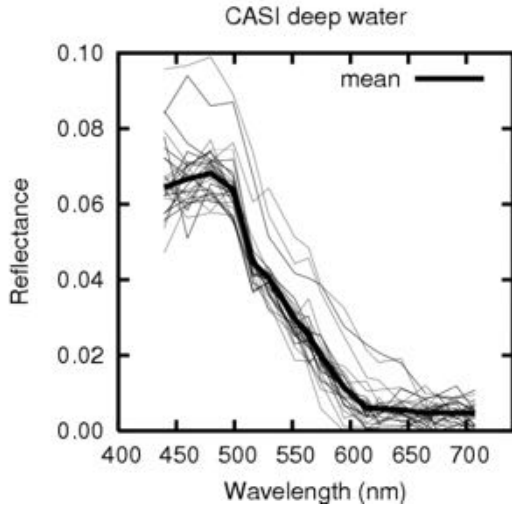
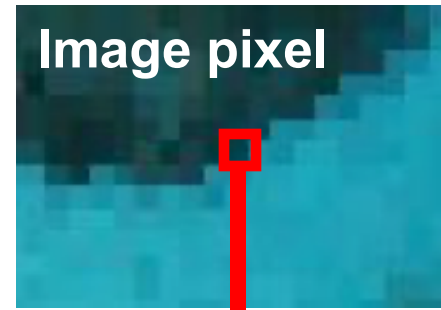


image noise
(multivariate
normal)



add random
noise term $\times 20$ times

20 reflectance spectra

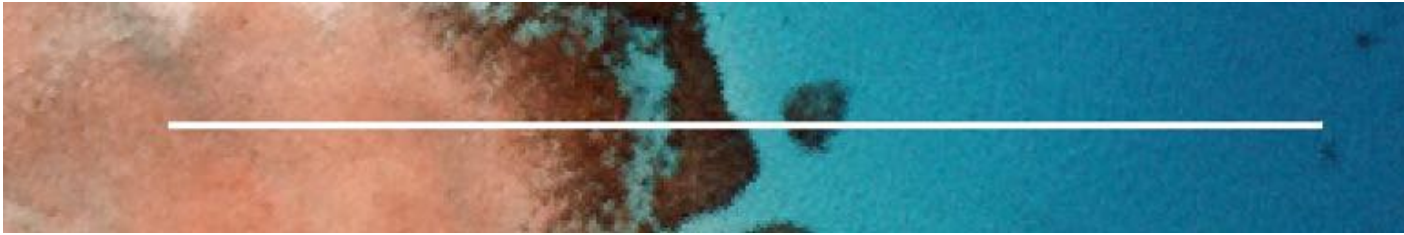
invert to retrieve
parameter estimations

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

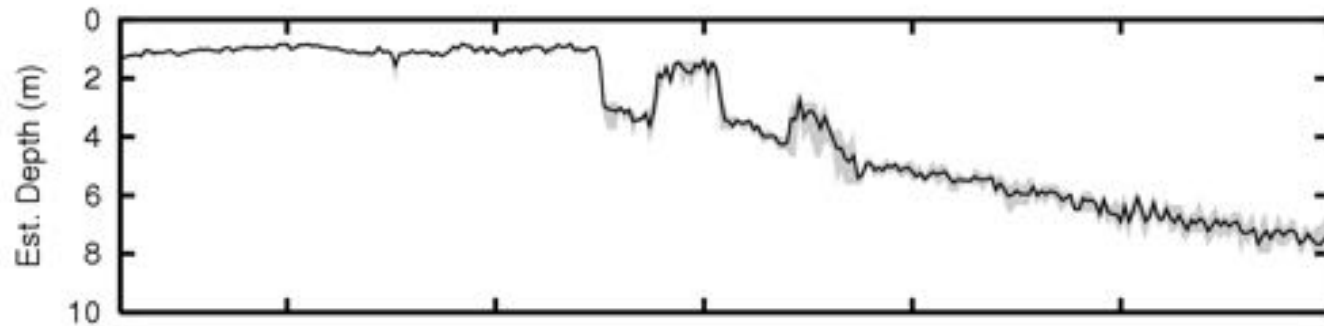
is actually better than direct
single-inversion result

**use mean for
actual result**

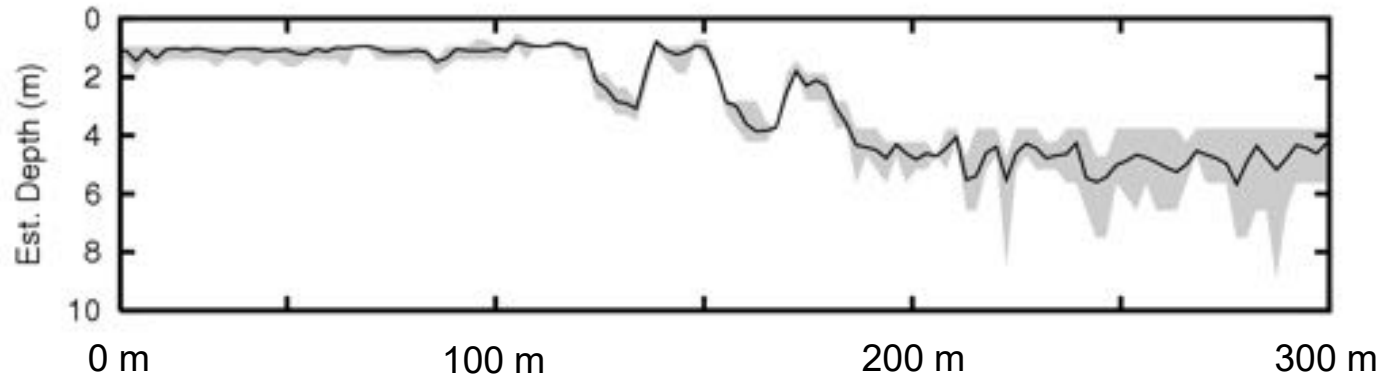
Bathymetry estimation with uncertainty

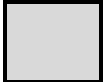


CASI



Quickbird

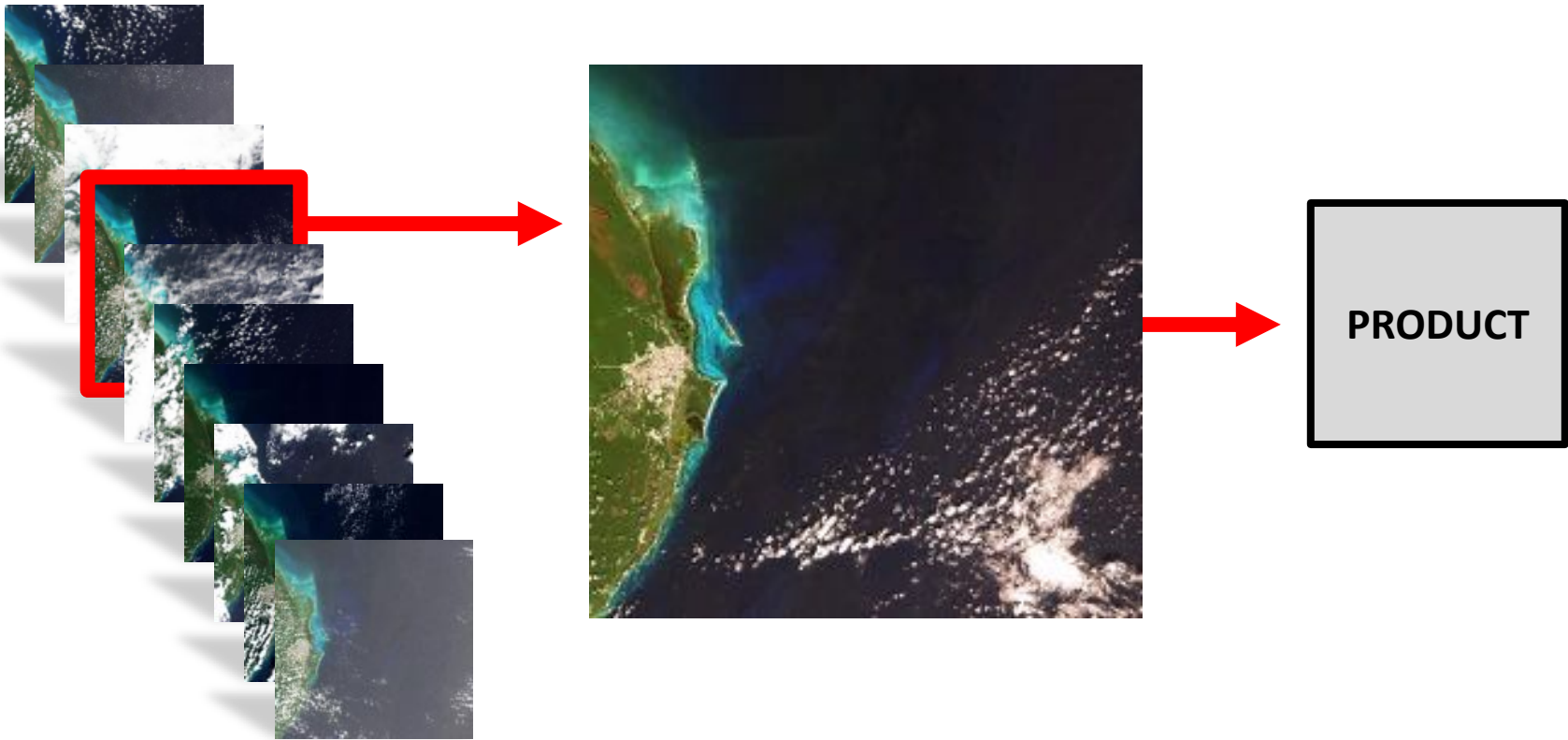


 = 90% confidence interval

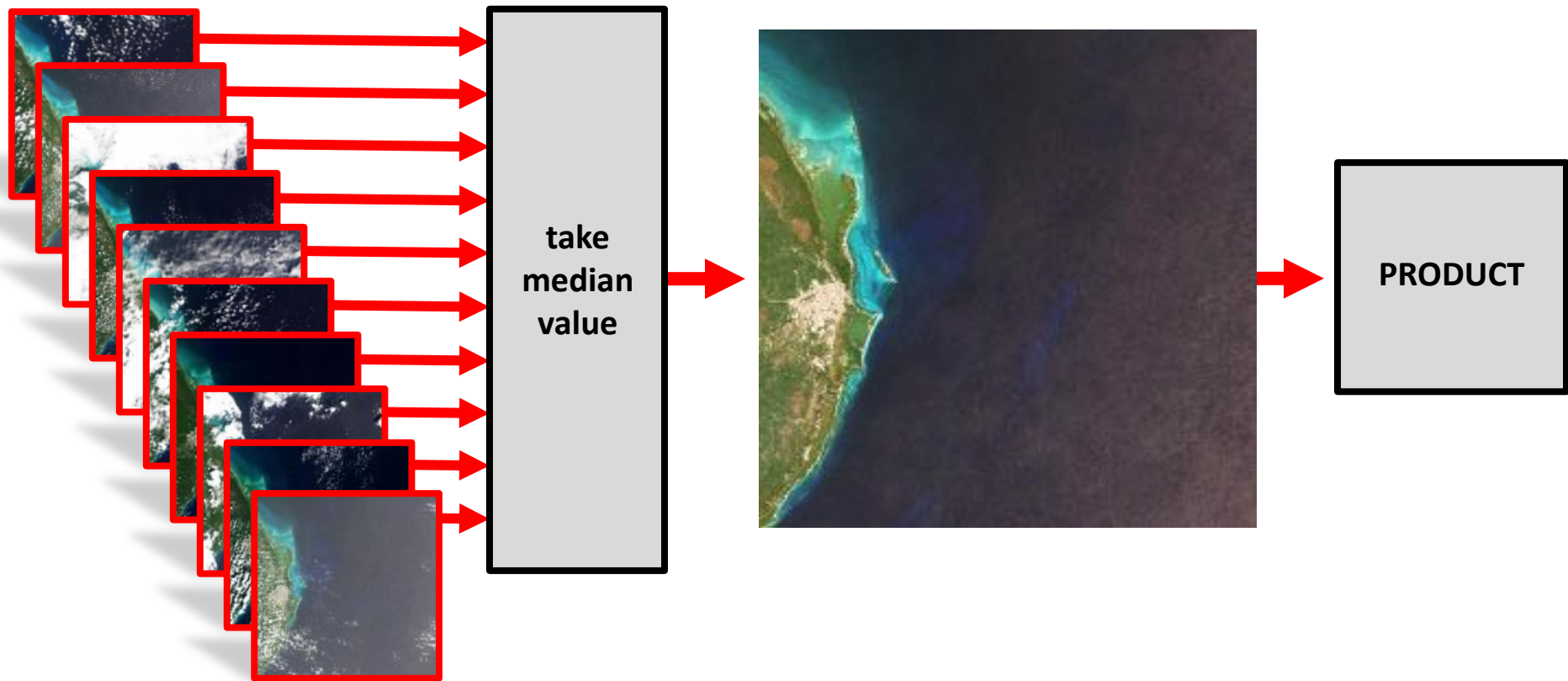
2. Multi-image analysis

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

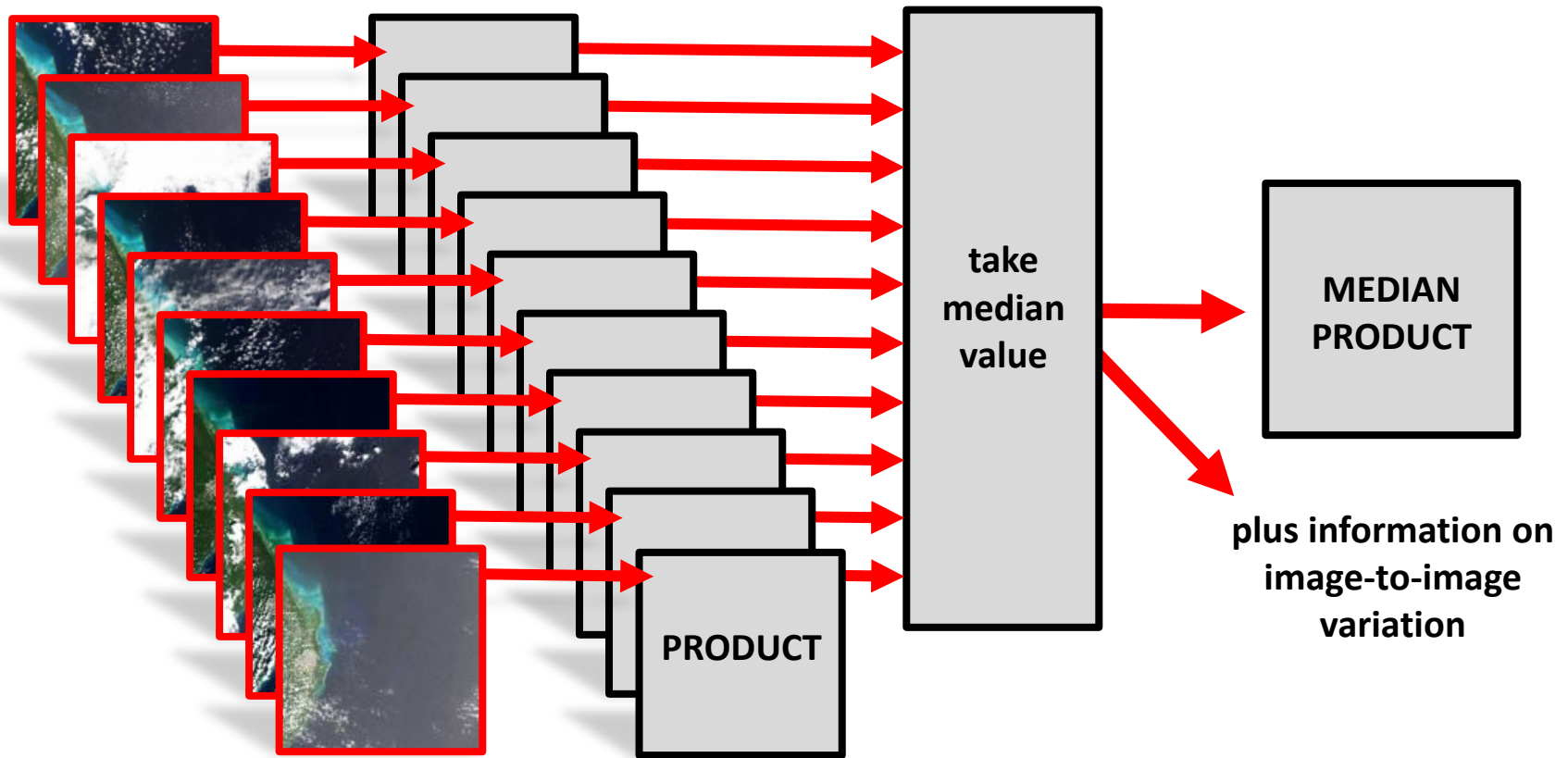
1. Pick a good image



2. Automated – make a median image



3. Automated – median product



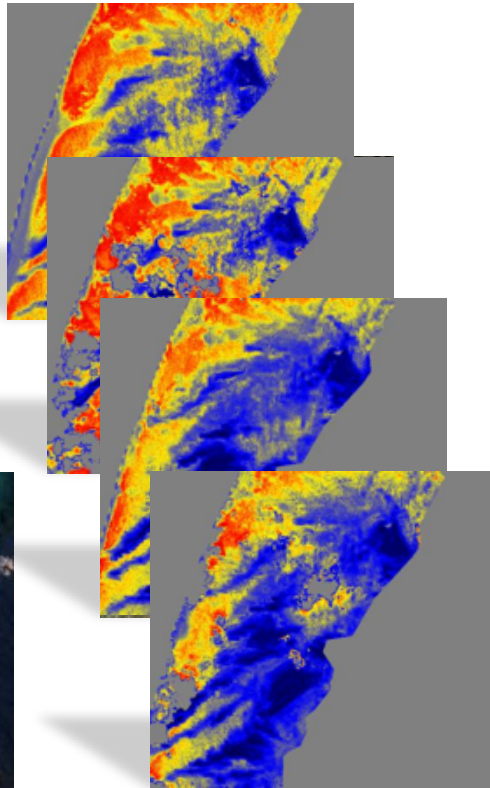
(still a good idea to do cloud screening first!)

Annual median LAI (canopy density)

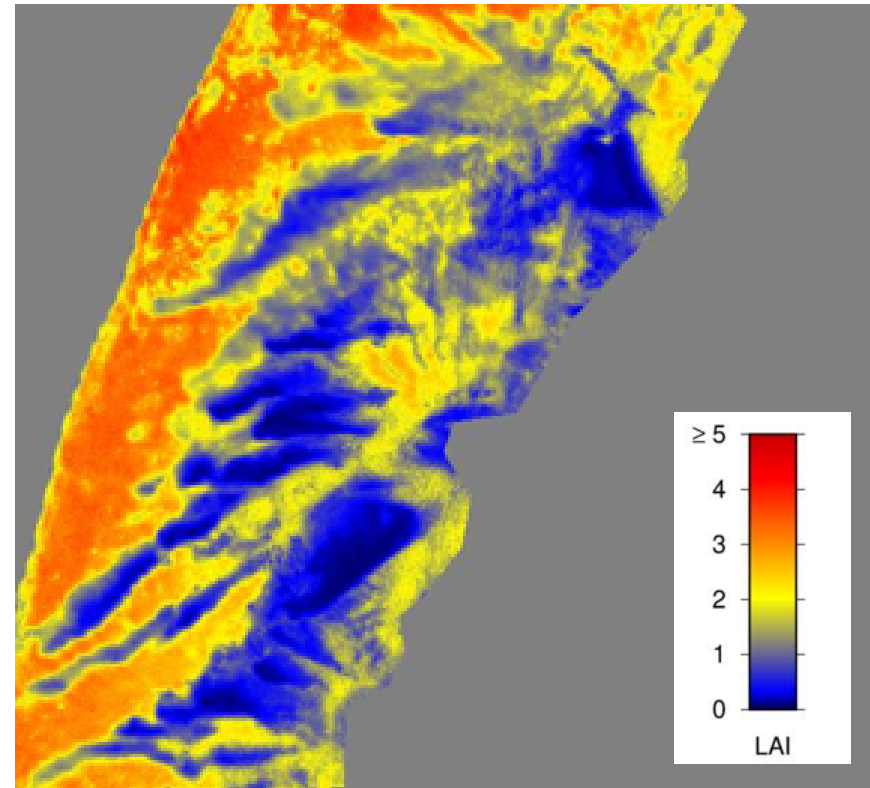
source images



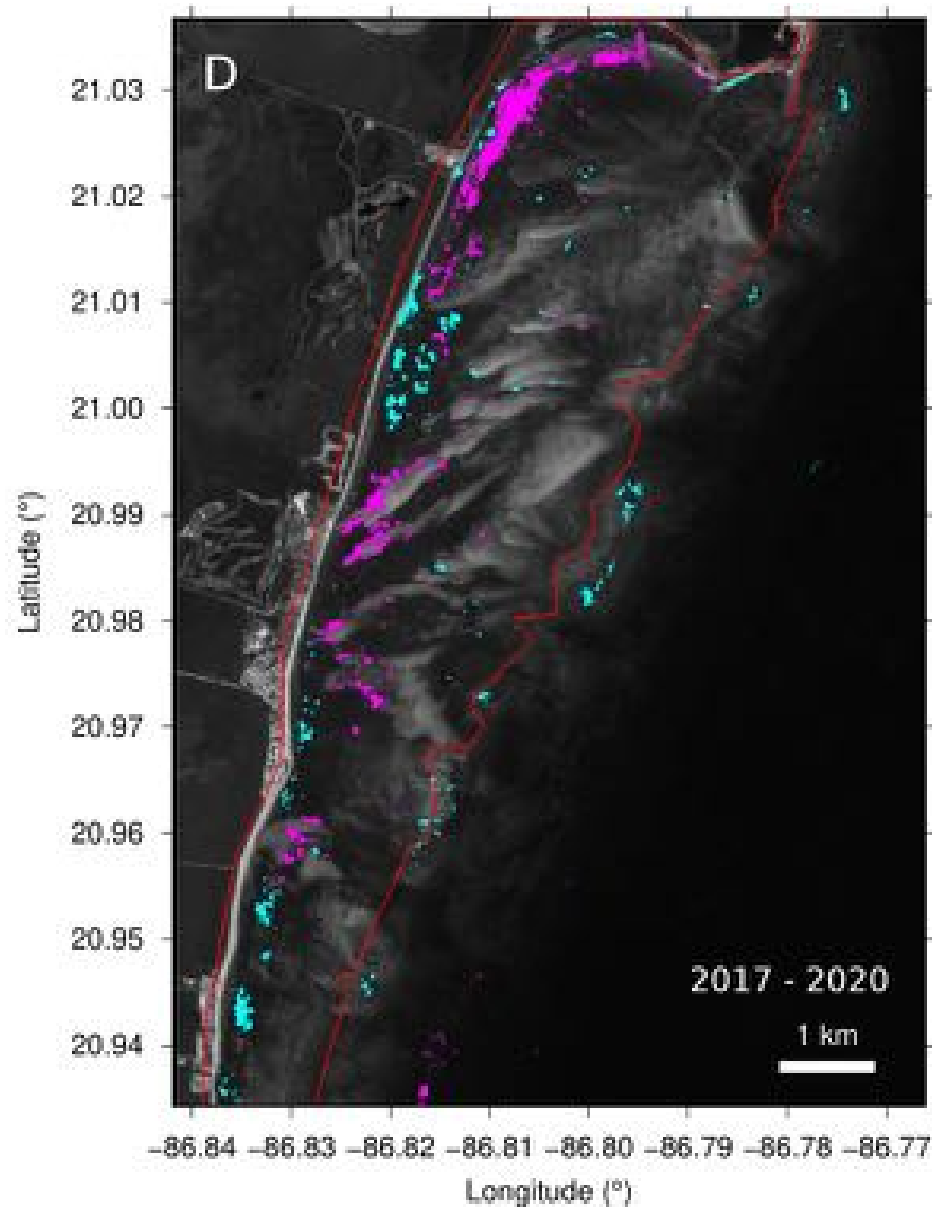
LAI



annual median LAI
(from 65 images)



Change detection in annual median LAI estimates - with statistical test



Increase

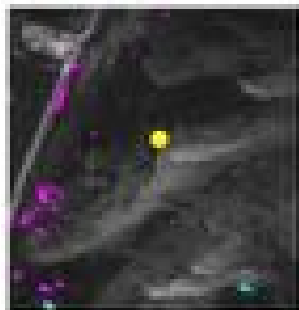
Decrease

$p < 0.01$

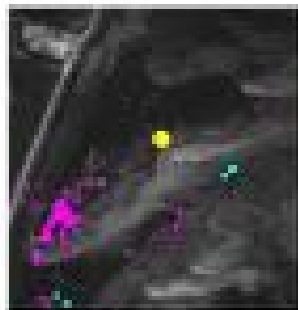
Mood's median test

Detail of one location (yellow dot)

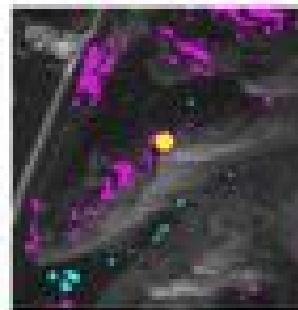
2016 -2017



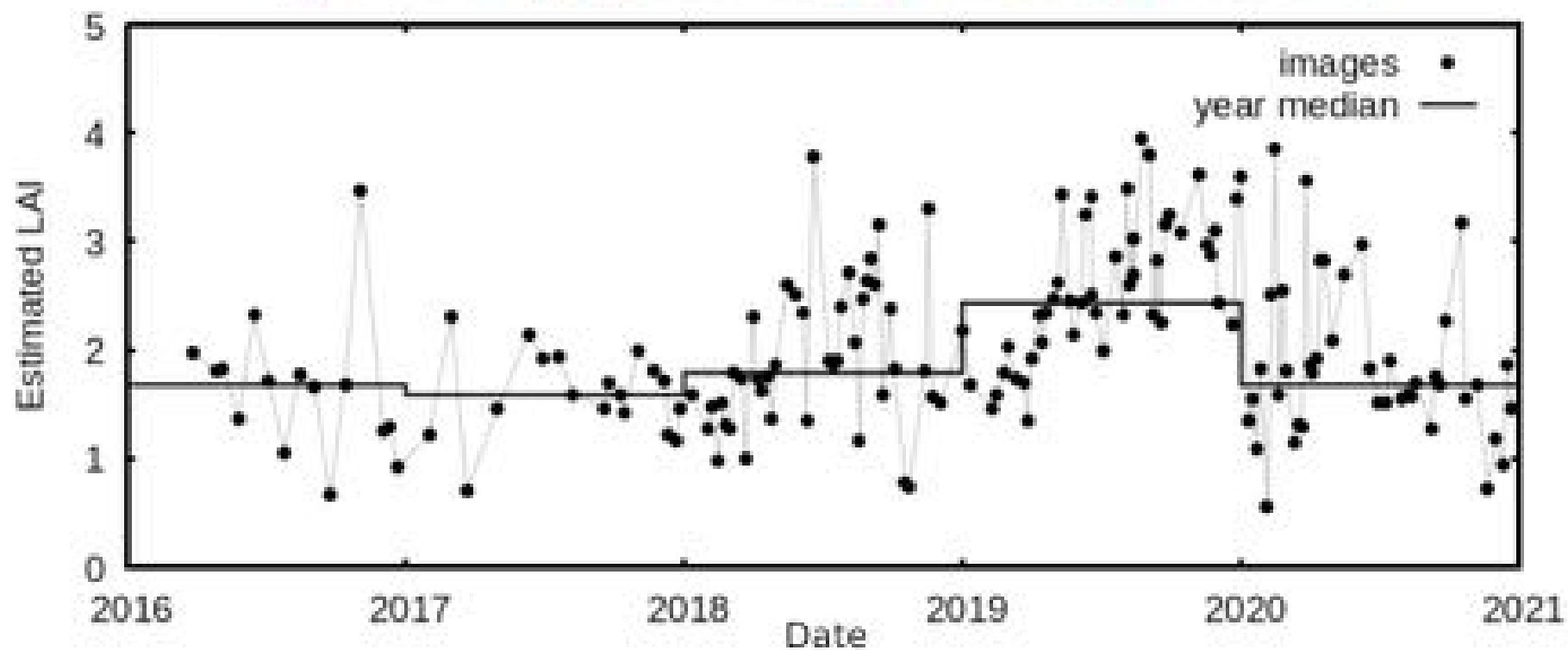
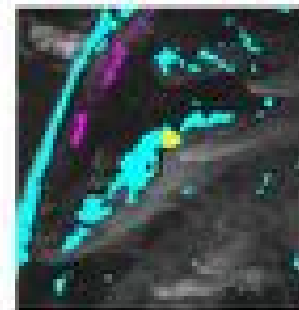
2017 -2018



2018 -2019



2019 -2020



ICESat-2

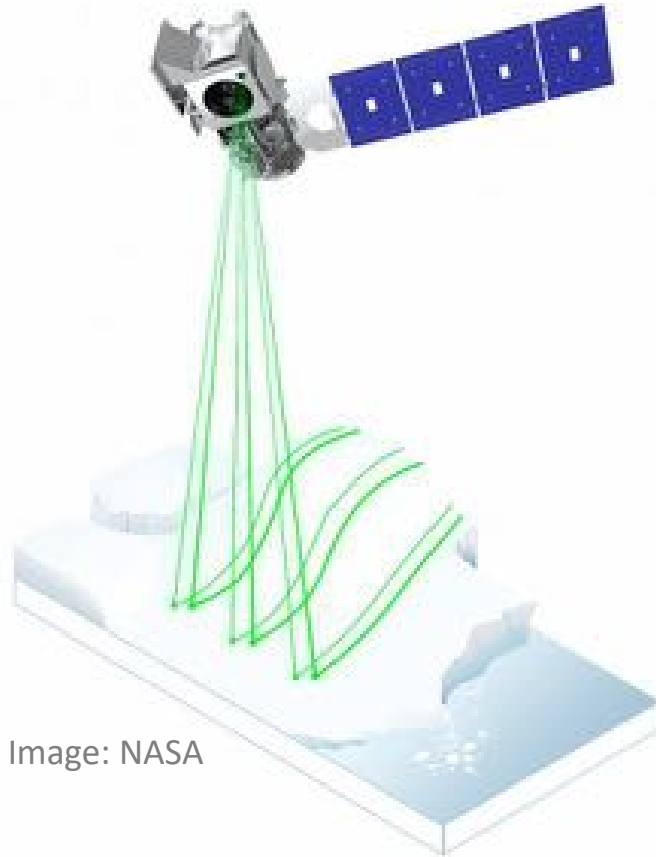
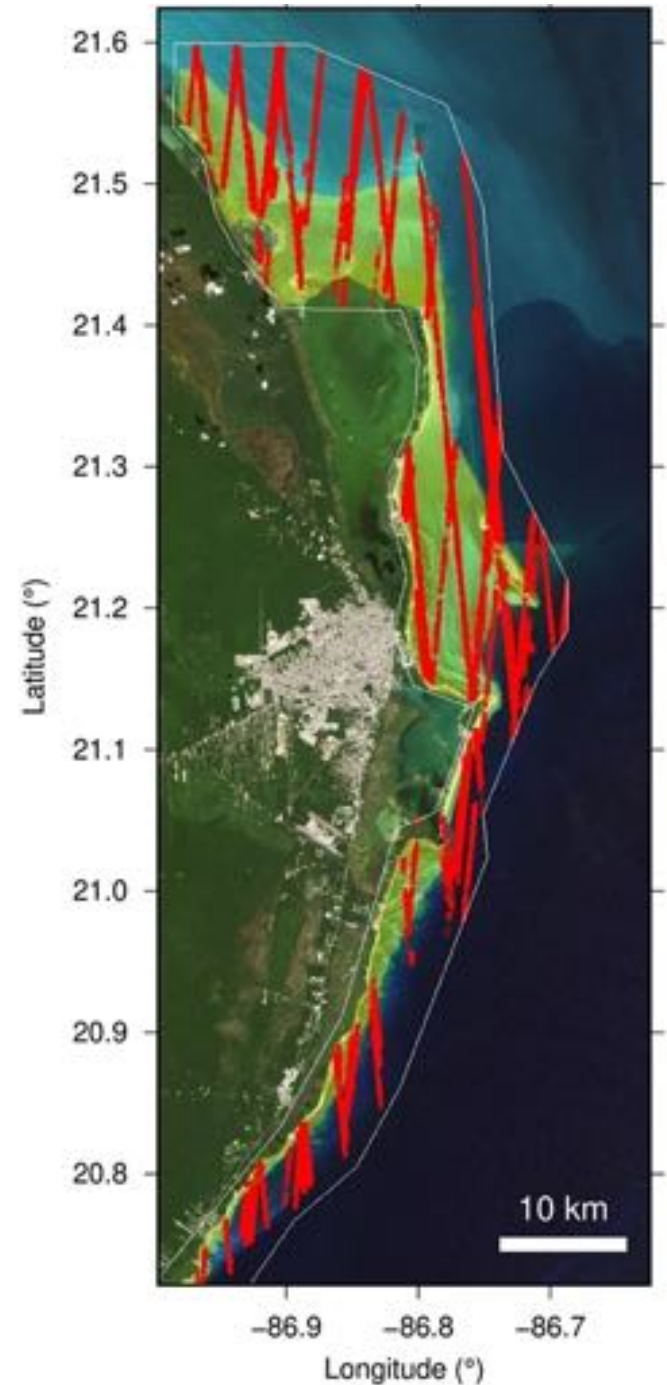
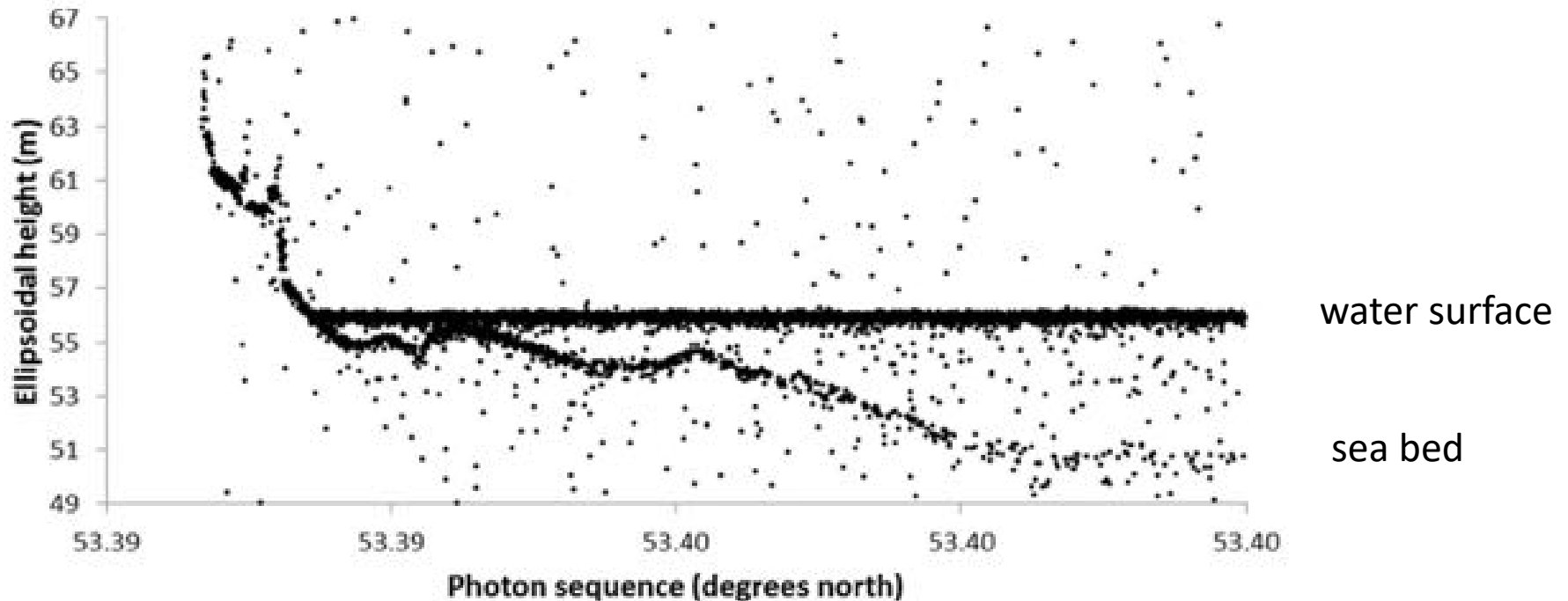


Image: NASA

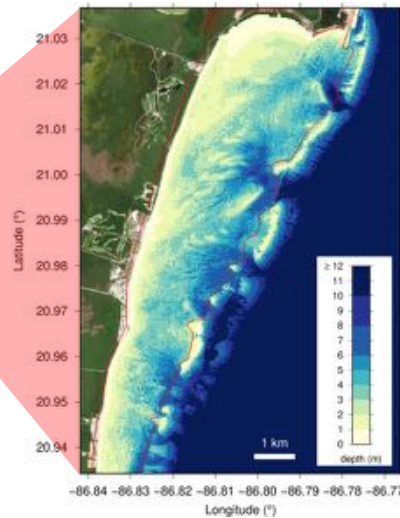
- Space-borne LIDAR
- Launched 15 Sept. 2018
- Global acquisition
- Data freely available on the web
- Possible to extract bathymetry



Typical ICESat-2 data



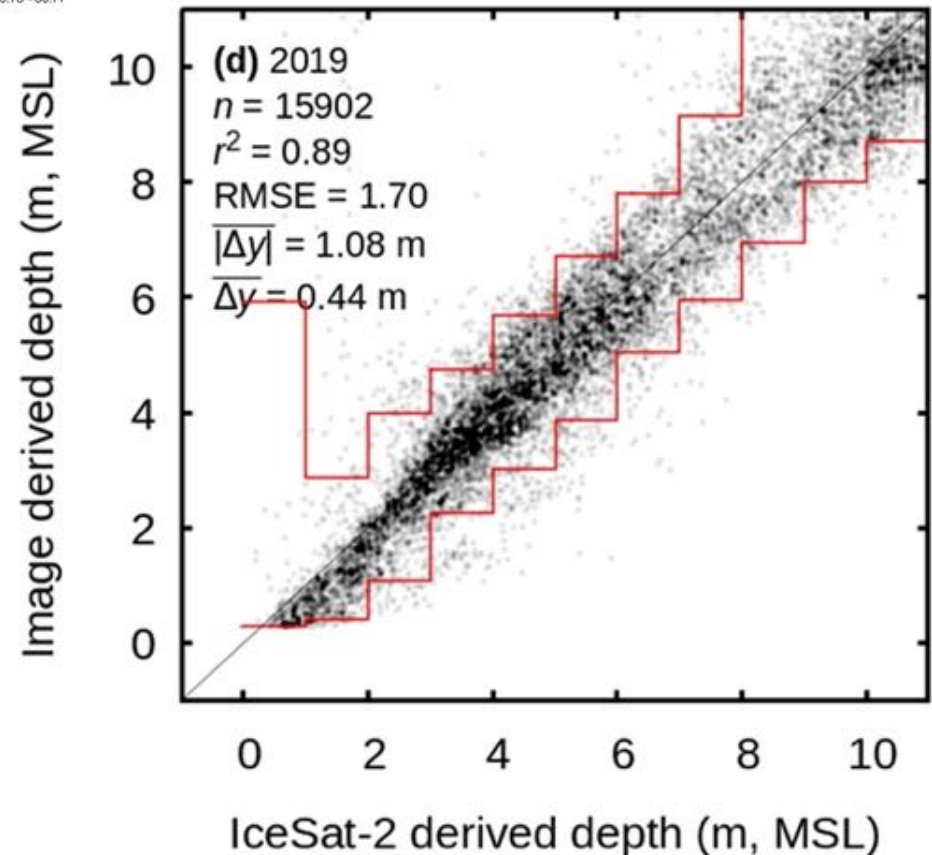
- Under favourable conditions depths to 20 m (or more) can be extracted
- Difficult to automate extraction
- Correct for refractive index, apparent depth is $\sim 1.33 \times \text{depth}$



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

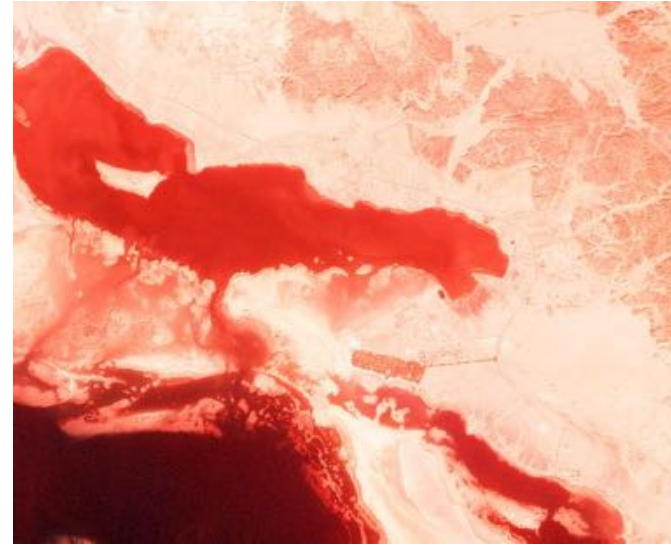


Adjacency effect on model inversion

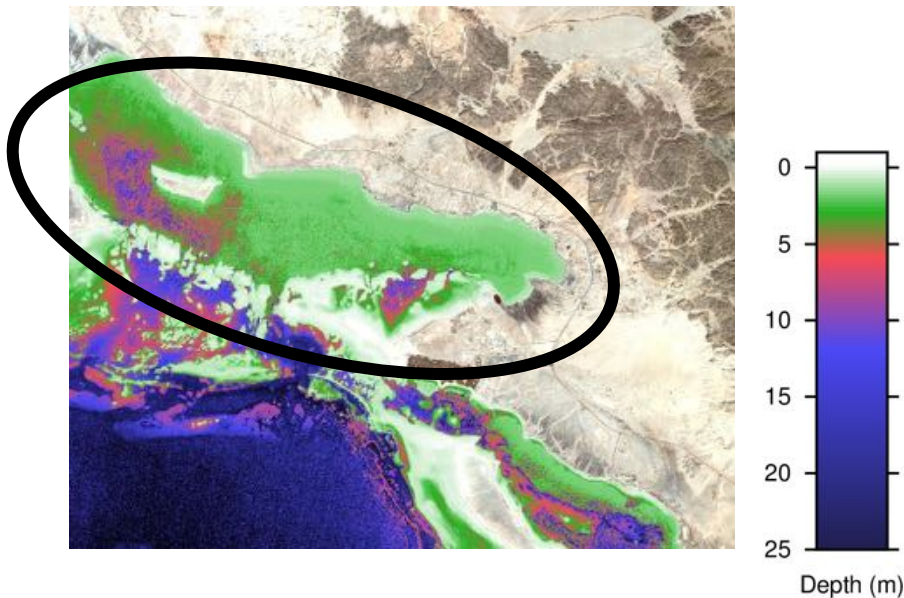
Red sea site - surrounded by bright land



Red stretch applied to RGB image



Bathymetry inversion, bands 1-4 (433 - 680 nm)



Could be a combination of:

- Suspended sediments
- Aerosols from land
- Adjacency effect (scattered land reflectance)

Adjacency effects are a problem for coastal and inland waters, especially when there is bright land next to dark water.

Questions...